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EECS-GT: Energy-Efficient Collaborative Sensing Model Using Game Theory for Wireless Sensor Networks

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KEYWORDS

Wireless Sensor Networks (WSN), Energy Efficiency, Game Theory, Random Learning, Collaborative Sensing

ABSTRACT

Wireless Sensor Networks (WSNs) are widely used for continuous monitoring and data acquisition in diverse application domains. As network scale and complexity increase, achieving energy efficiency while maintaining quality of service becomes a critical challenge. This paper proposes an energy-efficient collaborative sensing model based on game theory and Random Learning for WSNs. The model integrates strategic decision-making with adaptive learning to optimize sensor participation and communication, thereby reducing energy consumption without degrading network performance. A key contribution of the proposed approach is the b which guides the selection of appropriate sensors for sensing tasks based on energy and performance considerations. In addition, a Distributed Anticipatory Time-slot Selection Algorithm (DATA) is introduced to enable energy-aware collaborative communication among sensors by intelligently selecting transmission time slots. Simulation results demonstrate that the proposed model significantly outperforms existing approaches in terms of energy efficiency; The simulation results demonstrate that the proposed model outperforms existing approaches in terms of energy efficiency, packet drop ratio, and throughput. The framework significantly enhances network lifetime, improves data transmission efficiency, and reduces processing delay under full-load conditions, thereby validating its effectiveness for energy-efficient operations in wireless sensor networks.

I. INTRODUCTION

Wireless Sensor Networks (WSNs) have emerged as a key technology for a wide range of applications, including environmental monitoring, military surveillance, smart agriculture, and industrial automation. These networks consist of a large number of sensor nodes that collaboratively sense, process, and transmit data to a central system. Despite their versatility, one of the primary challenges in WSNs is the limited energy capacity of sensor nodes, as they are typically battery-powered and often deployed in inaccessible environments. As the network scales and data traffic increases, inefficient sensing and communication can lead to rapid energy depletion, reduced network lifetime, and degraded performance. Therefore, designing intelligent and energy-efficient sensing mechanisms is crucial for ensuring sustainable network operation. To address these challenges, the Energy-Efficient Collaborative Sensing model based on Game Theory (EECS-GT) provides a novel and effective solution. In this approach, sensor nodes are modelled as rational decision-makers that interact strategically with one another to optimize their individual and collective performance. Game theory offers a powerful mathematical framework to analyse and design such distributed decision-making processes, where each node aims to maximize its utility based on factors such as energy consumption, sensing accuracy, and communication cost. By incorporating cooperative and non-cooperative game strategies, nodes can dynamically decide whether to sense, transmit, or remain idle, thereby minimizing redundant operations and conserving energy. the EECS-GT model integrates adaptive learning mechanisms that allow sensor nodes to adjust their strategies based on network conditions and past interactions.

This enhances the network's ability to respond to dynamic environments, including node failures, varying traffic loads, and changing sensing requirements. The use of equilibrium concepts ensures stable and efficient operation, while incentive mechanisms promote cooperation among nodes. Additionally, the model supports optimized sensor selection and coverage, ensuring that the monitored area is efficiently observed with minimal overlap. the integration of game-theoretic principles with collaborative sensing significantly improves the scalability, robustness, and energy efficiency of WSNs. The EECS-GT framework not only prolongs network lifetime but also maintains high-quality data delivery, making it a promising approach for the development of sustainable and intelligent wireless sensor network systems.

Aim

The main aim of this work is to develop an Energy-Efficient Collaborative Sensing model using Game Theory for Wireless Sensor Networks (WSNs) that optimizes energy consumption while maintaining reliable sensing and communication performance. The model aims to enable sensor nodes to make intelligent and cooperative decisions regarding sensing and data transmission, thereby reducing redundancy and extending network lifetime. Additionally, it seeks to improve coverage efficiency, ensure stable network operation through game-theoretic strategies, and enhance overall quality of service in dynamic and resource-constrained environments.

Objective

- The first objective is to design a game theory-based sensing model that enables sensor nodes to make intelligent and autonomous decisions. By treating each node as a rational player, the system optimizes sensing and communication strategies. This helps in reducing unnecessary data transmission and conserving energy efficiently.
- The second objective is to enhance network lifetime and coverage through cooperative sensing and adaptive learning mechanisms. Sensor nodes dynamically adjust their behaviour based on network conditions and neighbouring actions. This ensures efficient resource utilization, improved reliability, and sustained performance of the Wireless Sensor Network.

Wireless Sensor Networks (WSNs) are widely used for monitoring and data collection in various applications such as environmental sensing, surveillance, and smart systems. However, sensor nodes in these networks are constrained by limited battery power, processing capability, and communication bandwidth. As the network grows in size and complexity, inefficient sensing and redundant data transmission lead to excessive energy consumption, reducing the overall network lifetime and performance. Additionally, the lack of coordination among sensor nodes often results in overlapping coverage, data congestion, and unreliable communication.

The work titled focuses on improving the performance and lifetime of Wireless Sensor Networks (WSNs) by introducing an intelligent and distributed sensing mechanism. In WSNs, sensor nodes are typically deployed in large numbers to monitor environmental or physical conditions, but their limited battery power and resources make energy efficiency a critical concern. This project addresses the challenge by applying game theory to enable smart decision-making among sensor nodes. In the proposed EECS-GT model, each sensor node is considered as a rational player in a strategic game, where it decides whether to sense, transmit, or remain idle based on its energy level and the behaviour of neighbouring nodes. The objective is to minimize unnecessary sensing and redundant data transmission while maintaining effective area coverage and reliable communication. By using cooperative and non-cooperative game strategies, the model ensures that nodes work together to achieve optimal network performance. The system also incorporates adaptive learning mechanisms, allowing nodes to update their strategies dynamically according to changing network conditions such as node failures, energy depletion, and varying traffic loads. This adaptability improves the robustness and scalability of the network. Additionally, equilibrium concepts from game theory are used to achieve stable operating conditions where no node has an incentive to change its strategy unilaterally. The EECS-GT project provides an efficient framework for collaborative sensing that significantly reduces energy consumption, extends network lifetime, and enhances the quality of service. It offers a promising solution for real-world applications requiring sustainable and intelligent wireless sensor network operations.

2.LITERATURE REVIEW

1. **Rao et al. (2016) [5]** introduced two Particle Swarm Optimization (PSO)-based algorithms focusing on cluster formation and energy-efficient Cluster Head (CH) selection in Wireless Sensor Networks. Their approach evaluated energy efficiency using parameters such as intra-cluster distance, distance to the sink, and residual energy of sensor nodes. The model aimed to minimize energy consumption and improve network lifetime. By optimizing these factors, the algorithm enhanced communication efficiency among nodes. It also contributed to better load balancing within clusters. The results demonstrated improved performance compared to traditional clustering methods. However, the methodology followed an unconventional sequence by performing CH selection before cluster formation. This may lead to suboptimal cluster structures. The lack of proper clustering prior to CH selection can affect overall efficiency. Hence, the approach requires better coordination between clustering and CH selection phases.

2. **Azharuddin and Jana (2016) [10]** developed PSO-based routing and clustering algorithms to extend the lifetime of Wireless Sensor Networks. Their routing mechanism effectively balanced energy efficiency and energy distribution among nodes. The clustering process aimed to optimize node grouping for efficient communication. The proposed system improved network stability and reduced energy consumption. It also enhanced routing performance under varying conditions. However, the clustering model relied on Non-Linear Programming (NLP), which did not yield satisfactory results. The optimization process was complex and computationally expensive. Additionally, fault tolerance was limited as only continuous CH failures were considered. Other node failures were not addressed effectively. This reduced the robustness of the overall network.

3. **Singh and Sharma (2017) [11]** proposed a programming framework integrated with a PSO algorithm to address energy-efficient clustering in WSNs. Their approach focused on reducing energy consumption through optimized cluster formation. The model ensured balanced energy usage among Cluster Heads, thereby extending network lifetime. It improved communication efficiency and reduced energy wastage. The framework also provided structured implementation for clustering strategies. Results indicated better energy balancing compared to conventional methods. However, the improvement in the number of active nodes was minimal. This indicates limited enhancement in network coverage and participation. The algorithm's impact on scalability was also not significant. Further optimization is required to improve node utilization.

4. **Wang et al. (2017) [12]** proposed a PSO-based clustering algorithm designed for Wireless Sensor Networks with a mobile sink. Their model used a virtual clustering approach combined with PSO-based routing techniques. Cluster Head selection was based on

residual energy and node position. The method improved energy efficiency and adaptability to mobile sink environments. It also enhanced data collection efficiency in dynamic scenarios. The use of mobile sinks helped in reducing communication distance. However, frequent movement of the sink negatively affected network throughput. Increased mobility caused instability in routing paths. This led to higher packet loss and reduced performance. Therefore, the model requires better handling of sink mobility.

5. Yadav et al. (2018) [13] enhanced the LEACH protocol by integrating a PSO-based Cluster Head selection mechanism. Their approach aimed to improve energy efficiency and identify optimal CHs using PSO optimization. The method improved network lifetime and reduced energy consumption. It also enhanced clustering performance compared to traditional LEACH. The PSO-based selection ensured better distribution of CHs across the network. However, the study did not clearly define the clustering phase before CH selection. This creates ambiguity in the implementation process. Additionally, the fitness function used in PSO was not clearly explained. Lack of clarity affects reproducibility and understanding. The model requires better definition of optimization parameters.

6. Kaur and Kumar (2018) [14] proposed a PSO-based Unequal Fault-tolerant Clustering (PSO-UFC) technique for WSNs. The method used uneven clustering to balance energy consumption among Master Cluster Heads. It aimed to reduce the burden on nodes closer to the base station. The model improved fault tolerance and network lifetime. It also enhanced load balancing across clusters. However, the algorithm required multiple optimization iterations. Inclusion of several fitness parameters increased computational complexity. This led to higher processing time and hardware requirements. The approach became less efficient for large-scale networks. Repeated optimization cycles consumed significant energy. Thus, the method needs simplification for practical implementation.

7. Deepa and Rekha (2018) [15] proposed a PSO-based solution addressing both clustering and routing in Wireless Sensor Networks. Their approach improved scalability by ensuring uniform distribution of nodes within clusters. This helped in avoiding residual nodes that consume excess energy. The clustering process enhanced energy efficiency and prolonged network lifetime. It also improved network organization and data handling. However, the routing mechanism lacked clarity. There was confusion in data transmission paths to the Base Station (BS). This affected overall communication efficiency. The model did not clearly define routing protocols. As a result, reliability of data delivery was compromised. Further refinement in routing strategy is required.

8. Preethiya et al. (2019) [6] introduced the Mobile Double Cluster Head PSO (MDCH-PSO) method to improve network lifetime and load balancing. The approach used two cluster heads to reduce energy consumption and improve efficiency. It minimized energy spent on monitoring member nodes and managing mobility. The method enhanced fault tolerance and network stability. It also improved load distribution among nodes. However, scalability remained a major issue. The model did not define a centralized sink for the network. This led to inefficiencies in data aggregation and transmission. Increased complexity also affected performance. The approach requires better scalability handling mechanisms.

9. Shinde and Bichkar (2020) [4] proposed a PSO-based Cluster Head selection approach focusing on optimal clustering. The method selected CHs based on residual energy, intra-cluster distance, and inter-cluster distance. This improved energy efficiency and network performance. The clustering process ensured better communication among nodes. It also enhanced load balancing within the network. However, the fitness function was not mathematically defined. Although discussed conceptually, it lacked proper formulation. This reduced clarity and reproducibility of the method. The absence of mathematical representation limits practical implementation. Further refinement is required for validation

10. Sahoo et al. (2020) [16] introduced the PSO-ECSM technique combining energy-efficient clustering and sink mobility. The approach optimized Cluster Head selection and routing using PSO. It also improved sink movement strategies for better data collection. The method enhanced network lifetime and reduced energy consumption. It addressed multiple optimization problems simultaneously. However, solving multiple PSO optimization tasks increased computational effort. The complexity grew significantly with network size. The fitness function included multiple constraints, increasing processing time. This made the model less efficient for large-scale networks. Optimization overhead remained a key limitation.

Wireless Sensor Networks (WSNs) consist of resource-constrained sensor nodes that must perform sensing, processing, and communication using limited battery power. As WSNs grow in size and complexity, uncoordinated sensing and communication among sensor nodes lead to excessive energy consumption, redundant data transmission, increased packet loss, and reduced network lifetime. Traditional energy management techniques often rely on static configurations or centralized control, which are inefficient in dynamic network environments and fail to adapt to changing network conditions.

3.EXISTING SYSTEM

Energy-Efficient Collaborative Sensing Using SLM:

In existing Wireless Sensor Network (WSN) architectures, energy efficiency is primarily achieved through conventional techniques such as basic power control, duty cycling, data aggregation, and traditional modulation schemes. These approaches focus mainly on reducing energy consumption at the individual node level rather than optimizing the overall network behavior. Collaborative sensing, when implemented, is often static or centrally controlled, where sensor nodes transmit raw or partially processed data directly to a sink node without intelligent coordination. This leads to redundant data transmissions, increased communication overhead, and inefficient utilization of limited energy resources. As the number of nodes increases, the problem becomes more severe, resulting in congestion and reduced network performance. the transmission of large volumes of redundant data contributes to a high Peak-to-Average Power Ratio (PAPR), which negatively impacts energy efficiency in wireless communication. To address this, some existing systems adopt Selective Level Mapping (SLM) techniques to reduce transmission peaks. While SLM can effectively lower PAPR, it introduces additional computational complexity and requires the transmission of side information, which itself consumes extra energy. This added overhead makes SLM less suitable for resource-constrained sensor nodes. Additionally, conventional SLM techniques are not adaptive to changing network conditions such as node mobility, varying traffic loads, or energy depletion. Another limitation of existing approaches is the lack of integration between PAPR reduction techniques and collaborative sensing strategies. Most methods treat sensing and communication as separate processes, leading to suboptimal system performance. Without proper coordination among nodes, energy consumption remains unbalanced, and certain nodes may deplete their energy faster than others, causing network partitioning. Moreover, centralized approaches suffer from scalability issues and single points of failure, making them unsuitable for large-scale deployments. As a result, current WSN systems experience reduced network lifetime, higher packet loss, and inefficient energy utilization. These challenges highlight the need for an intelligent, distributed, and adaptive sensing model that combines energy-aware communication with collaborative decision-making.

Selective Mapping Technique (SLM)

Numerous strategies are there to decrease the PAPR, however both unpredictability and repetition are high and just little gains in PAPR are achieved[12]. At the point when the periods of various sub-transporters include in stage the likelihood of PAPR being high is without a doubt. Subsequently one strategy to lessen the in-stage expansion is to change the stage before changing over the recurrence area motion into time space. Subsequently before taking the N point IDFT each square of info is increased by a φ vector of length N. Presently there is a probability that the PAPR may turn low.

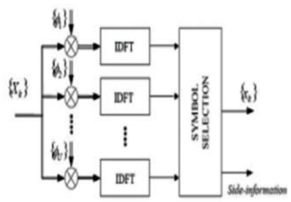

Figure 1: Scheme of modulator with a Selective mapping

The figure 1 shows the scheme of a modulator with selective mapping technique. The algorithm for selective mapping technique is as follows:

Step 1: Get the input vector(X) of length D and let N=integer

Step2: for i=1: N

Step 2.1: Generate φ (i) of length D

Step 2.2: Multiply φ (i) with the input vector and get Z (Freq domain)

Step 2.3: Compute IDFT and get z (Time domain)

Step 2.4: Determine PAPR using the formula

$$\mathbf{PAPR} = \frac{\max |x(t)|^2}{E\left[|x(t)|^2\right]}$$

Step 2.5: Increment the value of i

Step 3: Go-to Step 2

Step 4: PAPR of length N is obtained.

Step 5: Select a threshold Y. One with minimum PAPR is used for transmission

Step 6: If min of PAPR>Y then increment a count

Step 7: Perform Steps 1-6 M times
Step 8: Obtain final count
Step 9: Increment the value of N and repeat Steps1-8
Step 10: Plot Graph for various N values where
X axis: Threshold values
Y axis: Pr[PAPR low>Y]
Stage 11: It could be construed that as the estimation of N builds PAPR diminishes (It is required to illuminate the stage data controlled for the information sub-bearers to the beneficiary as side data)
As a result of the shifting task of information to the transmit flag, we call this „Selected Mapping". The center is to pick one specific flag which shows some coveted properties out of „N" signals speaking to a similar data.
The PAPR of discrete OFDM flag might be communicated as

$$PAPR = \frac{\max\{|x(n)|^2\}}{E\{|x(n)|^2\}}$$

In the event that OFDM flag is oversampled by a factor ≥ 4, its PAPR is a decent surmised to the one of constant OFDM flag. Oversampling by a factor of L can be accomplished by cushioning the images Sk with (L-1)*N zeros. After IFFT, the resultant images are changed over to serial and companding change (CT) is performed. To ensure that every changed flag are under a given edge, a computerized cutting "not appeared in Fig. 1" is utilized after the CT. Note that, because of the impediments of cut-out, the CT ought to be outlined warily with the goal that the measure of cut signs is as meagre as would be prudent. A cyclic prefix (CP) is then embedded to OFDM image interim to dispose of entomb image obstruction (ISI).

Drawbacks of Existing System

- Relies on static or centralized collaborative sensing, causing redundant data transmissions
- High peak-to-average power ratio (PAPR) increases transmission energy consumption
- Traditional SLM techniques introduce high computational complexity

4. PROPOSED SYSTEM

Energy-Efficient Collaborative Sensing Model Using Game Theory

The proposed model presents a novel and intelligent framework designed to significantly improve energy utilization in Wireless Sensor Networks (WSNs) while ensuring reliable Quality of Service (QoS). In traditional WSNs, sensor nodes often operate in a redundant and uncoordinated manner, leading to excessive energy consumption, frequent packet collisions, and reduced network lifetime. To overcome these limitations, the EECS-GT model adopts a distributed and adaptive approach by integrating game theory and Random Learning techniques. each sensor node is modelled as a rational and autonomous player in a non-cooperative game-theoretic environment. Every node independently decides whether to participate in sensing, data transmission, or remain idle based on its residual energy, local observations, and network conditions. The objective of each node is to maximize its utility function, which balances energy consumption with sensing contribution and communication efficiency. This decentralized decision-making mechanism eliminates the need for a central controller, thereby enhancing scalability and robustness in dynamic environments. A crucial component of the proposed model is the Selection Propensity Index (SPI), which plays a vital role in intelligent node selection. SPI is a composite metric that evaluates each node based on parameters such as residual energy, sensing reliability, historical participation, and communication cost. By prioritizing nodes with higher SPI values, the system ensures that only the most capable and energy-efficient nodes are selected for sensing tasks. This significantly reduces redundant data acquisition, minimizes unnecessary transmissions, and balances energy consumption across the network, preventing premature node failures. To further optimize communication efficiency, the EECS-GT model incorporates a Distributed Anticipatory Time-slot Selection Algorithm (DATA) powered by Random Learning. In this approach, each node learns optimal transmission strategies over time by interacting with the network environment. Nodes dynamically select time slots for data transmission based on past experiences, such as collision occurrences and successful transmissions. Through continuous learning and adaptation, DATA minimizes packet collisions, reduces retransmissions, and improves channel utilization. This leads to lower energy expenditure and enhanced throughput. Another key strength of the EECS-GT framework is its fully distributed operation. Unlike centralized schemes that suffer from bottlenecks and single points of failure, the proposed system allows nodes to self-organize and adapt to changing network conditions such as node mobility, energy depletion, and varying traffic loads. This adaptability ensures consistent performance even in large-scale and heterogeneous WSN deployments.

With the growing importance of Wireless Sensor Networks (WSNs), their integration with cloud computing has become increasingly essential to overcome inherent limitations such as constrained energy resources, limited storage, and low computational capacity. Cloud-assisted WSN architectures enable efficient data storage, large-scale processing, and real-time analytics, thereby enhancing the overall functionality of sensor networks. However, despite these advantages, energy conservation remains a critical challenge, as sensor nodes are typically battery-powered and often deployed in inaccessible or harsh environments. To address this issue, intelligent data collection techniques have been proposed to extend network lifetime by minimizing unnecessary energy expenditure. One effective approach involves the use of energy-aware disjoint dominating sets, which ensure that only a subset of sensor nodes actively participates in sensing and communication at any given time. This reduces redundancy in data collection and balances energy consumption across the network. Additionally, optimizing data gathering paths plays a crucial role in reducing transmission distance and energy usage. Techniques such as mobile sink deployment and energy-efficient routing protocols help in selecting optimal paths, thereby minimizing communication overhead. Energy harvesting methods further contribute to prolonging network lifetime by enabling sensor nodes to derive power from environmental sources such as solar, thermal, or vibration energy. These approaches are particularly beneficial in long-term deployments where battery replacement is impractical. In industrial Wireless Sensor Networks (IWSNs), especially those based on the IEEE 802.15.4 standard, improving energy efficiency requires specialized strategies that address industrial challenges such as interference, dynamic topology, and strict reliability requirements. Modifications at the MAC and network layers, including duty cycling, adaptive transmission power control, and collision avoidance mechanisms, are essential to ensure consistent performance and extended network lifespan. Battery consumption in WSNs is influenced by multiple factors, including hardware design, sensing frequency, environmental conditions, and routing protocols. Energy-efficient clustering protocols such as LEACH (Low-Energy Adaptive Clustering Hierarchy) and its variants like Sub-cluster LEACH play a significant role in reducing energy consumption by organizing nodes into clusters and rotating cluster heads to distribute energy load evenly. These protocols minimize long-distance transmissions and improve scalability.

Each interaction in a game-theoretic model results in payoffs, which are quantified based on the benefits or costs associated with a player's chosen strategy. In the context of Wireless Sensor Networks (WSNs), these payoffs are typically defined in terms of energy consumption, successful data transmission, and contribution to network performance. A key concept in game theory is the Nash equilibrium, a state in which no sensor node can improve its payoff by unilaterally changing its strategy. At this point, the system reaches a stable operating condition where all nodes act optimally with respect to their local information and constraints.

- Game theory provides a powerful framework for analyzing and guiding strategic decision-making in distributed environments where multiple nodes with potentially conflicting objectives interact. When applied to WSNs, it enables intelligent coordination among sensor nodes to optimize energy consumption and extend network lifetime. In particular, game-theoretic approaches can be effectively integrated into clustering mechanisms. By allowing nodes to decide cluster formation and cluster-head selection based on payoff functions, the overall communication distance is reduced, leading to lower transmission energy. This also ensures balanced energy utilization among nodes, thereby improving fairness and preventing early node depletion.
- Optimal sensing extending the network lifetime is paramount, but uneven energy consumption among nodes can lead to premature node failures, affecting the overall network performance.
- Efficient data aggregation techniques are required to reduce data transmission and processing overhead. However, designing optimal algorithms for these tasks is challenging, especially in dynamic environments.
- WSNs may be deployed in diverse environments, including urban, rural, and indoor settings. Ensuring that the same sensing

techniques can perform well in various conditions requires careful consideration.

- Energy-efficient collaborative sensing in WSNs using coalition game theory aims to optimize spectrum sensing operations by forming coalitions of sensor nodes that work together to achieve energy efficiency, accuracy, and adaptability. It leverages coop erativestrategies to enhance the overall performance of the WSN while efficiently utilizing available resources.

System Model

The high-level block diagram of the proposed models shown in Fig . This block diagram provides a generic view of the system developed in this work. The sensor networks generate data from various applications which is collected by the entities and ultimately stored in cloud infrastructures for specific analytics and critical decision making. Since these networks are resource-limited, game theory-based energy efficient mechanisms are developed. Game theory is often used as a potential tool to model, analyse, and design dis tribute systems where the nodes or devices interact with each other. Collaborative sensing in IoT refers to the scenario where multiple IoT devices work together to sense, collect, and process data so as to minimize energy consumption while maximizing the performance of collaborative sensing. In the proposed game model, the IoT devices act as players participating in collaborative sensing. Each player will adopt a strategy during the game and receive a pay-off for its sensing and energy cost. The game G is defined as G “ {N,S,U} where N is the set of players, S is a set of strategies available for the players, and U is the utility function that provides payoffs to the players based on the strategies they choose.

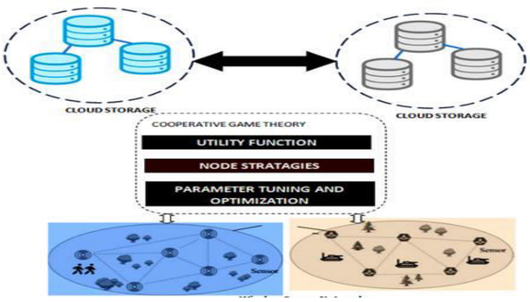

Figure 2: Block diagram of the proposed game-theory-based energy efficient sensor network model

The objectives of this research include:

To formulate a coalition game theory allows nodes to dynamically adjust their coalition memberships based 115660 on the changing environment.

This ensures that the network remains effective in different scenarios. , To form coalitions so that the nodes can collaborate on their sensing activities, reducing redundant work and conserving energy. This leads to extended network lifetime and reduced reliance on frequent battery replacements.

To strategically allocate sensing and communication tasks to the nodes based on their energy levels and assigned roles to distribute the load across the network The payoffs are determined by a combination of energy cost, the priority of the task, task proximity, and collaborative benefit Consider a network comprising N IoT devices denoted by

$$N = \{D_1, D_2, D_3, \ldots D_N\}$$

The sensing strategies for each device are defined as

$$S = \{S_L, S_H, S_{CS}, S_{NS}\}$$

where SL, SH, SCS, and SNS for low-resolution sensing, high resolution sensing, collaborative sensing and no sensing, respectively. Depending upon the chosen strategy and the potential strategies of the neighboring devices, the utility function is formulated. For a device i th

$$U(i, S, j) = w_1 \times A_i(s) - w_2 \times E(S, i) + w_3 \times COH_i(s) + w_4 \times C(i, S, j)$$

where, Ai psq is a function representing the sensing accuracy of sensor i under strategy S. E pS,iq is the energy consumed bythe sensor i when it adopts strategy S. COHipsq represents the communication overhead that could be in terms of energy or bandwidth for a sensor i under strategy S. C(i,S,j) is the collaborative sensing benefit for device i using strategy S on the task j. 1, 2, 3and 4aretheweightsthatdetermine the relative importance of sensing accuracy, energy consumption, communication overhead, and collaborative benefits, respectively.

Classification of cooperative sensing

There are three approaches in sharing the collaborative sensing outcomes: centralized , distributed and relay-assisted Figure adapted from illustrates these three models.

i) Figure 1(a) displays the centralized cooperative sensing model [ABR11]. Fusion center (FC) is an entity which plays a central role in controlling and organizing the collaboration. The centralized cooperative sensing process consists of three steps,FC selects the licensed spectrum to be sensed and sends a request to neighbors asking for cooperation.

ii) The primary difference between distributed cooperative sensing and centralized cooperative sensing is, the former does not rely on a centralized fusion center to decide the final sensing result. Actually, centralized behavior also exists in distributed cooperative sensing. Figure 1(b) shows a distributed sensing model, CR1 to CR5 are all cooperative CRs, and they operate as their own FC.

The cooperative CRs which respond to the request will sense PU channel independently and report their sensing result afterwards. When all sensing outcomes arrive at FC, it fuses the collaborative data using some decision fusion logic, such as AND, OR, MAJORITY, to reach a nal outcome, and returns the nal outcome to the cooperators separately.

In Figure 1(a), CR0 acts as the FC, and CR1 to CR5 are cooperators of CR0. The physical link between PU and each cooperative CR is called sensing channel. FC sends the sensing instruction to the cooperators via a control channel, and cooperative CR reports the local sensing result through a reporting channel, which may be the same channel as the control channel.

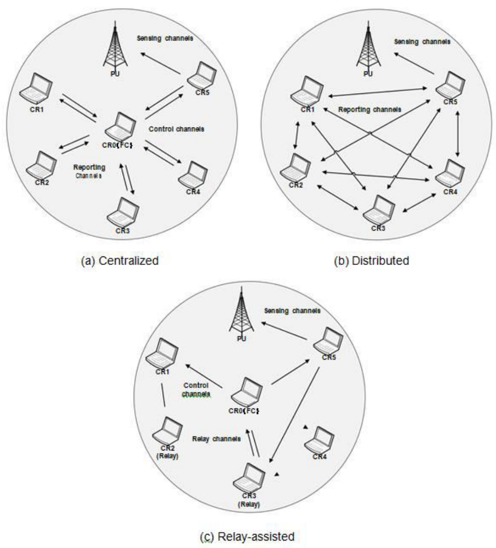

Figure 3: Classification of cooperative sensing

Three steps of distributed cooperative sensing:

- Each CR spreads its local sensing outcome to the neighbors within its trans-mission range.
- Based on its own decision fusion logic, each CR considers both the local sensing result and the received data to conclude a final outcome of PU state. Iterate the above steps until converge to a unified decision on PU channel state. In summary, the CR users communicate continually to generate a unified sensing decision via several times of iteration.
- Relay-assisted cooperative sensing applies to the situations when the sensing channel or reporting channel are non-ideal. From Figure 1(c) [ABR11] we can see, CR1, CR4, and CR5 have strong sensing channel but weak reporting channel, hence they request CR2 and CR3 as relay to transmit their sensing data to FC. Apparently, the relay-assisted manner eliminates the negatives by non-ideal reporting channel, thereby enhancing the global sensing performance.

The physical link from CR2 or CR3 to FC can be called a relay channel. Apart from centralized cooperative mode shown in Figure 1(c), relay-assisted cooperative scheme is also appropriate for distributed cooperative sensing. The state of PU channel is modelled as a two niter state machine, where the states are busy and idle, standing for the presence and absence of PU. Busy state suggests that PU is using the licensed spectrum currently; while idle state refers to the PU absence then CRs could utilize the licensed spectrum to transmit data. Figure 8 shows the model of primary user channel.

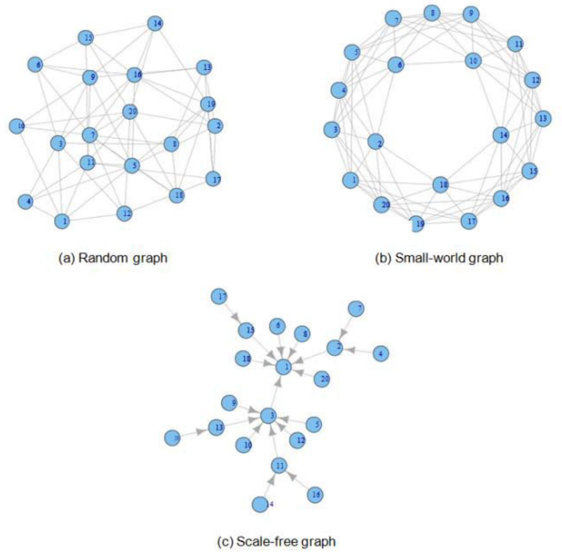

Figure 4: Three topologies of social networks

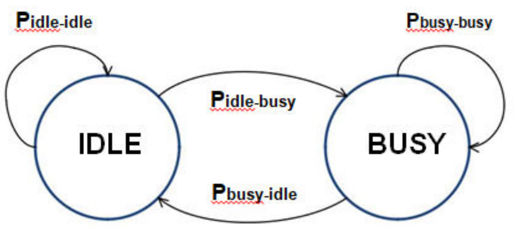

Figure 5: Primary user channel model

In wireless communication networks, the movement pattern of mobile devices exerts a crucial influence on system performance. Thus, the mobility model of wireless devices becomes a study point that attracts significant attention. In our system, we desire to exploit a social-based mobility model. More specially, the mobility model changes the physical location of CRs at the beginning of each timeslot, based on their social ties. One CR always set its next destination to the grid where most of its friends are located. Musolesi et al. in [17] propose a community-based mobility model (CMM), which is a primary social-based model. They present a concept of social attractively (SA). The SA of an area refers to the attraction of this area in terms of social factors. It is primarily determined by the social strength or social weight from this area.

A Random Learning (RL)-based algorithm provides an intelligent and adaptive approach for optimizing decision-making in Wireless Sensor Networks (WSNs), particularly for energy efficiency, routing, and transmission scheduling. In this paradigm, each sensor node acts as an autonomous agent that learns optimal actions through continuous interaction with the network environment, without requiring prior knowledge of system dynamics. In an RL-based WSN model, the problem is typically formulated using key components such as state, action, reward, and policy. The state represents the current condition of a sensor node, including parameters like residual energy, buffer status, channel condition, and neighbouring node information. The action refers to decisions such as whether to transmit data, select a routing path, choose a time slot, or remain idle. After performing an action, the node receives a reward based on the outcome, which may reflect energy consumption, successful packet delivery, delay, or collision avoidance. The policy defines the strategy that the node follows to select actions in different states, and it is continuously updated to maximize long-term cumulative rewards.

One of the most widely used RL techniques in WSNs is Q-learning, a model-free algorithm where nodes maintain a Q-table that stores the expected utility of taking a specific action in a given state. The Q-value is updated iteratively using the Bellman equation:

$$Q(s,a) \leftarrow Q(s,a) + \alpha\left[r + \gamma \max_{a'} Q(s',a') - Q(s,a)\right]$$

where s is the current state, a is the selected action, r is the immediate reward, s' is the next state, α is the learning rate, and γ is the discount factor. Over time, each node learns the optimal policy that maximizes its expected reward while minimizing energy consumption. In the context of the proposed system, RL can be effectively integrated into the Distributed Anticipatory Time-slot Selection Algorithm (DATA). Here, each node learns to select optimal transmission time slots based on past experiences of collisions and successful transmissions. For example, if a node experiences frequent collisions in a particular slot, it assigns a lower reward to that action and gradually avoids it. Conversely, successful transmissions yield higher rewards, reinforcing the selection of efficient time slots. This learning process reduces packet collisions, minimizes retransmissions, and conserves energy. RL can also be applied to energy-aware routing, where nodes learn the best forwarding paths based on factors such as residual energy, link quality, and hop count. Instead of relying on static routing protocols, RL enables dynamic adaptation to changing network conditions, thereby improving network lifetime and reliability. Additionally, RL-based clustering allows nodes to intelligently decide cluster-head selection and cluster formation, ensuring balanced energy usage across the network. The main advantages of RL-based algorithms in WSNs include adaptability, scalability, and the ability to operate in dynamic and uncertain environments. However, challenges such as slow convergence, exploration-exploitation trade-off, and computational overhead must be carefully managed, especially in resource-constrained sensor nodes

Listing. 2 Distributed RL-based Time-Slot Selection Algorithm

Step#1.for each user i:
- Initialize Q-table $Q(i, S, j)$
- Set initial values for $C(i, S, j)$
- Set exploration rate ε for ε -greedy exploration.

for each time-step or epoch:

Step#2. State Observation:
- Each user i observes its current state, which includes current strategy S, and possibly other parameters such as past history, signal strength, and so on.

Step#3. Action Selection:
- **for** each user i :
  - With probability $(1 - \varepsilon)$, select the time-slot j that maximizes the current predicted utility
  - With probability \(\epsilon \), select a random time-slot.

Step#4. Interaction with Environment:
- Each user i transmits using its selected time-slot on sub-channel and after transmission, each user observes:
  - Accuracy, $A_i(s)$
  - Energy cost, $E(S, i)$
  - Communication Overhead, $COH_i(s)$
  - Collision outcome to update $C(i, S, j)$:
    - If collision: Increase $C(i, S, j)$
    - Otherwise: Decrease or keep $C(i, S, j)$ the same.

Step#5. Reward Calculation:
- for each user i, calculate reward r based on the utility function:

Step#6.Update Q-values:
- for each user i:
  Update the Q-value for the chosen time-slot using the Bellman equation (8)

Step#7. Update Exploration Rate:
- Gradually decrease ε over time to reduce exploration and increase exploitation.

Step#9.Repeat from step 2 for the next time-step or epoch.

Figure 6: Random Learning Algorithm

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A Game Theory (GT)-based algorithm provides a powerful distributed approach for decision-making in Wireless Sensor Networks (WSNs), where multiple sensor nodes interact while competing for limited resources such as energy and bandwidth. In this framework, each sensor node is modeled as a rational player that aims to maximize its own utility (payoff) while considering the actions of other nodes in the network. In a GT-based WSN model, the system is defined using key elements such as players, strategies, and payoff functions. The *players* are the sensor nodes, the *strategies* represent possible actions (e.g., transmit, sleep, become cluster head, select route), and the *payoff function* quantifies the benefit of each action based on factors like energy consumption, successful data transmission, delay, and network contribution. Each node selects a strategy that maximizes its payoff while adapting to the behaviour of neighbouring nodes.

A fundamental concept in game theory is the Nash Equilibrium, where no node can improve its payoff by unilaterally changing its strategy. In WSNs, reaching a Nash equilibrium ensures a stable and efficient operating point where nodes balance energy usage and communication performance without centralized control.

One common GT-based approach in WSNs is the non-cooperative game model, where nodes independently decide their actions. For example, in cluster-head selection, each node evaluates whether to become a cluster head based on its residual energy and expected communication cost. Nodes with higher energy and better connectivity gain higher payoffs, increasing their probability of being selected. This results in balanced energy consumption and avoids overburdening specific nodes. Another important approach is the cooperative game model, where nodes collaborate to improve overall network performance. In this case, nodes may form coalitions (clusters) to share sensing and communication tasks. The payoff is distributed among participating nodes based on their contribution, ensuring fairness and encouraging cooperation. Cooperative games are particularly useful in data aggregation and collaborative sensing scenarios.

GT-based algorithms are also applied in energy-efficient routing, where nodes select optimal paths by considering both their own energy levels and the network's global performance. By modeling routing as a strategic game, nodes avoid energy-draining paths and reduce congestion, leading to improved throughput and longer network lifetime.

In addition, GT can be integrated with medium access control (MAC) protocols, where nodes compete for channel access. By assigning appropriate payoff values for successful transmission and penalties for collisions, nodes learn to access the channel efficiently, reducing packet loss and retransmissions. In a game-theoretic Wireless Sensor Network (WSN), each sensor node is modelled as a rational player that makes decisions to maximize its own utility (payoff) while considering network conditions. The goal is to achieve energy efficiency, fairness, and network stability.

$$U_i = \alpha \cdot R_i - \beta \cdot E_i - \gamma \cdot C_i$$

Where:

- Ui: Utility of node iii
- Ri: Reward for successful transmission or sensing
- Ei: Energy consumed
- Ci: Cost due to collision, delay, or interference
- α,β,γ: Weighting factors

```
        Start
          ↓
 Node Deployment
          ↓
Initialize Parameters
          ↓
 Observe Network State
(Energy, Distance, Load)
          ↓
 Select Strategy (s_i)
          ↓
 Compute Utility U_i
          ↓
 Is Utility Maximized?
     ↓           ↓
    Yes          No
     ↓           ↓
Keep Strategy   Update Strategy
          ↓
Check Nash Equilibrium
     ↓           ↓
    Yes          No
     ↓           ↓
   End         Repeat Process
```

Figure 7: Gamming Theory Algorithm

In Wireless Sensor Networks (WSNs) can be described as a sequence of distributed and iterative decision-making steps among sensor nodes. Initially, all sensor nodes are deployed and initialized with parameters such as residual energy, communication range, and sensing capability. Each node is then modelled as a rational player in a game-theoretic framework. In the next step, every node observes its current state, including energy level, neighbouring nodes, and network conditions. Based on this information, each node defines a set of possible strategies, such as participating in sensing, becoming a cluster head, forwarding data, or remaining idle. Following this, a utility (payoff) function is computed for each possible action, which typically considers factors like energy consumption, communication cost, data importance, and network contribution. Nodes then select the strategy that maximizes their individual payoff while indirectly contributing to overall network efficiency. As nodes interact with each other, they continuously update their strategies by comparing payoffs and adapting to the decisions of neighbouring nodes. This iterative process continues until the system reaches a Nash Equilibrium, where no node can improve its payoff by unilaterally changing its strategy. At this stage, stable clusters or communication patterns are formed, ensuring balanced energy consumption and reduced transmission overhead. Once equilibrium is achieved, selected nodes perform sensing and data transmission efficiently, while others conserve energy by staying idle or in low-power mode. The process is periodically repeated to adapt to dynamic network changes such as energy depletion, node failures, or varying traffic conditions. This continuous adaptation ensures optimal performance, prolonged network lifetime, reduced energy consumption, and improved reliability in WSN operations. The primary objective of the utility function is to in the proposed scenario is to maximize the sensing accuracy, minimizing the energy consumption and communication overhead. The sensing accuracy is treated as a regression problem and therefore the accuracy is represented as Mean Absolute Error (MAE). For node i, implementing strategy S, the MAE is given by

$$MAE = \frac{1}{N}\sum_{i=1}^{M} |R_i(S) - T|$$

|Ri (S)- T| is the absolute difference between the reading from node i using a strategy S and the ground truth value (actual reading), T. Therefore, while modeling the game, a strategy that maximizes the accuracy while minimizing energy con sumption can be adopted. Such a strategy is given

$$S^* = \arg max_S \left[A_i(S) - \lambda E(S, i)\right]$$

where λ is the weighing factor that provides a balance between accuracy and energy consumption. Sensing, processing, and communication are the major sources of energy consumption in wireless sensor networks. Communication overhead is a crucial component in the mod eling of the system as it influences the energy consumption considering the packet transmissions, control messages and re-transmissions. If di(S) is the size of the packet of the node i that uses strategy S, the COHipsq is given by

$$COH_i(s) = O_{packet} + O_{control} + O_{retransmissions}$$

A novel parameter known as the Selection Propensity Index (SPI) is defined for each node by considering how each node evaluates its utility against potential collaborations. The SPI of the node i is the average utility of the node i when it is collaborating with all the other nodes. The algorithm to calculate the SPI is given in Listing 1. The flowchart demon strating the process of selecting SPI for different strategies is depicted Game theory is used to model the interactions between autonomous agents (sensors in this case), where each agent's payoff depends on the strategies adopted not only by itself but also by other agents in the network. Random Learning, allow agents learn to make decisions by interacting with their environment. Nodes initially use game theory to estimate the potential payoffs of different strategies based on static or semi-static network models. As they operate, they gather real-time data and feedback on their performance and the state of the network. This real-world data feeds into the RL algorithms, allowing each node to learn and adapt its strategy based on dynamic conditions. The RL algorithms continually refine the strategies of the nodes based on on going interaction out comes, leading to an evolved strategy that is more nuanced and effective than what could be derived from static game theory alone

5. RESULTS& DISCUSSION

The proposed system for energy-efficient sensor network operations is thoroughly evaluated through extensive simulations to analyse its effectiveness under various network conditions. The results demonstrate that incorporating collaborative sensing and intelligent decision-making significantly improves both energy efficiency and data accuracy. By selectively activating only high-priority nodes using mechanisms such as the Selection Propensity Index (SPI), redundant sensing is minimized while maintaining reliable and accurate data collection. The collaboration among nodes ensures that sensing tasks are distributed efficiently, reducing unnecessary overlap and improving the overall quality of information gathered from the network. In terms of energy consumption, the results show a substantial reduction in per-node and overall network energy usage compared to conventional approaches. Nodes dynamically adjust their participation based on residual energy and network requirements, which prevents rapid energy depletion of specific nodes. This balanced energy utilization leads to a more uniform energy distribution across the network. The integration of the Random Learning-based Distributed Anticipatory Time-slot Selection Algorithm (DATA) further contributes to energy savings by minimizing packet collisions and retransmissions. As a result, communication overhead is significantly reduced, which is one of the primary sources of energy consumption in Wireless Sensor Networks (WSNs). The proposed system also exhibits strong resilience to node and communication failures. During simulation, scenarios involving node dropouts and link disruptions were introduced to evaluate robustness. The distributed nature of the model allows neighbouring nodes to quickly adapt by reconfiguring their strategies without requiring centralized control. This ensures continuous network operation and prevents significant performance degradation. The ability of the system to self-adapt under dynamic conditions highlights its suitability for real-world deployments where uncertainty and failures are common. Performance metrics such as network lifetime, throughput, and energy efficiency are quantitatively analysed and compared with existing state-of-the-art methods. The results indicate that the proposed EECS-GT model achieves a noticeable improvement in network lifetime due to reduced energy wastage and efficient load balancing. Throughput is also enhanced as a result of fewer packet collisions and improved channel utilization enabled by intelligent time-slot selection. Additionally, the packet delivery ratio increases, reflecting improved reliability in data transmission. The simulation environment is implemented on a high-end computing system running a Windows-based operating system, ensuring accurate modeling and performance analysis. Various network parameters such as node density, transmission range, initial energy levels, and traffic patterns are varied to test the scalability and adaptability of the system. The results consistently show that the proposed model outperforms traditional protocols in terms of energy conservation, stability, and overall network performance.

Table 1. Simulation parameters used for evaluating the proposed model

Simulation Parameter	Value
Area	$200 \times 200\ m^2$
No. of Nodes	$1 - 500$
Mobility Model	Random waypoint mobility
Transmission data rate	$5\ packets/sec$
RSSI	$-89.3\ dBm$
MAC protocol used	IEEE 803.15.4
Programming Language	Python 3.12
Matplotlib and Seaborn	For visualization and plotting
Numpy and Pandas	For numerical data operations
Gym	OpenAI's library for simulating reinforcement learning.

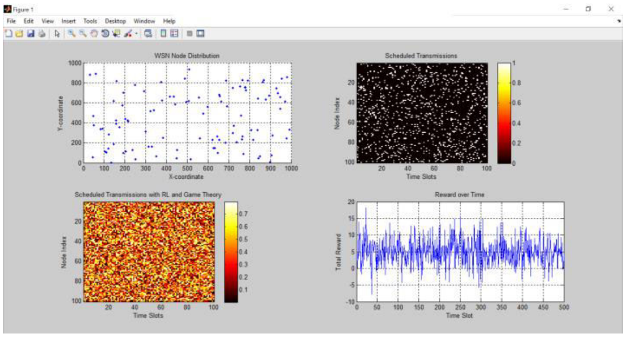

Figure 8 (a) Node deployment (b) Scheduled transmission slots (conventional) (c) Scheduled transmission slots with RL and game theory (d) Rewards for nodes in various time slots

Figure 8 shows the distribution of the nodes across the network. With scheduled Transmissions without RL Fig 8.1(b), there is a periodic, structured transmission pat terns across the node index. The transmissions seem to be more scheduled or deterministic. But, as shown in Fig 8.1(c), scheduled transmissions with RL and game theory, Simulation parameters used for evaluating the proposed model. a more random and scattered distribution of transmissions across the nodes. Dynamic scheduling is possible because of the reactive nature of the RL and the game theoretical strategies. Certain nodes might be prioritized over others during the transmissions. Modelling the policy based on RL and game theory will distribute the transmissions uniformly to accommodate diversified transmission strategies. Moreover, the proposed mechanism adapts to the priori ties of different nodes based on evolving criteria. Fig 8.1(d) shows the progressive reward over different available time slots

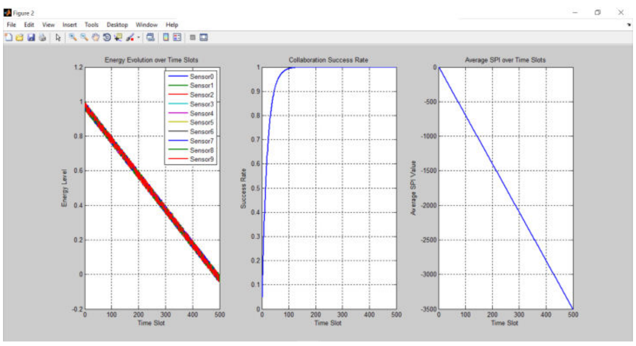

Figure 9: Critical aspects of the wireless sensor network are modelling using game theory over different time slots. (a) Energy evolution over time-slots (b) Success rate of collaboration in each time-slot (c) Average SPI over time-slots

All sensors exhaust their energy in a linear manner over a period of time (Fig 8.2(a)). Most of the nodes operate in similar conditions and hence potentially there is no much difference in terms of energy exhausting patterns among different nodes. However, the collaboration success rate tends to remain close to 1 throughout the time slots (Fig 8.2(b)). This indicates that the collaboration between the sensors is successful throughout the slots and hence the performance of the system will be optimal in terms of energy consumption. The average SPI of the sensors tend to decrease linearly over the time slots (Fig 8.2(c)). This SPI decrease can be attributed to the decreasing energy levels of the node sin the network as energy consumption is also one major aspect that contributes to the SPI calculation. As the energy of the node's exhausts over time, their ability to be selected for collaborations shrinks. Network lifetime is an important parameter in design, planning and deployment of the resource-limited nodes in wireless sensor networks and therefore maximizing network lifetime is paramount. Conventional clustering algorithms focus on node clustering based on energy profiles, where one node will act as a cluster head for aggregating and transmitting data. The other nodes in the cluster send data to these clusters. Since the number of nodes transmitting data over longer distances is reduced, the energy consumption I reduced. By careful balancing of the clustering process and cluster-head selections, lifetime of the network can be sig nificantly enhanced. The proposed network model provides a significant improvement in the life time of the proposed model with the use of DATA that aids in effective decision-making based on accuracy, energy consumption, communication overhead, and collaborative sensing

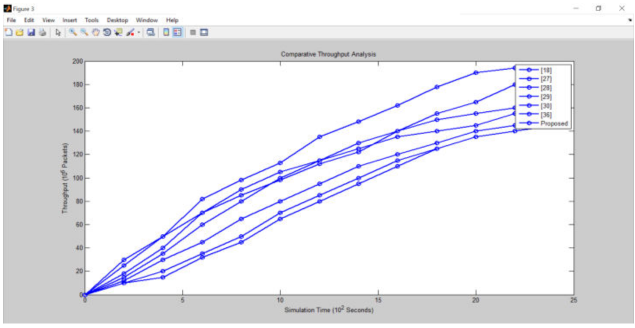

Figure 10: Comparative analysis of throughput of the network during the run-time under various strategies

Network throughput is another crucial metric that dictates the efficiency and performance of a sensor network. Fig 8.3 illustrates the comparison between the proposed model and the existing state-of-the-art methods in terms of throughput In cluster-based models, the random nature of cluster-head selection can sometimes result in non-optimal selections, which might reduce through put. The collaborative sensing model implemented in the proposed work reduces the collision and potentially improves the throughput. A key feature of the EECS-GT model is that it considers the readiness and ability of a node to participate in data communication. As nodes with higher propensities are given preference, it ensures that active nodes with better communication links are used more often, potentially increasing throughput. The utility function's components, such as accuracy, energy, communication overhead, and a custom metric (C), provide a balanced approach to decision-making in the network. This balance can lead to efficient routing and communication, further boosting throughput.

Table 2: Throughput comparison across different methods as function of time

	Throughput (× 10^5)					
Simulation Time (Sec)	[18]	[27]	[28]	[29]	[30]	[Proposed]
0	0	0	0	0	0	0
2	16.98	19.12	25.32	11.23	9.84	28.64
4	29.3	40.12	49.98	30.3	14.72	51.48
6	50.32	59.24	70.52	44.9	31.7	82.22
8	71.32	78.16	89.98	65.2	43.21	97.33
10	83.97	99.32	104.9	79.81	64.62	112.87
12	99.68	114.41	114.8	94.2	81.2	136.21
14	111.14	131.63	125.4	111.32	94.32	148.23
16	119.27	139.21	135.3	121.4	109.65	161.32
18	129.43	148.39	141.5	131.62	124.98	178.32
20	134.96	154.2	144.5	141.23	134.52	189.2
22	142.23	161.36	155.14	146.12	138.64	192.5
24	146.79	169.12	155.48	150.21	145.12	192.98

The table presents the throughput performance comparison of the proposed method with existing approaches over different simulation times. It is observed that the throughput of all methods increases as time progresses, but the proposed model consistently achieves higher values than the others. In the initial stages, the difference is moderate, but as time increases, the proposed system significantly outperforms the existing methods, reaching the highest throughput at each interval. This improvement is mainly due to efficient resource utilization, reduced packet collisions, and intelligent scheduling mechanisms. Overall, the results indicate that the proposed approach enhances data transmission efficiency and ensures better network performance compared to state-of-the-art techniques.

5. CONCLUSIONS

With the rapid growth in the applications built around wireless sensor networks, energy efficiency, and network longevity is a demanding need. The proposed method based on the game theory is a novel approach tailored to provide energy-efficient operation without compromising on the QoS in sensor networks. DATA algorithm based on RL leverages the power of reinforcement learning to reduce the concurrent transmissions thereby decreasing network collisions, re-transmissions and as a result minimizes the network delays. The utility function provides an effective way for the nodes to make decisions on whether to transmit data, when to transmit, and which node to communicate with. This data-driven approach ensures that decisions made are in the best interest of reducing delays. Additionally, the Q-learning aspect ensures that nodes learn from their past actions and the network as a whole evolves to adapt to changing conditions, leading to reduced delays over time. The use of SPI to select fewer and well-qualified nodes reduces unnecessary traffic and thereby avoids congestion. The proposed method provides network lifetimes greater than 202% compared to existing methods when running on full load. Additionally, the network's throughput saw an enhancement of around 23%, attributable to more efficient data transmission paths and reduced redundancy in sensing. By intelligently selecting collaboration partners, nodes were able to minimize over lapping sensing areas and communication overhead, leading to more streamlined data collection and transmission. The model's intelligent design and learning capabilities equip WSNs to adapt to different scenarios, making it a robust solution for real-world applications where reduced delays are crucial.

FUTURE SCOPE

For future enhancements, the system can be further improved by integrating advanced Artificial Intelligence

(AI) and Machine Learning (ML) techniques such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Forest algorithms. These models can be utilized for predictive decision-making, such as node selection, fault detection, traffic prediction, and adaptive routing. For instance, SVM can classify network states for optimal decision policies, KNN can assist in similarity-based node clustering, and Random Forest can improve decision accuracy through ensemble learning. Combining these supervised learning techniques with reinforcement learning can create a hybrid intelligent framework that enhances prediction accuracy, reduces convergence time, and improves overall network adaptability. Such advancements will further strengthen the robustness, scalability, and efficiency of WSNs in complex and dynamic environments.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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