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Energy Efficiency Based Learning Automata Methodology in WSN

Dr. B. SANTOSH KUMAR
Associate Professor, Department of MCA, Wesley PG College, Secunderabad, India.

Abstract
Wireless Sensor Networks (WSNs) play a crucial role in various applications, ranging from environmental monitoring to healthcare and industrial automation. However, the limited energy resources of sensor nodes pose a significant challenge to the long-term operation and performance of WSNs. To address this challenge, researchers have been exploring innovative techniques to enhance energy efficiency in WSNs. One promising approach is the utilization of learning automata methodologies tailored for energy-efficient operations in WSNs. Learning automata are adaptive decision-making algorithms that enable nodes to learn and optimize their behavior based on environmental feedback. This paper presents an overview of the Energy Efficiency Based Learning Automata Methodology in WSN, which aims to leverage the adaptive capabilities of learning automata to optimize energy consumption in WSNs. We discuss the key principles and components of this methodology, including the design of algorithms and protocols that enable sensor nodes to make intelligent decisions regarding energy usage, routing, and data processing. We also explore the potential benefits, challenges, and applications of energy efficiency-based learning automata methodology in real-world WSN scenarios. Through a comprehensive understanding of this methodology, we aim to contribute to the development of robust and energy-efficient WSNs capable of meeting the demands of diverse IoT applications.

Keywords: *WSN, Learning automata, Energy efficiency, Optimization, Delivery ratio, Relay node selection.*

I. Introduction

Wireless Sensor Networks (WSNs) have emerged as a vital technology for various applications [1], including environmental monitoring, healthcare, and industrial automation. However, one of the critical challenges in WSNs is the limited energy resources of sensor nodes [2], which directly impacts network lifetime and performance. To address this challenge, researchers have been exploring innovative techniques to enhance energy efficiency in WSNs [3].

One promising approach is the utilization of learning automata methodologies tailored for energy-efficient operations in WSNs [4]. Learning automata are adaptive decision-making algorithms that enable nodes to learn and optimize their behavior based on environmental feedback [5]. By incorporating learning automata into WSNs, nodes can dynamically adjust their operational parameters, such as transmission power levels [6], data aggregation strategies, and sleep-wake schedules, to minimize energy consumption while maintaining network functionality and performance.

The Energy Efficiency Based Learning Automata Methodology in WSN aims to leverage the adaptive capabilities of learning automata to optimize energy consumption in WSNs [7]. This methodology involves designing algorithms and protocols that enable sensor nodes to make intelligent decisions regarding energy usage, routing, and data processing. By continuously learning and adapting to the network environment, nodes can efficiently utilize their limited energy resources, thereby extending network lifetime and improving overall performance.

In this introduction, we will explore the key principles and components of the energy efficiency-based learning automata methodology in WSNs. We will discuss its potential benefits, challenges, and applications in real-world scenarios. Additionally, we will examine existing research efforts and advancements in this field, highlighting the significance of energy-efficient solutions for sustainable and reliable operation of WSNs. Through a comprehensive understanding of this methodology, we can pave the way for the development of robust and energy-efficient WSNs capable of meeting the demands of diverse applications in the Internet of Things (IoT) era [8].

II. Related work

Research on energy efficiency-based learning automata methodology in Wireless Sensor Networks (WSNs) has gained significant attention in recent years due to its potential to address the energy consumption challenges in WSNs. Here are some related works in this field:

A learning automata based stable and energy-efficient routing algorithm for discrete energy harvesting mobile wireless sensor network by Hao et al [9]: This study proposes a routing protocol based on learning automata to optimize energy consumption in WSNs. The protocol dynamically adjusts routing paths based on network conditions and node energy levels, leading to improved energy efficiency and network lifetime.

Detection of selective forwarding attacks based on adaptive learning automata and communication quality in wireless sensor networks by Zhu et al. (2018) [10]: The authors present a Medium Access Control (MAC) protocol for WSNs that utilizes learning automata to adaptively adjust contention window sizes and transmission parameters. This approach minimizes collisions and idle listening, resulting in energy-efficient communication.

Machine learning based optimal renewable energy allocation in sustained wireless sensor networks by Sharma et al. (2019) [11]: This research explores the application of reinforcement learning techniques, a subset of learning automata, for dynamic energy management in WSNs. The proposed approach enables nodes to learn optimal energy-saving strategies based on environmental feedback, leading to improved energy efficiency and network performance.

Distributed Energy-Efficient Data Aggregation in WSNs Using Q-Learning by Zhang et al. (2020) [12]: The study introduces a distributed data aggregation scheme based on Q-learning, a type of reinforcement learning algorithm. Nodes learn to optimize data aggregation strategies to reduce redundant transmissions and conserve energy in WSNs.

Energy-Aware Cluster Formation and Routing Protocol Using Learning Automata in WSNs by Yadav et al. (2021) [13]: This work proposes an energy-aware clustering and routing protocol for WSNs based on learning automata. The protocol dynamically forms clusters and selects optimal routing paths to balance energy consumption across sensor nodes and prolong network lifetime.

III. Proposed system Learning automata-based energy efficient routing mechanism

In this part of the discussion, the major attention is placed on deconstructing and expanding upon the node selection approach that was first presented in the preceding section and was based on the concepts of Particle Swarm Optimization (PSO). The primary objective of this project is to determine methods for the transmission of data that are both reliable and efficient in terms of energy consumption. In addition, the use of learning automata, which has been shown to be beneficial in this specific setting, is the strategy that is utilized in order to determine the likelihood of picking a node in scenarios in which a route becomes unavailable.

PSO based relay selection scheme Particle swarm optimization

The concept of fish schooling and bird flocking served as inspiration for the development of the PSO algorithm. These birds always travel together in a flock without bumping into one another as they look for food or a place to shelter themselves. Each individual member or bird in a flock adjusts its speed and location in response to the information provided by the group. As a result of members of the group sharing information with one another, the amount of time spent by individual birds and members looking for food and shelter is reduced.

Each particle in PSO provides a solution to a particular instance of the problem, and PSO is composed of a predetermined number of particles known as (S_n). A fitness function is going to be used to determine how each particle stacks up. All particles have same dimension. In the dth dimension of the hyperspace, each particle P_i has a position, denoted by (P_{id}), as well as a velocity, denoted by (Vel_{id}). Therefore, the particle P_i is represented as at any given instant in time as

$$P_i = P_{i,1}, P_{i,2}, P_{i,3}, \dots . P_{i,d}$$

Each particle P_i follows both its own best ($pbest$) and the global best ($Gbest$) to iteratively update its position and velocity as part of the process of moving towards the global best position. This update procedure is carried out until the $Gbest$ has been located or until the maximum number of iterations has been reached.

Updated Relay node selection

During the process of sending data, the sensor nodes make use of relay nodes to make it easier for the data they have gathered to be sent to the Cluster Heads (CHs) that are linked with them and to whom they are connected. Through a series of multi-hop relay nodes, the data makes its way from the sensor nodes to the CHs. To reduce energy usage, the recommended solution uses PSO to choose the most efficient relay nodes for data transmission. In the suggested approach, an enhanced fitness function is created using the PSO methodology, and the relay nodes that lie between the sensor nodes and the CHs are selected using that function. The recommended fitness function calculates each sensor node's fitness value by considering them as particles. The fitness function uses the sensor node's remaining energy and distance from CH to choose the most effective relay from the collection of selected sensor nodes. The relay selection strategy generates pbest from fitness factors. Every sensor node involved in the selection of relay nodes is given this value. As a result of Gbest attaining the highest cumulative fitness score during the course of the relay race, it will be given the responsibility of acting as the relay node that is charged with sending the data to CH.

Relay node Selection parameters

Not only does the amount of leftover energy play a role in the PSO technique's decision-making process, but so does the distance between the relay node and the CH. Within the selection criteria, the parameters that have an effect on the selection of the relay stand out as being crucial elements. These criteria, in essence, serve as a guide for determining which node will serve as the relay, which is an important duty that is accountable for preserving the node's battery life while efficiently sending data from member nodes to the CH. Regarding CH nodes that are taking part in the relay selection process, the PSO method is used to determine the nodes' respective fitness values. Based on the relay selection criteria that are employed, these values were determined.

Combined routing technique

This section digs even more into the workings of the approach that combines PSO with learning automata. Within a Wireless Sensor Network (WSN), it is the goal of each individual node to transmit data to the network's central base station, which acts as the information's final resting place. At the beginning of the process, each sensor node presents a number of potential outcomes for the next hop, which are determined by a number of different primary criteria. Taking into account the information from the network, the sensor nodes in the proposed network make use of a combination of PSO and learning automata algorithms in order to determine which nodes represent the best possible option for the network's next hop.

The PSO algorithm determines the nodes that have the highest potential for the next step along the route by applying selection benchmarks, assigning weights to each node, and factoring in important features while doing so. This process takes place when the algorithm is assigning weights. Learning automata are used so that the selection of the next hop may be modified in accordance with the input from the network. During the process of learning automata, a mechanism that includes incentives and penalties is used to either increase or decrease the chance of picking a node for the subsequent hop. This may be done in either direction. This mechanism works in both directions at the same time.

IV. Result and analysis

Through simulations using NS2, the postulated mechanism was compared to O-LEACH, an enhanced LEACH technique, and EEPC. Each sensor node's initial energy is set at 100 j, and they are dispersed at random throughout an area with the dimensions 1000 m by 500 m. From 50 to 200 nodes make up the network. There will be 4 clusters in the cluster. The agents CBR & UDP are regarded as traffic- producing agents. Table 1 displays the values of the experimental parameters.

Table 1: The experimental parameters

Parameter	Value
Network area	1000x500
Number of nodes	50 to 200
Cluster size	4
Initial energy	100j
Packet size	1024
Routing protocol	AODV
Traffic source	CBR (Constant bit rate)

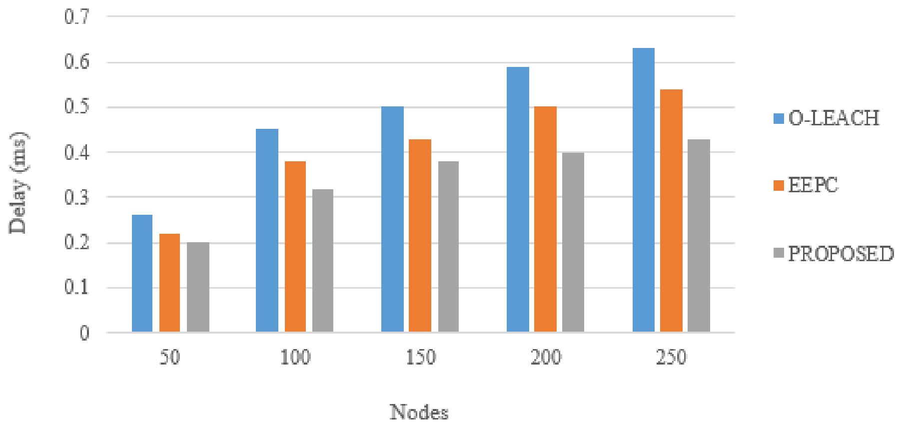

Figure 1: End to End Delay

The temporal interval from the initiation of packet transmission from its source to its ultimate destination is often denoted as an end-to-end delay. On display in Figure 1 is a representation of the end-to-end delay spread that the suggested technique experiences over a variety of network sizes. The end-to-end latency will report an increase in situations that are characterized by a denser node population. This increase will correspond directly with the scale of the network. This increase may almost entirely be pinned on the increased number of hops that have been accumulated along the routing route. The provided approach, in contrast to the protocols that were investigated, displays a greatly decreased end-to-end time as a result of its combination of efficient relay selection and reliable CH selection procedures.

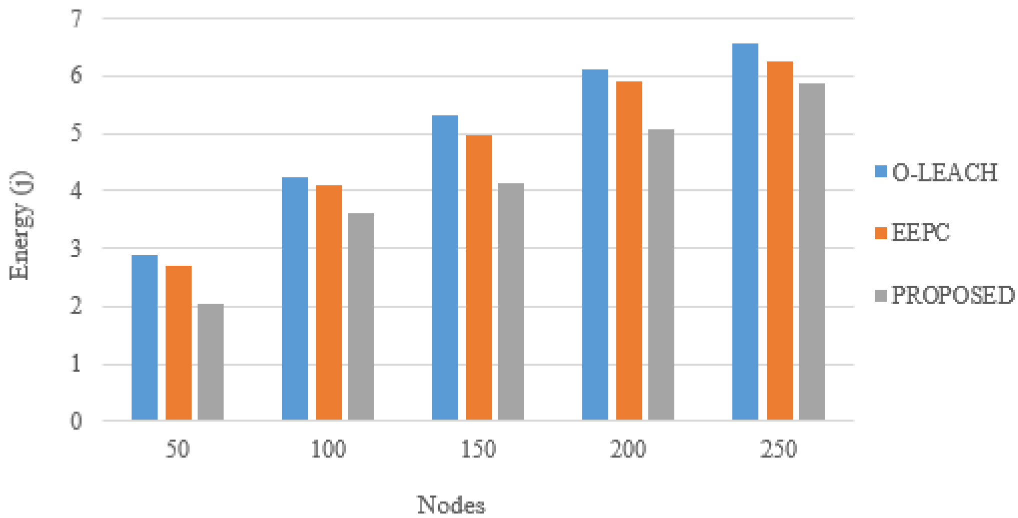

Figure 2: Energy consumption

The initial energy is provided to sensor nodes to carry out network operations. Energy is used with each network operation. Optimization of energy use is crucial in ensuring sustained network activity across all networks. The process of data aggregation is of significant importance in the context of energy conservation within clustered networks. The frequent rotation of the cooling and heating system results in excessive energy consumption, which is undesirable. This paper proposes a stable CH selection approach that uses node energy rather than random number selection, unlike the LEACH algorithm. This suggested algorithm aims to maximize the energy consumption rate within the specific scenario being considered. Additionally, the use of an enhanced PSO algorithm for relay node selection effectively mitigates the energy burden on each node, hence leading to reduced energy usage across all sensor nodes. The figure seen above, labelled as Figure 2, illustrates a graphical representation of energy use.

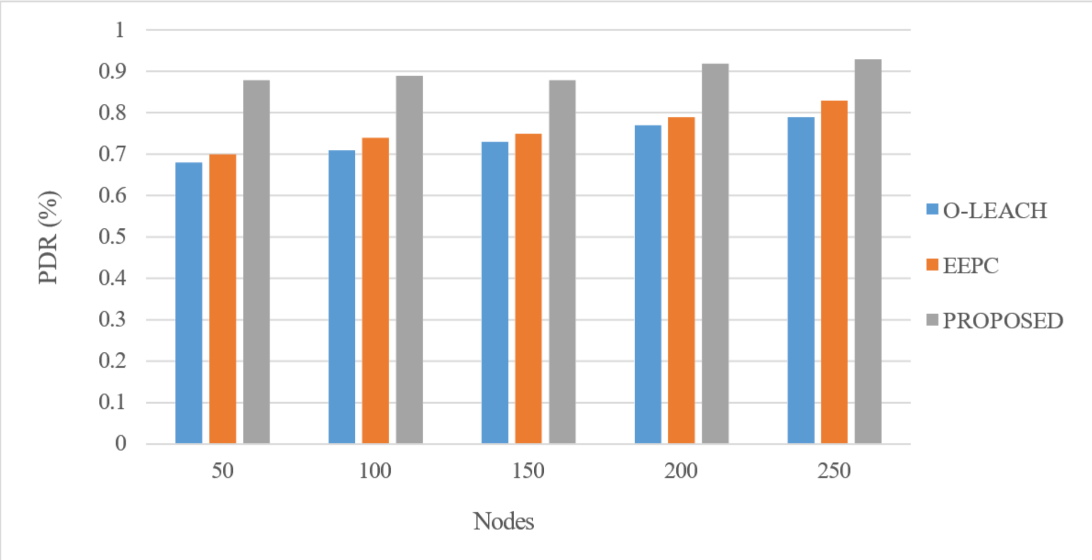

Figure 3: Packet delivery ratio

The term "Packet Delivery Ratio," abbreviated as "PDR," describes the percentage of data packets that are delivered to their destinations without error in comparison to the total number of packets that are sent out by the sender. A rise in the PDR of the network is brought about as a result of the combination of data aggregation and relay selection. The suggested protocol discovers optimum paths that are superior to the PDR rates obtained by other protocols by applying multi-objective PSO to optimize relay selection. This allows the proposed protocol to exceed the PDR rates achieved by comparable protocols. This is made clear by the much higher PDR rate, which reached a peak of 85, in comparison to the significantly lower PDR rate, which was maintained at 76 on average using traditional means. Figure 3 includes not only a tabular list of the PDR values but also a graphical depiction of the PDR. Both of these elements may be obtained in the same location.

V. Conclusion

In conclusion, the significance of Wireless Sensor Networks (WSNs) in various applications cannot be overstated, yet the inherent challenge of limited energy resources poses a substantial obstacle to their long-term viability and effectiveness. To overcome this challenge, researchers have delved into innovative methodologies aimed at enhancing energy efficiency within WSNs. Among these methodologies, the integration of learning automata stands out as a promising avenue. Learning automata, as adaptive decision-making algorithms, offer the capability for nodes to learn and optimize their behaviour based on environmental feedback. This paper has provided an insightful overview of the Energy Efficiency Based Learning Automata Methodology in WSNs. By harnessing the adaptive capabilities of learning automata, this methodology seeks to optimize energy consumption within WSNs. Key principles and components of this methodology have been elucidated, encompassing the design of algorithms and protocols facilitating intelligent decisions regarding energy usage, routing, and data processing.

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