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Game Theory based Resource Identification Scheme for Wireless Sensor Networks

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Abstract: In modern world of sensing and distributive systems, traditional Wireless Sensor Networks (WSN) has to deal with new challenges, such as multiple application requirements, dynamic and heterogeneous networks. Senor nodes in WSN are resource constrained in terms of energy, communication range, bandwidth, processing delay and memory. Numerous solutions are proposed to optimize the performance and to increase the lifetime of WSN by introducing new resource management principles. Effective and intelligent resource management in WSN involves in resource identification, resource scheduling, and resource utilization. This paper proposes a Bayesian Game Model (BGM) approach to efficiently identify the best node with the maximum resource in WSN for data transmission, considering energy, bandwidth, and computational delay. The scheme operates as follows: (1) Sensor nodes information such as residual energy, available bandwidth, and node ID, etc., is gathered (2) Energy and bandwidth of each node are used to generate the payoff matrix (3) Implementation of node identification scheme is based on payoff matrix, utilities assigned, strategies and reputation of each node (4) Find Bayesian Nash Equilibrium condition using Starring algorithm (5) Solving the Bayesian Nash Equilibrium using Law of Total Probability and identifying the best node with maximum resources (6) Adding/Subtracting reward (reputation factor) to winner/looser node. Simulation results show that the performance of the proposed Bayesian game model approach for resource identification in WSN is better as compared with the Efficient Neighbour Discovery Scheme for Mobile WSN (ENDWSN). The results indicate that the proposed scheme has up to 12% more resource identification accuracy rate, 10% increase in the average number of efficient resources discovered and 8% less computational delay as compared to ENDWSN.

Index Terms: Wireless Sensor Networks, Resource Identification, Bayesian Game, Nash Equilibrium.

1. Introduction

Wireless Sensor Networks (WSNs) provide major contributions to new emerging areas like the Internet of Everything (IoE), distributed ubiquitous computing and smart systems. Wireless sensor motes are powerful tiny devices that are self-aware and deployed in diverse geographical areas for some multiple applications. Fast computation with accurate results makes modern sensors more powerful than traditional single task enabled sensor motes [1,2,3,4]. Sensors consist of a power supply unit, actuator/sensor, micro-controller and radio antenna. Sensor motes are constrained with resources in terms of processing power, CPU speed, memory, bandwidth, transmission range, and more prone to network failure. In WSN, resource management gets complicated when it is shared for multiple applications [5,6,7,8,9].

In general, resource management applies to all types of networks. Usually, sensor networks are developed without considering resource management techniques. As a result, optimizing the use of existing resources is critical for increasing the efficiency of WSNs. In a realistic environment sensor with multi-tasking, high node density, limited battery capacity, and resource constraints, efficient resource utilization is a challenging task that requires resource identification/discovery, resource allocation, and resource scheduling [10,11,12,13].

Resource Management (RM) is systematic plan using intelligent computing methods for acquiring and storing available network resources considering Quality of Service (QoS) factors [14]. Discovering the appropriate available network resources is defined as resource identification. Resource Identification [RI] is referred to the available number of alive/dead sensor motes, their batteries status, radio resources, bandwidth, and routing information of the WSN [15,16].

In distributed networks resource discovery considers network complexities such as heterogeneity, dynamic nature, and other network resource restrictions with different resource management approaches [17,18]. Computational Intelligent (CI) techniques are effective techniques for addressing WSN's challenges and issues. CI is often a collection of artificial intelligence (AI), bio-inspired algorithms, and other techniques used to address real-time issues. Examples of CI include bio nature inspired algorithms based on plant and animal behavior, evolutionary computation, artificial immune systems, artificial intelligence, game theory, convolutional neural networks, fuzzy inference system approaches, machine learning, deep learning, intelligent multi-agent systems, cognitive agents and so on [19,20,21].

The integration of CI and RM techniques improve the lifetime of a WSN in a resource constrained environment. Advanced intelligent techniques for resource identification helps in uninterrupted services, effective use of resources consistently and accountability [22,23,24,25].

1.1. Game Theory

The game theory refers to the situation of conflict and competition in which two or more players are involved in deciding anticipation of certain results (outcome) over some period. A game is a strategy in which activities are determined by skill or by the chance of the player. Game Theory (GT) is decision making model that is very useful in making complex decisions, where intelligent opponents with conflicting objectives are trying to outdo better [26,27].

The strategy for the player is the list of all possible actions that will take for every outcome (payoff) that might arise. The expected outcome per play (game) when players follow optimal strategy is called the value of the game. The payoff or outcome is quantitative measures of the player gets at the end of the game are discussed in [28,29].

In game theory, reputation is considered as a strategic asset and resulting in the design of a reputational intelligent skill that has the potential to solve critical game [30]. An Intelligent Resource (IR) identification technique based on a non-cooperative game theory strategy for resolving the resource identification problem is solved considering energy and bandwidth [31]. The motivations for using game theory model to solve the resource identification problem in WSN are as follows.

- Game theory intelligence is used to solve real-time complex problems, and to make justified decisions. Some of the benefits of game theory (Bayesian Game Theory) for resource management i.e., efficient node identification with maximum resources in WSN.
- It has been proven in the recent literature that the use of game theory techniques can be used for distributed sensor networks and cloud based WSN to achieve various resource management policies.
- Game theory is used in the design and development of resource management algorithms in WSNs to drop-off energy consumption and maximize packet delivery ratio with utilizing minimum bandwidth and communication delay.
- In heterogeneous and decentralized networks, game-theoretic model can be used to analyze interactions among each node for resource identification in the network.
- The Bayesian game is used to make the distributed decision making process of the individual sensor node in WSN.
- A Bayesian game provides solution based on payoff matrices, utilities, and reputation factor can solve the problem of active node discovery during data transmission in dynamic and heterogeneous WSN.
- The complicated interactions among sensor nodes are considered, and the game theory mechanism is applied to maximize the identification of channel bandwidth for efficient information transmission.

The restrictions for using game theory model to solve the resource identification problem in WSN are as follows.

- It is easy to understand a two-player game. But as the analysis is elaborated to three or four player games, it becomes complex and difficult. However, the theory of games has not been developed for games with more than four players, but most problems involve many players.
- Each player moves on this presumption that his opponent will always make a wise move and then he adopts a countermove. This is an unrealistic assumption because players do not always act rationally.
- The use of mixed strategies in games determinate is unlikely to be found in real time situations. The random choice of strategies introduces secrecy and uncertainty in the game.
- Despite these limitations, game theory is helpful in providing solutions to some of the complex network problems even though as a mathematical technique, it is still in its development stage.

1.2. Problem Statement

WSN is a distributed network made up of hundreds of battery-powered nodes that have a low communication range, limited bandwidth and frequent disconnections owing to dynamic network topology. To increase WSN lifetime by resource optimization should be approached with caution. Due to limited resources, the design of WSN hardware differs from that of distributed networks, resulting in protocols and algorithms that differ from those of distributed networks.

In real-time applications, WSN with high node density, limited battery, heterogeneous applications and dynamic environment is resource constrained. In such situations, effective resource utilization is a challenging job that involves efficient node discovery and resource identification. Hence resource identification problem should be addressed carefully, which refers to the process of discovering resources in the WSN such as the number of alive/dead nodes, their battery status, available bandwidth and other radio resources.

The proposed scheme describes, identification of sensor node with the maximum resources using a Bayesian Game Model (BGM) that considers network resource information such as active/dead nodes, individual node energy and available communication bandwidth. The sequence in which WSN nodes or resources are identified has a significant impact on the overall performance of WSN.

1.3. Our Contributions

The proposed scheme is motivated by several inherent drawbacks of existing resource identification schemes such as less efficient, maximum bandwidth utilization and high computational delay to dynamic network topology. The paper proposes a Bayesian Game Model (BGM) for resource identification scheme using set of node attributes like energy, bandwidth and degree of connectivity with other nodes in the network etc., to identify the efficient node with the maximum resources as winner node of the game. Our contributions to the proposed scheme are as follows:

- Use of Bayesian game technique to deal with WSN incomplete information about the network i.e., uncertainty, and dynamicity.
- Based on the resources like energy and bandwidth of each node that participates in the game is used to build the payoff matrices.
- Implementation of node identification technique is based on payoff matrix, utilities and reputation factor of each node.
- Find Bayesian Nash Equilibrium state in the game using the Starring algorithm.
- Solving the Bayesian Nash Equilibrium using Law of Total Probability and identifying best-of-best node as a winner in the game.
- Adding/subtracting reward (reputation) to winner/looser node.
- Bayesian game mechanism is used for node identification that informs WSN about the availability of the best active nodes in the network with maximum resources, and this critical information is forwarded to nodes to adjust their attributes w.r.t variation in dynamic topology of WSNs.

Rest of the research paper is organized as follows. The literature survey is discussed in section 2. The proposed Bayesian game based resource identification scheme is discussed in section 3. The simulation model, simulation inputs, performance metrics, result analysis, and result discussion are presented in section 4. The conclusion and future work are presented in section 5.

2. Related Works

Artificial Neural Network (ANN) algorithms for resource identification in wireless distributed sensors networks increases sensor motes operating level in terms of sensing and communicating information to the server based on multi-layer perception is presented in [32]. In [33], radio resource management approach for Vehicular Cloud Networks (VCN) employing the Honey Bee Optimization (HBO) scheme integrated with multi agent mechanism is presented. The vehicle mobile agent gathers cloud data, while the vehicular static manager agent intelligently determines the vehicle's required resources.

Hybrid resource identification technique based on Soft Set Symbiotic Organisms Search is presented in [34]. The algorithm handles unpredictability concerns in static and dynamic systems quite effectively. The scheme is efficient in dealing with unstable situations to pursuit optimal solutions.

The Cloud Resource Discovery using Cognitive Intelligent Technique (CRDCIT) is presented in [35]. CRDICT method improves resource availability and reduces resource identification latency. Blockchain based Inter-Cloud Resource Discovery (BIRD) framework for the non-federated inter-cloud is employed in the secure resource identification and selection process, which eliminates the requirement for a trusted third-party or broker between sharing Cloud Service Providers (CSPs) is discussed in [36].

Resources identifying and organizing in Vehicular Cloud Networks (VCN) is presented in [37]. The roadside unit and vehicle centered resources are discovered in the scheme based on their usage priority. In [38,39] authors presented the solution for power conservation in WSNs, by discovering the best neighbor node schemes, considering energy as an important factor of the node. The average power consumption of each node is dependent on its degree of connectivity to the neighboring nodes in the network.

In clustered based WSN, faulty/malicious node is identified using mobile agents [40]. The proposed scheme operates in two steps: in the first step resources information of the node are collected using mobile agents and verification of the available information is cross verified with the database using a static verification agent.

An efficient neighbor node identification scheme for mobile WSN, based on available resources like bandwidth and battery of the sensor motes is presented in [41]. Based on the resources identified, nodes are classified into active and passive nodes in the network. The probabilistic neighbor identification technique is used to identify the best node with maximum resources for sensing and communication from set of active and passive nodes.

In wireless networks, Repeated Bayesian Game (RBG) is used for resource management and security purpose considering the available resources such as power, bandwidth, and degree of connectivity, etc. The RBG model is used to capture the interactions between the nodes and macro base stations to compute the best strategies for resource discovery and allocation with security attacks is presented [42,43].

In Cognitive Wireless Sensor Networks (CWSNs) resource discovery and allocation using intelligent reasoning and learning model are proposed in [44]. Dependency relationship is built using BNM for optimum utilization of energy and bandwidth, to maximize the WSN life span. In [45], the authors investigated a balanced model of emergency information dissemination using Bayesian Game Model [BGM] with a mixed strategy to improve network lifespan in WBAN.

The network uncertainty due to limited resources on the Internet of Battle Things (IoBT) is solved using Bayesian Game formulations. The energy, limited bandwidth, and less communication ranges of IoBT sensors are considered to construct a payoff matrix. BGM is potential, and guarantees to find a Nash Equilibrium (NE) of the game is proposed in [46]. Each node's transmission power level reduces the communication interference and keeps energy consumption to a minimum level using Bayesian Nash Equilibrium (BNE) [47]. The convergence of the dynamics of return functions to the Bayesian Nash Equilibrium under reasonably wide topological assumptions is thought to address the resource problem in the distributed network [48,49].

Table 1. Summary of Resource Identification Schemes in WSN

Resource Identification Scheme	Mechanism Used	Type of Network	No. of Resources Identified	Resource Identification Complexity	Computational Delay	Resource Identification Accuracy	Overall Performance
IR [31]	Resource identification using non cooperative game theory	WSN	More	Medium	Low	Medium	Better
ANN [32]	Resource discovery using artificial neural network	WSN	More	Less	Low	High	Good
HBO [33]	Intelligent agent integrated with honey bee optimization scheme	VANET, VCN	Medium	Less	High	Less	Good
SSSOS [34]	Hybrid resource identification scheme	Cloud, IoT	Medium	Less	Medium	Less	Good
CRDCIT [35]	Cognitive intelligent technique is used to identify resource	WSN, Cloud, Edge	Medium	Medium	Medium	Moderate	Good
BIRD [32]	Blockchain based inter/intra cloud resource discovery	WSN, Cloud	High	Medium	Medium	High	Good

Table 1 shows existing resource identification schemes using different computational intelligence algorithms and highlights the benefits and limitations of existing protocols. The following are the inherent drawbacks of current research work on resource discovery and node identification in WSN: effective resource discovery in a network with limited resources, efficient resource identification over a diverse and dynamic network topology, inability to handle resources appropriately in unpredictable node density in mobility conditions, maximized computational delay, and complex computational methods.

The rapid advancement of technology necessitates the use of intelligent strategies to manage available resources in WSN for effective resource identification in order to achieve high performance and increase the lifespan of WSN. To accomplish this, an efficient procedure based on the Bayesian Game Model (BGM) is defined. The proposed scheme addresses the difficulties in effective resource management for WSNs, considering high node density with multi-tasking capabilities, low battery, less bandwidth for communication, and so on.

3. Proposed Work

In this section, we describe WSN environment considered for efficient resource node identification in WSN.

3.1. Network Architecture

Fig. 1, shows the typical WSN architecture considered for our proposed node identification scheme and it comprises sensors nodes (N1-N10) that are battery operated with built-in sensing and processing unit, restricted battery, sensors are equipped with GPS receiver for obtaining location and time of the node, and a communication device using Dedicated Short Range Communications (DSRC).

The base station's location is chosen in such a manner that it is connected to the WSN, consuming less power for sensing and transferring the information. The information gathered by the nodes is communicated via gateway and base station to outside world through the Internet using a single/multi-hop technique. Each node's transmission range is limited to a certain distance, limiting direct connection with sink node in the sensor network. As a result, it necessitates the use of intermediary nodes in order to connect with the sink node. Neighboring nodes are defined as nodes that are within the transmission range of that specific node, allowing it to connect directly without the use of an intermediary node.

When an event occurs in the network, source node (N1) senses the change, gathers the relevant sensed information, and then forwards it to the distant sink node (N9) through intermediate nodes N4-N7 and to external world via base station. The base station in the network has information of the all sensor nodes; such as each node ID, there residual energy, available bandwidth for communication, and channel capacity to transmit and receive the data with varying bit rate. To perform sensing, computing and forwarding the information, we have to identify the best node with maximum resources so that information delivery is guaranteed to the base station.

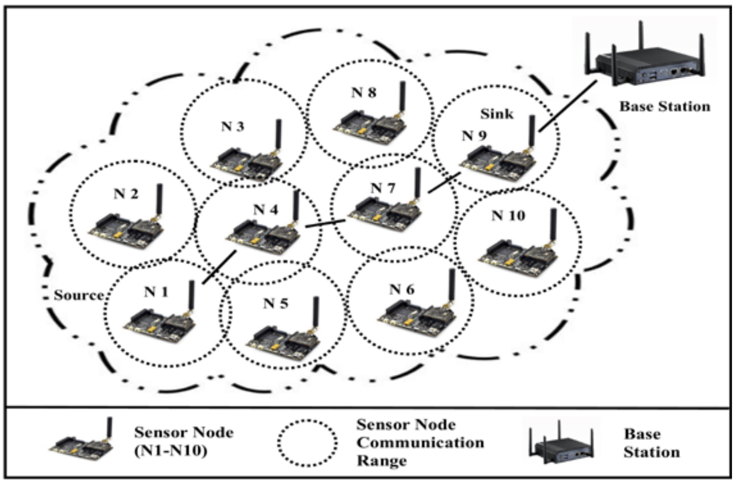

Fig.1. Wireless Sensor Network Architecture.

3.2. Preliminaries

In game theory, a game consists of N players; each player selects a strategy from a set S. The objective is in maximizing the utility U to win the game and increase their reputation factor. Proposed Bayesian Game is described using empirical model and case studies considering incomplete information about the players and game. A node discovery using game theory can be modeled as:

N = (N1, N2, N3, ... Nz), where *N* is a set of sensor nodes;
A = (A1, A2, A3, ... Ai), where *A* is a set of available actions for a sensor node to finalize a decision, example (N_1 has an action A_1);
S = (S1, S2, S3, ... Si), where *S* is a set of strategies, example (N_1 chooses a strategy S_1);
U = (U1, U2, U3, ... Ui), where *U* is a pay-off set (matrix), payoff matrix contains numerical values generated from the strategy profile.

Some of the definitions that will help in proper understanding and visualization of proposed scheme are as follows:

a) ***Bayesian Game Model***: In Bayesian game players have incomplete information about the other players. A player for example may not know the actual payoff functions of the other players, but instead have set of beliefs about payoff functions. A probability distribution over the possible payoff functions is used to express these beliefs.
b) ***Players:*** A strategic decision-maker within the context of the game, here a sensor node is considered as a player.
c) ***Strategy:*** A comprehensive plan of action that a player will employ in response to a set of situations that may

emerge throughout the course of the game. A strategy is an algorithm for playing the game, instructing a node what to do and what not do in every possible circumstance throughout the game. Strategies are rules that govern what action to be taken in response to any possible information throughout the game.

d) ***Payoff:*** The numerical value is assigned to the resources of each node.

e) ***Payoff Matrix*****:** A payoff matrix in Bayesian game theory is a table in which the strategies of one node are given in rows and those of the other node are listed in columns, and the cells represent payoffs to each node. The payoff is determined by the parameters/attributes of the node in the context of a game.

f) ***Utility:*** The numerical value is assigned to each node in the game during the terminal state.

g) ***Bayesian Nash Equilibrium:*** A pair of strategies of nodes in the game is said to be at a Nash equilibrium state if neither node can increase/decrease their expected payoff by unilaterally deviating from their strategy.

h) ***Starring Algorithm:*** The starring algorithm is used to identify the Bayesian Nash Equilibrium condition of the game by considering the payoff matrix and strategies of the nodes.

i) ***Law of Total Probability:*** It states that summation of individual nodes payoff for a strategy made in the game, multiplied by the probability of the game's outcome.

j) ***Reputation Factor:*** A measurable entity that is added/subtracted to the winning or losing node that participates in the game. The reputation factor of each node is updated after the result of every game.

3.3. Bayesian Game Model (BGM) for Node Identification

Fig. 2, shows the working of the proposed scheme i.e. identification of efficient node with maximum resources available for sensing, processing, and forwarding the information in the WSN. The proposed model uses of Bayesian game mechanism to deal with uncertainty, dynamicity condition, and incomplete information about the WSN.

Initially, parameters like energy, bandwidth, number of nodes and degree of their connectivity, their computational capabilities, and other resources of each node present in the network are recorded in form of data set in a base station and it is updated periodically to each node present in the network. BGM uses these data set to build the payoff matrices of the nodes that participate in the game. Construction of payoff matrix is based on the resources of the nodes like energy `E' \& bandwidth `B' and utility values assigned to these resources. Based on the payoff matrices, utilities, and reputation factor of each node the strategies are made by each node that participates in the game. Based on the strategy profile of each node and by using the Starring algorithm Bayesian Nash Equilibrium state is identified. Solving the Bayesian Nash Equilibrium using Law of Total Probability and identifying best-of-best node as a winner node of the game. Adding/subtracting rewards (reputation factor) to winner/loser node and update their database after each game.

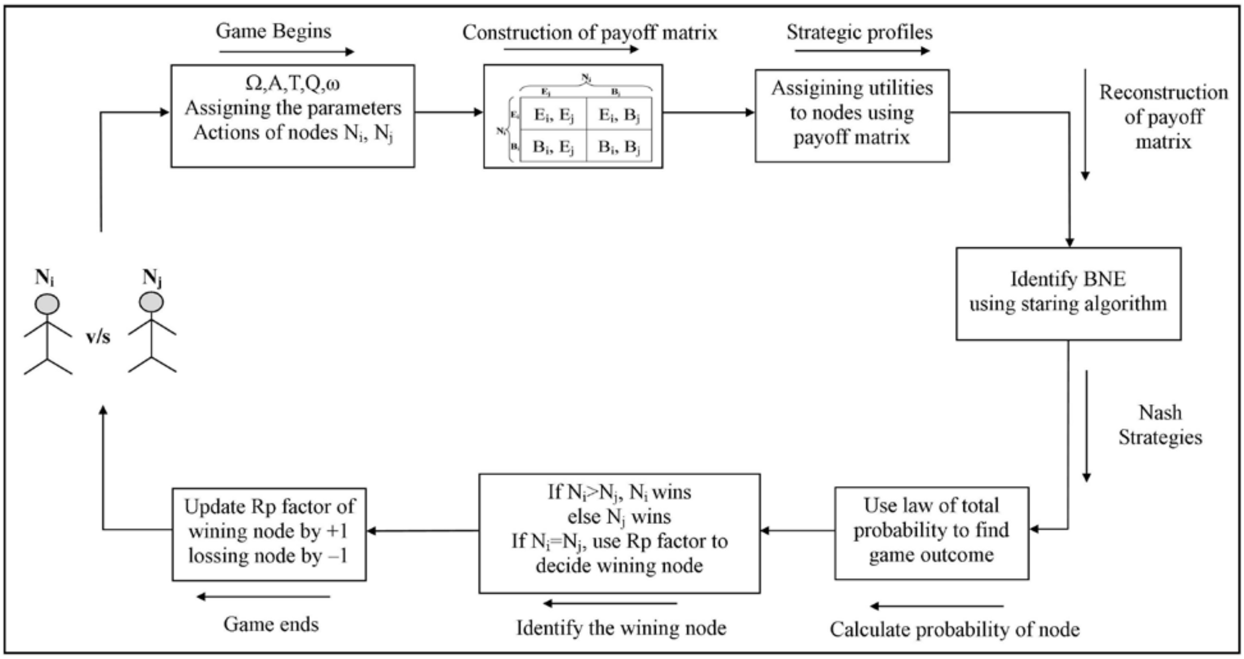

Fig.2. Proposed Bayesian Game Model.

The proposed Bayesian game mechanism is used to inform WSN about the availability of the best active nodes in the network with maximum resources, and this information is conveyed to WSN to adjust their parameters w.r.t variation in environment/topology. Incomplete information of dynamic and distributed WSN is considered for efficient sensor node discovery based on the parameters of each node such as active nodes, remaining energy, the available bandwidth for communication and degree of connectivity, etc. Bayesian Game Model is represented by ``G'' as is shown in (1).

$$G = (N, \Omega, P, R_p, (A_i, U_i, T_i, t_i, Q_i)_{i \in N}) \tag{1}$$

Where,

N = Set of sensor nodes in WSN, $N = (1, 2, 3, ... z)$
Ω = Nature of each node in WSN
P = Probability distribution over W
R_p = Reputation factor of each node
A_i = Action set of node a
U_i = Payoff matrix
T_i = Set of types of parameters for node a is having
Q_i = Set of segregated nodes in WSN
i = One sensor node from set of N nodes in WSN i.e. $i \in N$

By the set of resources available in the network such as active nodes, residual energy, bandwidth etc., the node *'i'* is the given by the function. Where for set of parameters T_i the game will have different types of nodes i.e. t_i as shown in (2).

$$t_i : \Omega \rightarrow T_i \tag{2}$$

Based on set of actions of nodes A_i, resources T_i, and nature of sensor node **Ω**, the payoff matrix U_i belongs □ is represented as a function shown in (3).

$$U_i : (T_i^* A_i) \rightarrow \Re \tag{3}$$

The probability of the game is written as shown in (4). Where, probability P contains Q_i for all $i \in N$ and $\in \Omega$.

$$P[Q_i(\omega) > 0] \tag{4}$$

Throughout the game we restrict attention to incomplete information of WSN and sensor nodes parameters, where every information set of each node is possibly the same as shown in (1), (2), (3) & (4) respectively.

The payoff matrix for node/resource identification using Bayesian game is constructed considering the node's parameters such as energy 'E' and bandwidth 'B'. We assume that each sensor node has different bandwidth and energy levels, so we have assumed the range of energy and bandwidth from low to high as shown in (5) & (6) respectively.

$$E = (Low, Medium, High) \tag{5}$$

$$B = (Less, Medium, High) \tag{6}$$

Based on the energy and bandwidth values of the payoff matrix, the nodes make the strategies to gain maximum utility value to prove that it is the best node with maximum resources. Utility is numerical value assigned to each node in the game during terminal state, i.e. $+n$ add for node with high energy/ bandwidth and $-n$ subtracted for the node if its energy/bandwidth is less than other node, where *'n'* ranges between $(-n, ..., -3, -2, -1, 0, +1, +2, +3 ..., +n)$. Strategies *'S'* is made once again and is given by the function as shown in (7).

$$S_i : T_i \rightarrow A_i \tag{7}$$

A strategy of node n1's Vs. the strategy of nodes n2's to gain the highest payoff or utility is a Nash Equilibrium if node 1 strategy is the best response to what node 2 does and vice versa.

The situation modeled in this game is between two nodes N_i and N_j, where $(N_i$ & $N_j \in N)$, $(i \neq j)$ and $(N_i$ & $N_j)$ have different range of energy and bandwidth. Considering the utilities assigned to each node, the payoff matrix is reconstructed as shown in the fig. 3a.

During the game at certain strategies (values of energy and bandwidth) of the nodes, game entry into quasi-state called as Nash Equilibrium (NE) state. A pair of strategies made by nodes in the game is said to be at NE state i.e. neither node can increase/decrease their expected payoff by unilaterally deviating from their strategy.

To identify Bayesian Nash Equilibrium (BNE) state we use the "Starring Algorithm", considering different dominant preferences i.e. parameters such as energy and bandwidth of the nodes participating in the game. The starring algorithm works as follows: 1) For each column, add an asterisk '*' superscript to the highest value corresponding to node Ni payoff in that column. 2) For each row, add an asterisk '*' superscript to the highest value corresponding to node Nj payoff in that row. 3) Any cell which has two asterisks '*' is considered to be in BNE state, as shown in fig. 3b, 3c, & 3d, with different dominant resources as strategies in each case.

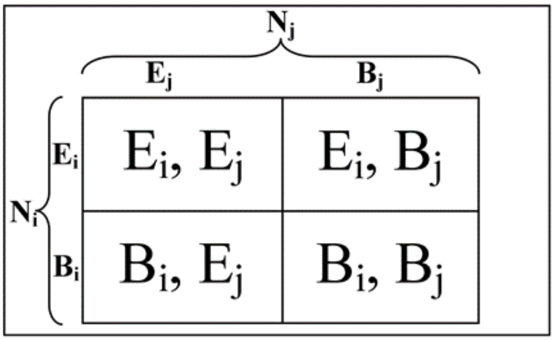

Fig.3a. Payoff Matrix.

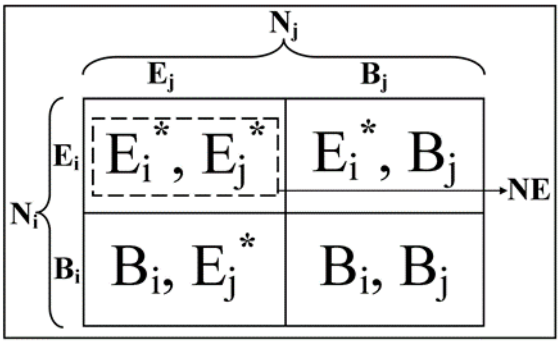

Fig.3b. Payoff Matrix, NE with Energy as Dominant Strategy.

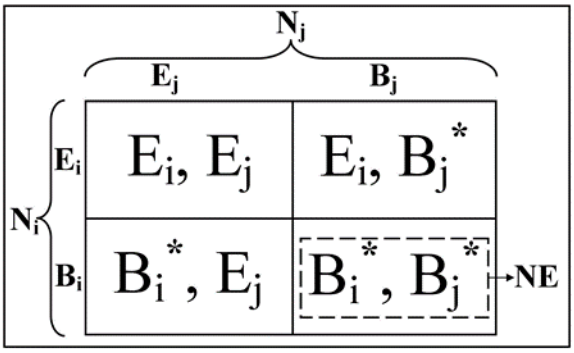

Fig.3c. Payoff Matrix, NE with Bandwidth as Dominant Strategy.

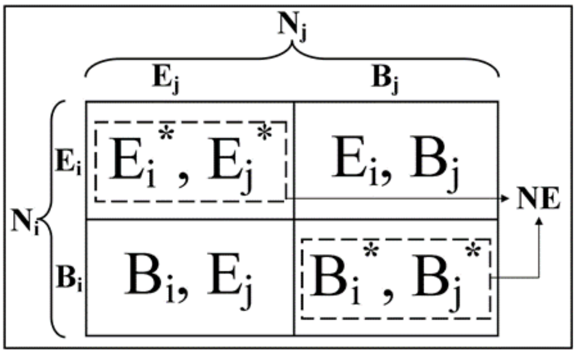

Fig.3d. Payoff Matrix, NE with Energy & Bandwidth as Dominant Strategy.

Further the BNE is defined as strategy profile that maximizes the expected payoff of each node given their beliefs and given the strategies played by other node. A strategy profile for node N_i is a Q_i is a measurable function as shown in (8).

$$\sigma_i : \Omega \rightarrow \Delta(A_i) \tag{8}$$

Where $\sigma_i(A_i \mid \omega)$ is the probability that action A_i for node '*i'* is chosen ω under σ_i and $\omega \in \Omega$. The strategy profile is a function $\sigma = (\sigma)_{i \in N}$, where σ_i is strategy of node *i*. We write $\sum$ for collection of such strategy profiles. We denote the same for node *'j'* $\sigma_j(A_j \mid \omega)$.

We extend the domain of each U_i to mixed strategies and thus write $U_i(\sigma(\omega), \omega)$ for $\sum_{Ai \in A} U_i(A_i, \omega)(A_i \mid \omega)$. Now the payoff strategy profile σ of node *'i'* is given by the expected utility as shown in (9).

$$\sum_{\omega \in \Omega} \sum_{A_i \in A} U_i(A_i, \omega) \sigma(A_i \mid \omega) P(\omega) \tag{9}$$

A strategy profile ω is a Bayesian Nash Equilibrium for the game 'G' for all $A_i \in A$ and $\omega \in \Omega$, is shown in (10).

$$\sum_{\omega' \in Q_i(\omega)} U_i(\sigma(\omega'), \omega) P(\omega' \mid Q_i(\omega)) \geq \sum_{\omega' \in Q_i(\omega)} U_i(A_i, \sigma_j(\omega'), \omega') P(\omega' \mid Q_i(\omega))) \tag{10}$$

In the case of Nash Equilibrium from equation (10) further, the game is solved using the Law of Total Probability (LTP). It is used to find the probability of a game when we don't have enough knowledge about players. The Law of Total Probability is a basic rule that connects marginal and conditional probabilities. It indicates the entire likelihood of an event that may be attained by playing multiple different games.

For Bayesian game the law of total probability is stated as payoff for strategy is the sum of each payoff for the outcome multiplied by the probable outcome of the game as shown in (11).

$$LTP = \sum (Payoff\ of\ each\ Column) * (Probability\ Outecome\ of\ the\ Game) \tag{11}$$

From LTP, we get best of best node as winner with maximum resources i.e. $N_i > N_j$ then N_i is the winner. After winning the node N_i reputation factor (R_p) is incremented by '1' and node N_j, R_p is decremented by '1'. If there is a tie between nodes i.e. $N_i = N_j$ then the best player is selected by the R_p value of that node from previous game database. If $R_p = 0$ then best node is selected based on the values of available resources of nodes.

3.4. Numerical Analysis

To simplify the simulation and ensuring numerical analysis without losing generality. The game modeled here is between two sensor nodes N_1 and N_2. We assume that each node belongs to the same network and has the same set of resources namely energy and bandwidth. From (5) & (6) values assigned to resources and payoff matrix is constructed using Energy, '*E*' (*Low = 1, Medium = 2, High = 3*) and Bandwidth, '*B*' (*Less = 1, Medium = 3, High = 4*). Similarly, the utilities are assigned to the payoff matrix highest and a lowest value i.e., 3 is added to the highest payoff value and 2 is subtracted from the lowest payoff value, the payoff matrix is reconstructed after assigning the utility values.

A. Case 1

Node N_1 has energy (Medium=2) & bandwidth (High=4) where node N_2 has energy (Low= 1) & bandwidth (High=4). The payoff matrix for case '1' is shown in fig. (4a).

Now assign the utility values to the highest and lowest values of the payoff matrix i.e., 3 is added to the highest payoff value and 2 is subtracted from the lowest payoff value the payoff matrix is reconstructed after assigning the utility values. The payoff matrix is reconstructed and after assign utilities and considering the strategy profile of nodes is as shown in fig. (4b).

Apply starring algorithm to find Nash Equilibrium as shown in fig. (4c). To solve NE state, we use the Law of Total Probability from (as shown in 11).

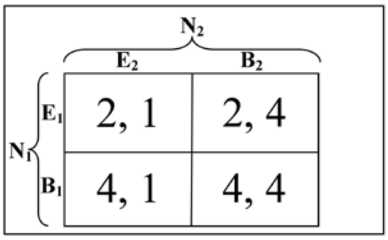

Fig.4a. Payoff Matrix

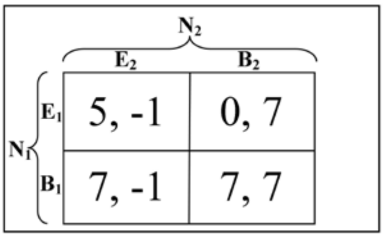

Fig.4b. Payoff Matrix after Utilities

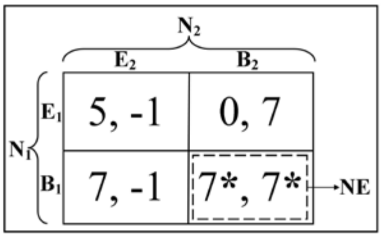

Fig.4c. Payoff Matrix after Starring Algorithm

Payoff of $N_1 = (5+0+7+7) * (0.5)$
Payoff of $N_1 = 9.5$
Payoff of $N_2 = (-1+7-1+7) * (0.5)$
Payoff of $N_2 = 6$

We find that payoff values $N_1 > N_2$ so node N_1 wins, now the reputation factor R_p of N_1 is incremented by '1' and R_p of N_2 is decremented by '1' in the nodes database. Node N_1 is selected for further level in the game based on its present payoff, utilities and strategies.

B. Case 2

Node N_1 has energy High = 3 & bandwidth High=4 where node N_2 has energy High=3 & bandwidth High = 4. The payoff matrix for case '2' is shown in fig. 5a.

Now assign the utility values to the highest and lowest values of the payoff matrix i.e., 3 is added to the highest payoff value and 2 is subtracted from the lowest payoff value the payoff matrix is reconstructed after assigning the utility values. The payoff matrix is reconstructed and after assign utilities and considering the strategy profile of nodes is as shown in fig. 5b.

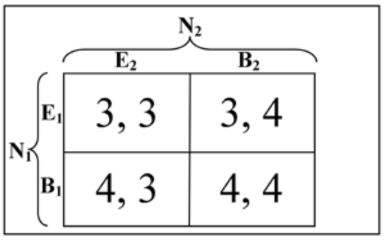

Fig.5a. Payoff Matrix

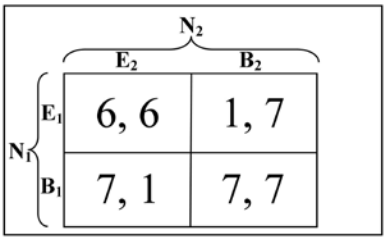

Fig.5b. Payoff Matrix after Utilities

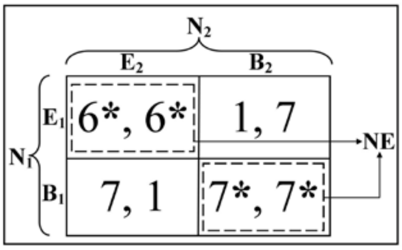

Fig.5c. Payoff Matrix after Starring Algorithm

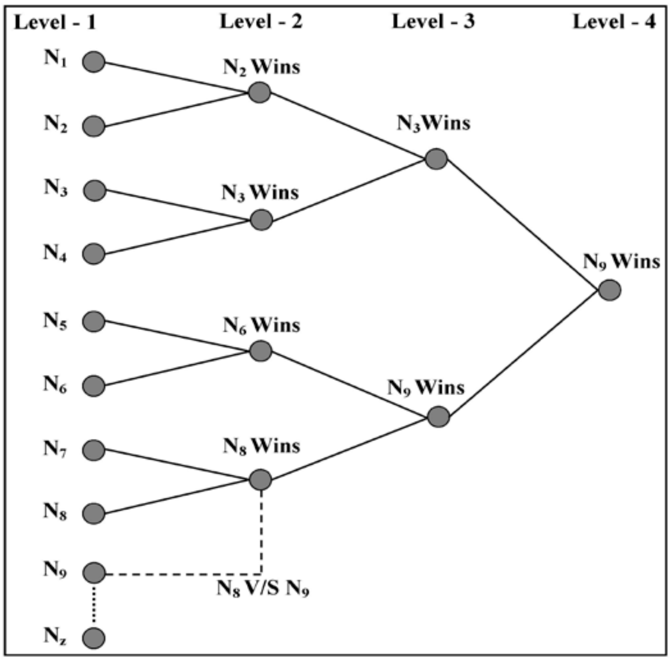

Fig.6. Bayesian Game Model in Tree Diagram.

Apply starring algorithm to find Nash Equilibrium as shown in fig. 5c. To solve NE state, we use the Law of Total Probability from (11).

Payoff of N1 = (6+1+7+7) ∗ (0.5)
Payoff of N1 = 10.5
Payoff of N2 = (6+7+1+7) ∗ (0.5
Payoff of N2 = 10.5

We find that payoff values N_1 = N_2 so no node wins, now the check the reputation factor *Rp* of node N_1 and N_2 based on previous values of *Rp*, if node N_1 wins then *N1 Rp* is incremented by '1' and *Rp* of *N2* is decremented by '1' in the nodes database or vice-versa. Hence winning node N_1 or N_2 is selected for further level in the game based on its present payoff, utilities and strategies.

The fig. 6 shows the proposed Bayesian Game model for node discovery in tree diagram representation. From tree diagram we notice that the wining node enters into next level how the game is played with different utilities and strategies.

3.5. Bayesian Game Model (BGM) Algorithm

The proposed Bayesian game based efficient node identification scheme with maximum resources in WSN is mentioned in algorithm 1 and algorithm 2.

Algorithm 1: Bayesian Game based Efficient Node Identification Scheme

1: *Nomenclature: Efficient Resource Identification Scheme for WSN using Bayesian Game Model BGM, Sensor Nodes - N, Energy - E, Bandwidth Available – B, Reputation Factor -* R_p
2: *Input: Number of Sensor Nodes - N, Available Energy of Nodes- E, Bandwidth Available - B, Reputation Factor –* R_p*, Number of game levels - n*
3: *Output: Efficient node identification with maximum resources*
4: **Begin**
//*Initialize each node*
5: **for** *i*←0 *to* N **do**
6: Node ←E, B, R_p = 0
7: **end for**
//*Game is played between two sensor nodes* N_i *v/s* N_j
8: **for** *i*←0 *to* N **do**
9: Construct payoff matrix for nodes N_i & N_j
10: Apply utilities to nodes N_i & N_j and update payoff matrix
11: Apply Algorithm-2 to find BNE
12: Apply LTP to find winner from of N_i & N_j
13: Update strategic profile of nodes and R_p of winning node by +1 and losing node by -1
14: Consider winning node to next level in game 'n'
15: **end for**
16: **if** There exists 'N' nodes **then**
17: Goto step 8 and continue game until (N=n)
18: **else**
Game ends with node having maximum resources
19: **end if**
20: **End**

Algorithm 2: Starring Algorithm

1: *Nomenclature: Find Bayesian Nash Equilibrium (BNE) from payoff matrix for Sensor Nodes -* N_i & N_j
2: *Input: Payoff matrix of nodes* N_i & N_j
3: *Output: Bayesian Nash Equilibrium for Payoff matrix of nodes* N_i & N_j
4: **Begin**
5: Each column add asterisk (∗) as superscript to highest number corresponding to N_i player payoff in that column
6: Each row add asterisk (∗) as superscript to highest number corresponding to *Nj* player payoff in that row
7: **if** Cell contains two asterisk (∗) **then**
8: Bayesian Nash Equilibrium exists
9: **else**
Bayesian Nash Equilibrium does not exist
10: **end if**
11: **End**

4. Simulation

The proposed scheme has been simulated using C++ programming language as a discrete event simulator. In this section, we discuss simulation model, inputs, and performance metrics.

4.1. Simulation Model

Some of the assumptions made during the simulation are as follows: We consider "N'" numbers of wireless sensor nodes which are deployed randomly in a given area of length "L" meter and breadth "B" meter. The communication link range for each sensor node is considered a "CR" meter. The coverage area around each node has a bandwidth of "BW" Mbps shared among all neighboring nodes. The available energy is considered as "E" joules, and reputation factor as "Rp".

Contingent on the battery lifetime, bandwidth, and scope of data sensing, gathering & transmission, we figure out the neighbors of every node and store them in a neighboring lookup table which is to be updated frequently. The Bayesian game theory model works to identify a best node among deployed all sensor nodes in the network based on payoff matrix & utility function of the nodes that participate in the game. The node with the highest resources in terms of energy and bandwidth is considered for sensing, and communication in the network.

To assess the efficiency of the proposed research scheme, we make some assumptions for the nodes in the proposed scheme are as follows:

- For easy analysis, we assume that nodes are randomly deployed in a two-dimensional area.
- Each node owns unique identification (ID) to distinguish them from other nodes.
- The transmitted power and signal frequencies (bandwidth) of all nodes are the same, respectively.
- Each node is the same in terms of memory, CPU, and radio equipment, but they vary in terms of battery (residual energy), and available bandwidth for communication).
- The nodes which participate in the Bayesian game apply 3 strategies, these strategy profiles of each node are explained in below table 2.
- The numerical analysis section 3.4. shows the details of strategy profiles and how it is applied in BGM to identify resources of the network.

Table 2. Strategy Profile Details

Strategy Profiles (SP)	Description
SP1	Energy is considered as dominant strategy by the node in game
SP2	Bandwidth is considered as dominant strategy by the node in game
SP3	Both energy & bandwidth are considered as dominant strategy by the node in game

4.2. *Simulation Inputs*

To illustrate the results of the proposed scheme, the simulation input parameters are summarized in table 3.

Table 3. Simulation Inputs

Sl. No.	Input Parameters	Specifications
01	No. of Sensor Nodes	10-100
02	Area (L*B)	(500*500) m^2
03	Deployment Strategy	Random
04	Communication Range	50 m
05	Primary Energy	100 J
06	Bandwidth	Upto 2 Mbps
07	Packet Size	100 Bytes-128 KB

4.3. *Simulation Procedure for Proposed Scheme*

Algorithm 3 shows the procedure for simulation of the proposed efficient node identification scheme using Bayesian game theory.

Algorithm 3: Simulation Procedure

1: **Begin**
2: Deploy N number of sensor nodes randomly
3: Apply Bayesian game model to identify the efficient node
4: Based on energy and bandwidth of nodes N_i & N_j generate the payoff matrix
5: Apply utilities, and strategies to nodes N_i & N_j, reconstruct payoff matrix
6: Starring Algorithm is used to find Bayesian Nash Equilibrium state
7: Apply Law of Total Probability to find winner node from of N_i & N_j
8: Reward +1 for winning node and -1 for losing node and update R_p data base
9: Consider winning node to next level in game
10: Identifying best-of-best node as a winner node of the game
11: **End**

4.4. *Performance Parameters*

To test the performance evaluation of the proposed scheme, some of the performance metrics evaluated are as follows.

a) ***Resource Information Acquisition Delay:*** It is the time taken to gather each node resource information such as energy, bandwidth, degree of connectivity, and computational capabilities. It is represented in milliseconds (ms).
b) ***Strategy Computational Delay***: The time taken by nodes to make their strategy to win in the game and enter for next level, strategy is made based on residual energy, and available bandwidth. It is expressed in milliseconds (ms).
c) ***Overall Game Strategy Delay:*** It is the overall computational time taken to identify best of best node by the game using their strategy. Expressed in milliseconds (ms).
d) ***Number of Qualified Nodes for Game*:** It is the quantity of best nodes identified for the game based on their available resources at the various strategy of nodes and reputation ranges.
e) ***Resource Identification Delay**:* It is the time taken by the system to calculate the average number of efficient nodes with maximum resources, good for sensing, gathering, and communication. It is measured in milliseconds (ms).
f) ***Memory Utilization:*** Memory utilization refers to amount of dynamic memory used by the node during the resource identification phase in game. It is expressed in terms of percentage (%).
g) ***Energy Consumption:*** Energy consumed by the sensor node to perform resource identification of the node for sensing, transmission, and reception of the information. It is measured in terms of Joules (J).
h) ***Bandwidth Utilization:*** It is the ratio of the bandwidth utilized by nodes to identify the resources of the network to the total bandwidth available. It is measured in percentage (%).
i) ***Control Overheads:*** It is defined as the ratio of the total number of control messages to the total number of packets generated to perform resource identification of the network. It is measured in percentage (%).

4.5. Result Analysis

To test the operative effectiveness of the proposed scheme which uses the Bayesian game theory strategy to identify available resources of WSN, we have analyzed some of the performance metrics which are mentioned in the underneath graphs. Simulation results show that the proposed algorithm is effective and efficient. The performance of the proposed Bayesian game theory approach for efficient resource identification is better as compared with the existing an efficient neighbor discovery scheme for mobile WSN [41] (referred to as ENDWSN scheme in graphs). Result shows that the strategy profile of each node in the game plays a vital role in identification of efficient node with highest resources from the network.

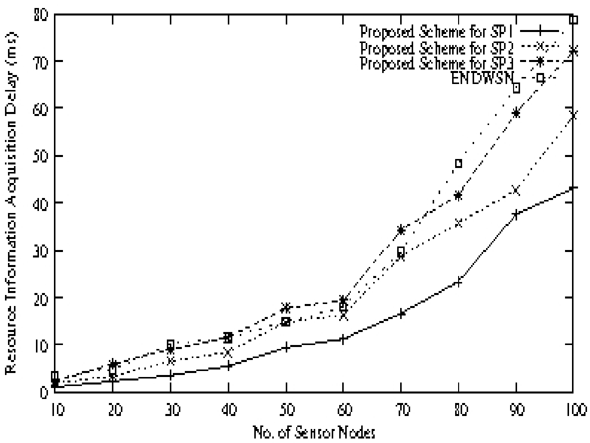

Fig.7. Resource Information Acquisition Delay Vs. No. of Sensor Nodes.

Fig. 7 presents resource information acquisition delay w.r.t. number of sensor nodes for different strategies. The time taken to gather the node's basic information increases as the number of nodes with different strategies in the network. ENDWSN protocol exhibits 10% to 12% more delay for information acquisition than the proposed scheme. Fig. 8 shows the strategy computational delay w.r.t. variation of number of sensor nodes. Strategy time of node increases as the node density increases, we also identify that as strategy profile changes there is an increase in delay.

Fig. 9 shows overall game strategy delay vs. node density. Variations in the strategies made by the node will impact the computational delay. The delay increases with strategy profile values and number of nodes. In fig. 10, the average number of efficient nodes qualified for the game for the variation in number of sensor nodes along with varying strategy profile and node density. The average numbers of nodes identified are increasing with an increase in the number of nodes.

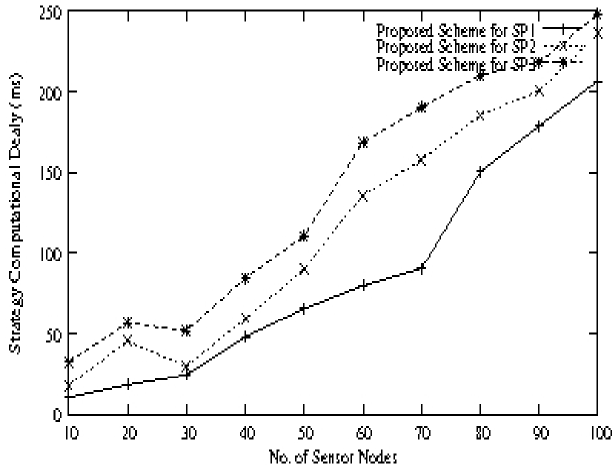

Fig.8. Strategy Computational Delay Vs. No. of Sensor Nodes.

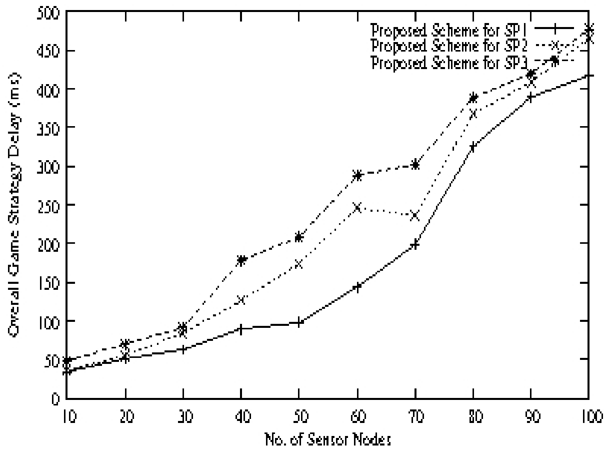

Fig.9. Overall Game Strategy Delay Vs. No. of Sensor Nodes.

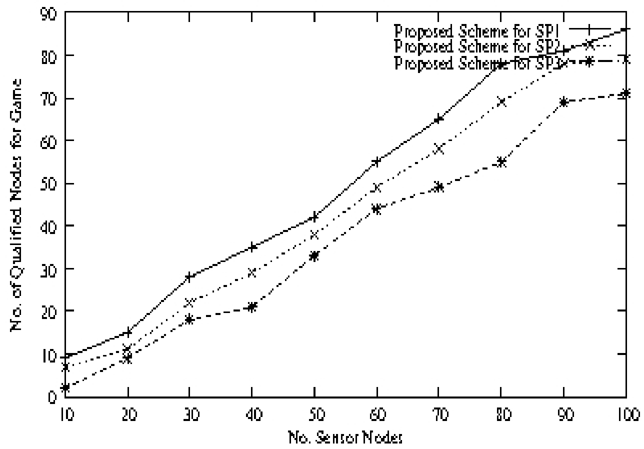

Fig.10. No. of Qualified Nodes for Game Vs. No. of Sensor Nodes.

Fig. 11 shows that the performance of the proposed BGM scheme takes less time as compared with the ENDWSN. The delay is decreased by 8% to 10% which makes the BGM scheme effective for resource identification. Fig. 12 outlines the comparison of memory utilization for the proposed scheme and ENDWSN scheme. As number of nodes increases with different strategy profiles the memory consumption also increases this is due to need of memory for computational requirement for resource identification of the WSN.

Fig. 13 shows the performance of the proposed scheme is better in terms of energy consumption w.r.t. EDNWSN scheme, it is observed that the energy consumption of nodes increases with increase in node density and varying strategy profiles of node involved in the game. It is also observed that change in strategy profile and increasing node density, the performance is better in terms of bandwidth utilized than ENDWSN protocol as shown in fig. 14.

Bandwidth utilization increases as there is an increase in the number of sensors in the network. This is due to increase in the resource information of each node.

Fig. 15 outlines the control overheads for varying node values in the network and different strategies in the game. Because of the network connectivity, other information of the network control overheads is also increased. It is observed that ENDWSN scheme is slightly inferior in terms of control packet overheads.

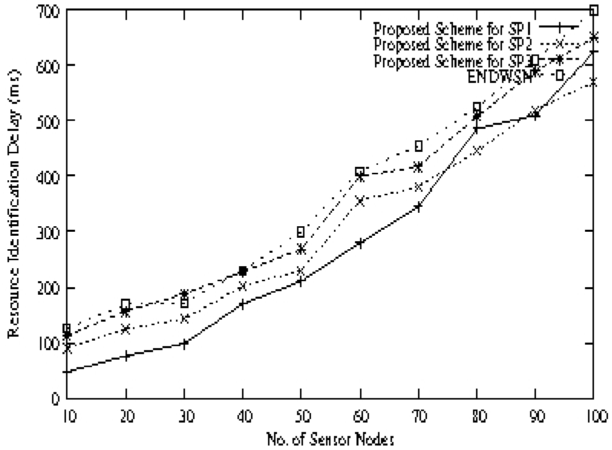

Fig.11. Resource Identification Delay Vs. No. of Sensor Nodes.

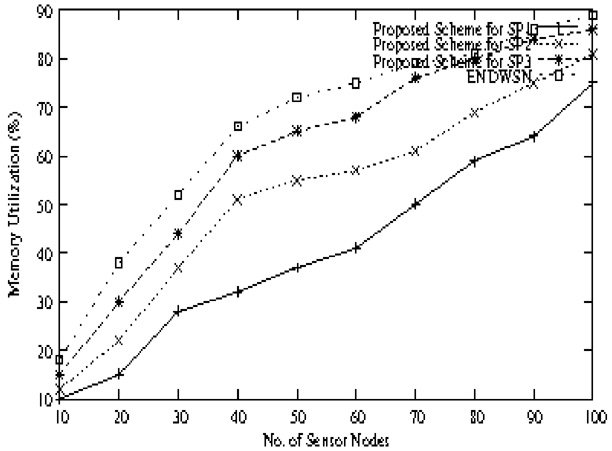

Fig.12. Memory Utilization Vs. No. of Sensor Nodes.

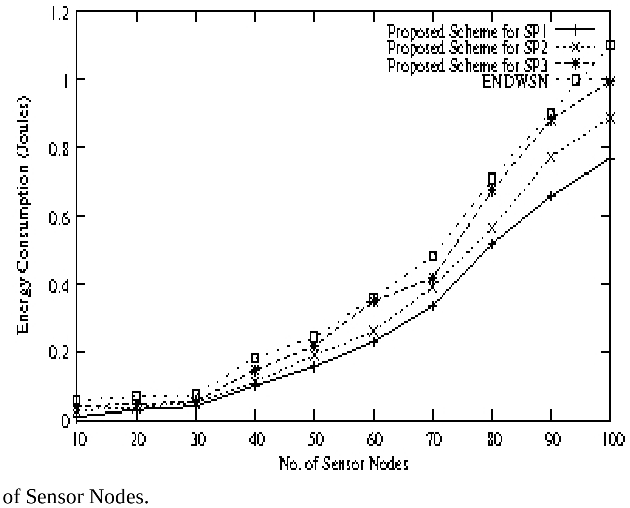

Fig.13. Energy Consumption Vs. No. of Sensor Nodes.

The proposed algorithm will be very influential w.r.t. to strategies of the node made in the game to win and increase its reputation factor. And thus, it can be seen that as the reputation is greater, the node is declared as the best-of-best node with maximum resources. Therefore, the proposed algorithm progressively performs at a good rate and the network is maintained for a long period. The nodes with greater reputation have good performance factors and it is the factor on which mainly the game theory concept works hence overall performance can be improved.

The obtained results show that, in resource constrained networks the parameters like energy consumption, bandwidth utilization, resource identification accuracy and computational delay are better as compared with ENDWSN protocol. The proposed algorithm progressively performs at a good rate and the network stable in resource constrained situation. With the increasing number of efficient nodes identified considering suitable parameters the overall network performance and lifespan can be improved.

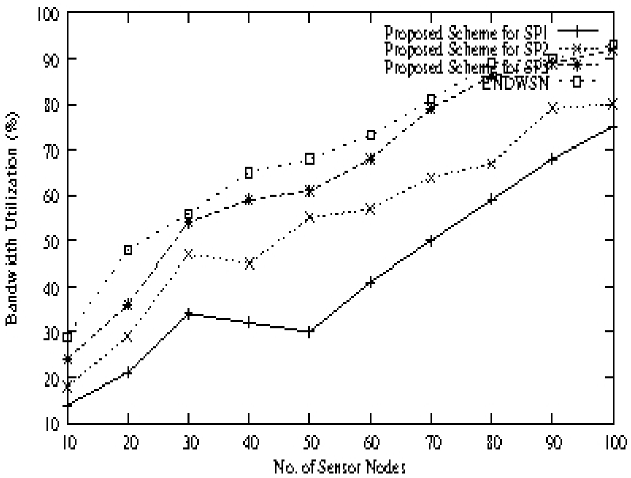

Fig.14. Bandwidth Utilization Vs. No. of Sensor Nodes.

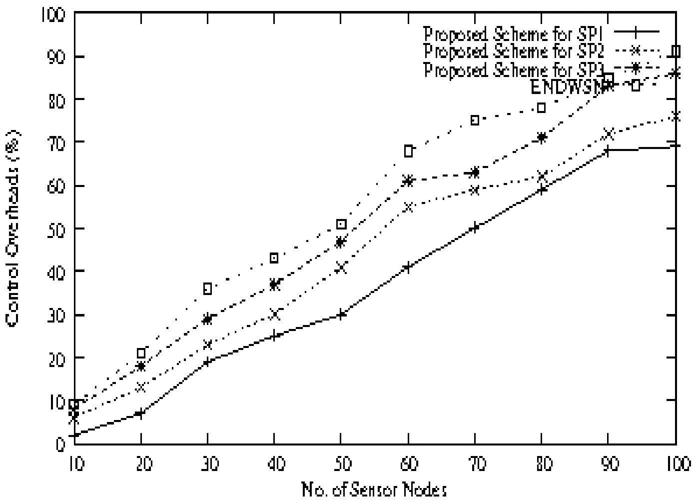

Fig.15. Control Overheads Vs. No. of Sensor Nodes.

5. Conclusion

Game theory has influenced the design of future heterogeneous WSN and their multiple applications. The game theory mechanism makes more versatile, adaptive and customizable for future next generation applications of WSNs. As the wireless sensor network is resource constrained, it becomes quite difficult to track and identify the resources of the nodes. Resource identification (efficient node discovery) based on the Bayesian game scheme in WSN is a new concept with the advantages of its accuracy in the resource's identification. Results show that the proposed node identification accuracy, computational delay, energy consumption and bandwidth utilization are better compared with the ENDWSN protocol.

The resources should be intelligently identified and utilized to the application depending on the desired performance level to preserve available resources w.r.t. consumption tradeoffs. The resource identification algorithms are responsible for ensuring increased resource usage for ubiquitous WSN applications. The intelligent resource identification approaches will ensure increased usage of resources for extensive WSN applications.

In WSN use of BGM has less practicability as player has minimum knowledge of the strategies of the opponent. The proposed scheme is designed for two nodes only, further the work can be considered for multiple nodes simultaneously. The fading and interference caused in wireless environments, special provisions in the scheme to handle a burst in the traffic by considering multiple sources to single sink can be done. Resource identification may be accomplished at several levels of WSN including node level, gateway level, network level, and fog/cloud level. Further the research work can be extended to a higher level by considering multiple networks and heterogeneous networks for making communication easier in remote areas.

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