



An Adaptive Deep Learning Framework for Energy-Efficient Clustering in Wireless Sensor Networks

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ABSTRACT

Wireless sensor networks (WSNs) are used for the indoor monitoring system, biological applications in healthcare, and other day to day applications. However, the biggest problem is that they currently have very limited life indeed since the only apparent stopping force for them is the energy stored in the battery. The traditional clustering protocols, such as LEACH, concentrate on a probabilistic forward feedback approach for determining who the Cluster Head (CH) is to be. This has resulted to more of the power bias in the network, makes it a hundred less fault prone and thus lasts even fewer years. This research study recommends the application of an Energy-Efficient Clustering Algorithm (EECA) that employs the use of the Artificial Neural Network (ANN)-based procedure in the cluster head selection process since it relates with many system parameters. The result is the efficient placement of the nodes according to each CH, then their communication in every round is through TDMA and multi-hop. We demonstrate in a detailed fashion how our EECA models provide strong enhancements in quality of network operations. Specifically, it was observed that comparing with the performance of the LEACH protocol, the last extended the network liveliness to a larger optimization time of about 3200 rounds rather than LEACH's 1600 rounds in operation. In addition to this, more than 50% of the energy was sustained as compared to the same LEACH cycle not failing any Packet Delivery Ratio (PDR) of 0.96. This helps to solve the problem by putting more emphasis on the increased rates and throughputs at the comfortable latency level for the best communication. In this sense, clustering decisions integrated with deep learning offer a proven and scalable means of improving the energy performance and operational activity of WSNs.

Keywords: Wireless Sensor Networks, Energy Efficiency, Clustering, Artificial Neural Network, Cluster Head Selection, Network Lifetime

1. INTRODUCTION

Wireless Sensor Networks (WSNs) are emerging as one of the most utilized technologies across multiple applications. This is because they provide surveillance on a real-time basis by constantly monitoring events and collecting relevant data. Irrespective of the use of the products, several prevalent applications include monitoring of environmental-friendliness of healthcare systems, automation in factories, military operations, and the development of smart cities. The primary intention of a network design is to construct a Wireless Sensor Network of a considerable size incorporating a multitude of small nodes typically spread over a large geographical range in order to collect data on temperature, humidity, pressure, motion or other environmental parameters of interest as suggested by some previous studies. These

data are then transported from the sensor nodes to the headquarters of the Base Station or sink, according to the resources allocated, by the network architecture.

In particular, WSNs are facing a myriad of issues such as those created by the architectural constraints caused by most, if not all, sensor nodes such as the short battery life, low processing capability, and limited communication range. Top among the challenges is energy, and holds the most significance because in practice there are no sources of power where a sensor might be deployed. Thus, controlling power is essential in increasing the range of life of a network and increasing chances that the data is transmitted successfully. The durability of a Wireless Sensor Network (WSN) can be quantified in terms of network lifetime which could apply to the sooner by which a node or a network fails, the sooner by which the whole network as a whole failure or the last node in the network dies given the first node has already died. Through unequal use of energy by diverse nodes, the first change involves the sooner demise of the first node; the second change is network sectioning and Quality of Services (QoS) which however captures an overall degradation in performance.

Considering the inherent energy inefficiency in a network structure, the most commonly practiced techniques are those involving Routing. During the lifetime of the sensor network, the available sensor nodes are then combined into clusters. Each cluster is allocated an elected leader—the cluster head (CH) who is responsible for data collection from the nodes in his/her cluster and forwarding it to the BS. This reduces data redundancy which consequently lessens communication costs; however, the effectiveness of clustering is highly debatable as the primary CH selection many times lack of uniformity therefore some of the nodes may decay more frequently and in turn consume more energy, hence result in a slightly shorter lifetime of the network [5]. As traditional clustering protocols have been shown to be easy to implement and can work efficiently in a distributed mode; such techniques have caught the attention of numerous scholars and practitioners. Without providing even coverage of cluster heads, as well as without observing the effects of provided a direct manner of energy draining, node distribution and distance in a straight line, low energy has been spent during the selection of cluster heads resulting in a very fast presentiment and deterioration. Semi-randomize-based EEM-LEACH has been proposed as revised versions of leach and attempts have been made to enlarge the parameter space or to manipulate the member selection process so as to improve the said models [6]. In fact, they mainly focus on heuristic and causal-rule based approaches which are not equipped to deal with the systems that keeps changing rapidly and most of the times these approaches do not correspond to good performance and accuracy under many different types of WSN scenarios.

The principal objectives of this plan are as follows:

- An ANN-based cluster head selection mechanism was developed to improve decision-making and overcome the limitations of heuristic and probabilistic algorithms.
- Energy efficiency was enhanced through omnidirectional broadcasting, reduced sleep-state dependency, and multi-hop communication techniques.
- Network lifetime optimization was achieved by balancing battery consumption and maintaining active node participation for longer durations.



- Deep learning integration enabled adaptability for both large-scale and specialized wireless sensor network (WSN) deployments.

The proposed AI-enhanced framework provides a scalable and intelligent solution to overcome the limitations of conventional WSN protocols.

2. RELATED WORK

There have been significant advances in research on wireless sensor networks (WSNs) whereby machine learning (ML) and deep learning techniques have been introduced to combat the main problem of energy efficiency and network lifetime. In particular, Akram et al. [1] suggested machine learning-based routing protocol called (EEMLCR) which aims to effectively choose the cluster head using supervised learning thus leading to a significant improvement in the network life, energy consumption and delivery ratio that LEACH and similar simple approaches cannot provide. In the same token, Kang et al. [2] offered various solutions to the problem by proposing an adaptive machine learning-based scheduling that enabled dynamic adjustments in the operational coverage corresponding to the nodes' working pattern based on environmental conditions thus eliminating nodes' transmissions that were not required for efficient power usage. A different solution was provided by Juwaied and Jackowska-Strumillo [3], where a DL-assisted model based on the HEED protocol in particular, DL-HEED, has evened energy outflows at the nodes and improved clusters such that energy persists in the WSN devices for longer duration.

The design scheme of Wang and Zhang [4], however, identified the existing gap in data cantered demographic and proposed a model whose common denominator was a data mining technology from the data base, including deep learning model. The proposed machine learning based deep-learning driven mechanism suggested by Du and Lee [9] was not only about data gathering, also more importantly it suggested including significant modifications that would improve information exchange. If we shift to a different context, Wibowo et al. [5] showed some results, which offered a new way of using ML in the re-design of the routing/clustering adaptive framework for static WSN, having improved slightly its energy efficiency and stability, nevertheless having certain issues in term of scalability when applied to large-scale deployments. On the other hand, Gherbi et al. [6] proposed a way of solving the problem of load distribution while distributing energy among concurrent clusters, though there appear to be some preliminary glitches in the system, an intelligent approach has still not been incorporated. Abu-Baker et al. [7], who found themselves disadvantaged without the ability of CS, succeeded to achieve more power over channel-assisted transmission, the position was significantly enhanced over disabilities of peak power and the direct results of channel decisions.

Zhang et al. [8] followed the “dark route” and opted to raid with the so-called hybrid routing HSOP implementation in which the main tasks were to search optimal and sub-optimal clusters achieving good routing while consuming minimal energy despite the high processing costs. Also, neural networks were given in Jalili and Babakordi [9] trained adaptational model based on fuzzy logic which along with the neural networks was used to build a hybrid system of document clustering. The next paragraph contains a ‘throw-in statement’ regarding the

most recent surveys that were conducted by Ding and others (2007), acknowledging that instead of the conventional method some machine learning routing strategies were more effective in energy conservation and changing system settings, while pointing out the forthcoming problems of using the technical process of making it trainable and putting it to practice. Even recent research has observed smart WSN has different addressing just emphasis on the fabrication of the WSN in the Figure 2, supplemented by a bingo cube 11 provided the extent effect in the form of improved adapted density-oriented adjustment of the goal avoidance movement group mobile environments which were common, that is, they were movable together with, on the end-device. Of them, the secure deep learning-based node centric routing [12] must be termed important for the case of the omission of the intrusion detection system which exhibits many encouraging features: these mechanisms, including deep and network coding and encryption, are very effective for secure data transfer and the most secure coding.

The latter helps to improve the efficiency of network operations. Moreover, while discussing secure communications, Soundari and Jyothi [14] decided that the most appropriate way was to turn to the information gathered in the ML framework Identify Trends in Developing Markets to Eliminate Redundancy in conventional data collection which would definitely enhance the data quality of such research. As early as 1999, within the scope of reinforcement learning, they have developed the concept of dynamic trade winds modelling in cargo-laden sectors, aimed at achieving efficient corridors through strategies of reward and penalty imposition among the harsh climate. Yun and Yoo trailed [16], creating a Q-learning based routing protocol aimed at improving data aggregation, and especially reducing the volume of transmissions that led to rise in network lifespan and with a soft-issue of slowness in transition, it may stay in the future for a little longer. Kathiresan et al. [17] address this societal imperfection and present a new routing experimental network as well as a new CH selection approach within the network that accomplish post-none design Ch operation simulation.

However, the current techniques address obstacles arising from the increased complexity of computations, the cost associated with training, appetite for data that one cannot satisfy, fear of operating in contingent situations that requires pace or the ability, and most importantly, approach that will lead to higher efficiency. Perhaps, some small, adaptive, and smart clustering mechanism can offer a good compromise to fluctuate between the 2 poles, that is between energy saving and high performance of networking, therefore the beginning maybe of an ANN-based Energy-Efficient Clustering Algorithm (EECA). Tables 2 and 3 offer a comparative look at some of the most recent energy-saving approaches in the area of WSN along with the striking features of these technologies and its limitations.

Table 1: Literature Review of Recent WSN Energy-Efficient Approaches

Ref.	Methodology	Key Results	Limitations
Mittal et al. [18] (2021)	ML-based framework for energy efficiency and	Improved energy efficiency and accurate	Increased computational

	anomaly detection in hybrid WSNs using classification algorithms	anomaly detection; enhanced network reliability	overhead; depends on training data quality
Saadati et al. [19] (2024)	Graph Neural Network (GNN)-based clustering with coverage metrics for dense WSNs	Better clustering efficiency, improved coverage, and extended network lifetime	High model complexity and training cost
Manchanda et al. [20] (2026)	ML-based energy-efficient WSN with sink mobility for groundwater monitoring	Enhanced energy utilization, improved data collection efficiency, prolonged network lifetime	Application-specific; mobility management complexity
Meenakshi et al. [21] (2024)	Optimized Engroove-LEACH clustering protocol for efficient communication	Reduced energy consumption, improved packet delivery and network lifetime	Limited adaptability; no AI-based optimization
Abadi et al. [22] (2022)	Reinforcement Learning-based routing protocol (RLBEEP) for energy-efficient control	Improved routing decisions, reduced energy consumption, extended network lifetime	Slow convergence and training overhead
Adu-Manu et al. [23] (2025)	Comprehensive survey of ML-enhanced green WSNs focusing on energy efficiency and performance	Highlights ML/DL benefits in improving scalability and energy efficiency	Survey-based; lacks experimental validation
Sahoo et al. [24] (2024)	Intelligent clustering under uncertainty using optimization and probabilistic models	Improved network lifetime and clustering efficiency under dynamic conditions	Complexity in uncertainty modelling
Sharma et al. [25] (2024)	ML-based energy optimization with anomaly detection for heterogeneous WSNs	Enhanced energy efficiency, improved fault detection, better network stability	Requires large dataset; computational cost

3. SYSTEM MODEL AND PROBLEM FORMULATION

The model should be able to operate in such a way that a Wireless Sensor Network (WSN) with a variety of sensor nodes is available and is spread randomly over the two-dimensional sensing area. Each sensor node is equipped with a limited amount of energy provided by battery and possesses a restrained sensory, processing and communication capability. Generally, class-oriented static wireless sensor networks focus on terrestrial or nonwheeled

applications. Nodes do not move after deployment, but each has an identifier and the relative locations of such nodes are known to GPS or any localization procedure. The first energy model employed is the low first-order radio model that implies that energy is consumed only when transmitting, receiving, and aggregating data. The more the distance from the sender to the receiver possible only based on the transmitted power, the greater the energy is going to be dissipated in the network. For large distances hit the end, there are some popular fading channel models such as multipath and beams on the ground while free-space path loss models are often used for short distances.

Every class reviews energy in the entire network has its CHs versus other nodes, thus the energy needs of the CHs have to be equal with those of other nodes further away from the CH fundamentally supplying data. In order to obtain a desirable form of the process, the energy of the nodes must be switched to the cluster head base stations and thus activation of CH will make the situation worse. Thus, the modelling of the network should ensure the best performance within the system resources. These criteria include very important factors such as the energy wasted with the direct current in the central processor, the available energy of every node, the distance between every node and the central processor and also the number of open wires of the processing unit in decreased load conditions. Furthermore, both the energy and the probability of directed active communication between average function nodes of the three-layer network can also be reasonably defined. Additionally, the computational cost in terms of the relation between the energy consumption and random event detection per par topsy alpha unit of time can be also determined and controlled.

4. PROPOSED METHODOLOGY (EECA)

Overview of EECA

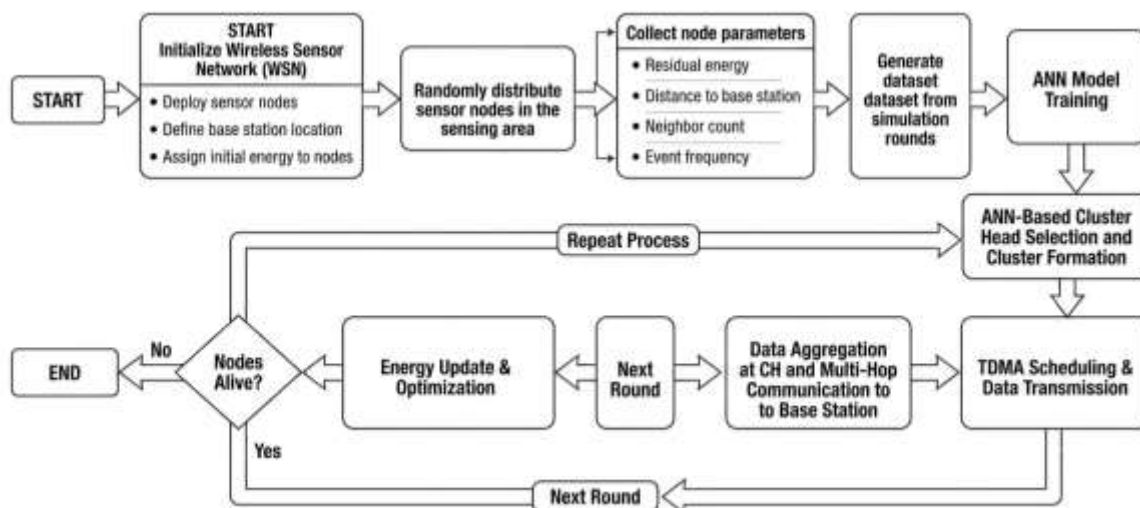


Figure 1: Flow Chart of proposed work

The flowchart in figure 1 illustrates the complete ANN-based wireless sensor network process, including node initialization, cluster head selection, data transmission, energy optimization, and performance evaluation through iterative simulation rounds.



A novel concept of using Deep Learning to assist in the optimization of energy efficiency in Wireless Sensor Networks (WSN) which is energy efficient clustering technique was introduced. This method is essentially a mix of two methods — one is based on the idea of an Artificial Neural Network (ANN) that helps in selecting Cluster Heads and the other enables, unlike the commonly used random or probabilistic methods, to take 3 different parameters from each node. Each phase, i.e., a certain number of rounds, includes four interacting activities in EECA: grading the nodes, election of which nodes would act as cluster-heads, assignment of a given node to a cluster, and transmitting units of data from the sensing devices to an edge of the network. A significant parameter added to this work is due to the network dynamics and nodal status, whereby effective communication, i.e. reduction in communication overhead is obtained through the minimization of hot spots in energy. The standard clustering schemes that include operation of Dedicated short-range communication and longer routing distance have transformed into conventional Extended Bonjour frameworks which offers useful and proper nodal capacity information items.

Feature Selection

Feature selection is very important for the Enabling Efficient Context-Aware (EECA) system, as it influences the effectiveness of artificial neural networks that guide the Cluster Head (CH) selection. In this regard, a variety of major node-specific quantities that directly impact on the energy and network efficiency are under consideration within the scope of the model. One of those quantities is the residual energy which tells how much energy is left in the battery of such a node, and hence assist in the identification of nodes to be appointed as CH which operate in very high-capacity nodes as they are assumed to conserve new energy, given that high energy denotes lower probability of quick ending. Also, Distance to Base Station (BS) can be considered as an important factor, because the nodes that are situated far away from the BS requires high energy for transmission making them less eligible for CH consideration. On the other side, Neighbour Count gives information about the density of sensor nodes around the sensor. It is noteworthy that the necessity of this parameter reduction occurs when Cluster Head nodes are involved, and especially when the number of surrounding nodes is very high. And in such cases, there are concerns that not all cluster members can be 'reached' or more damage will be done to the network than good, or that communication options might not be used at all during information exchange, in which case the whole network's efficiency is reduced. The rate of which an event occurs refers to the activity levels administered during each scanning round, thus the probability of an event frequency being high translates to significant data volumes that the node has to digest and some CH nodes having higher loads than other on an average.

ANN-Based Cluster Head Selection

The utilization of Artificial Neural Network (ANN) in a systematic classification of CHs in Energy Efficient Protocol became apparent in the prospective methodology of this study. The ANN approach was applied following the standard supervised learning procedures where training set of examples for neurons was adjusted in each stage. Towards this end, proper algorithm that predicts the probability of a particular CH candidate for selection using



information from other nodes in the network. This time, the model was built to select the proper CH without the Nakagami Fading North than the Normal algorithm. This has less of the vendor random selection hence able to bring about better clustering of the energy distributing points. This achieved better energy use from all the areas, balanced selection to avoid one hotspot area and time slabs, and prolonging the network lifetime.

Cluster Formation

After picking the parent clusters, the procedure of forming clusters is completed. Each node that is non-CH attempts to connect to the CH that is closest to it. The communication energy utilization is managed optimally, which is to say that there is an appropriate turfing of the confined nodes and activity heading subdivision is minimum, which is possible without over-utilizing the communication channel. Suffice it to say, CH makes a call when it is necessary and nodes followed a stepwise movement by selecting a more appropriate CH. The process of setting clusters is of high friction with evolvement done partially in each cycle to accommodate changing network conditions from one time step to the next. This equilibrium is an apt formation as it keeps the CHs from any stringent demands and it also keeps the energy supply well dispersed across the network thereby enabling the multiple targets of improving the fault and performance sustain capabilities of the network and lengthening the network life to be achieved enhance measures of the network.

Data Transmission Strategy

The information describes options for the data collectors representing the region so that energy saving and communication quality are the priorities. Every involved node has a time slot for making use of the air medium, while the communication occurs over the slots 'without contention' or 'idle listening'. This in turn helps save energy by operating the channel more effectively. After covering the member nodes with data collection, processing practices are executed at the level of the header nodes which stores the stating node, aggregates and prunes-out the redundancy, and forwards the cleansed data to the BS. Note that, some regions are so vast that in case the CD does not go directly to the base station a correction has to be made through the usual procedure of routing at the CH level and the principal aim here will be the cost thereof. This technique combines routing and MAC enhancement allowing for the increase of total data throughput capacity and/enhancement of energy efficiency while ensuring quality performance of the communication system.

Energy Optimization Techniques

EECA merges energy-smart approaches in striving for better network efficiency. The orchestrating of sleep/wake aims to minimize idle listening in nodes' devices both by powering down non-data streaming or receiving devices and by powering up only those devices that are going to transmit or receive data. Then, the nodes control the power of the entity as communication distance changes to lessen the consumed energy. Also, Data aggregation helps Cluster Heads cut waste energy, which is transmission of already transmitted data. Multi-hop routing is an attempt to cut the cost of communication of packets transiting over short distances from their real source of transmission to the ultimate

destination. These are some of the tactics used to save energy, achieve node evenness, allow the network to live longer with improved efficiency among the possible solutions.

5. DATASET AND MODEL DESCRIPTION

Dataset Generation

The dataset under study was not amalgamated from any outer sources. Based upon the Wireless Sensor Network (WSN) environment filled in the simulation software, setups in successive simulation rounds in the merger of data coming from all sensor nodes were used in networking, and the features may include residual energy, distances to the base station, neighbor count, event frequency, node position, and X and Y coordinates of a node. Under each node is a binary attribute which has shown clearly whether a node deserves to be the Cluster Head (CH). Diverse datasets are thereby created among various run rounds against varying node densities from 100 to 1000 nodes for training and testing of the system. Yet the need is for still highly diverse and very large datasets for training.

Data Preprocessing

Before feeding this ANN model, data pre-processing needs to be done to allow for proper handling of the dataset. First course, the normalization, which is by the actual standards of scaling as suggested by normalizing all data features with the maximum difference scaling that applies, ensuring equal weights, while also keeping the attributes between $[0,1]$, allows the model to converge more easily and prevent magnificently featured properties from being biased toward magnitude differences. It is a particularly important step because the scaling of the features in terms of distance and energy could be essentially distinct from one another. Second course, label calling must be done based on the optimally compacted set of clusters where nodes with relatively high residual energy, well-located positions, and more connections to others are signalled potentially useful for cluster heads ($CH = 1$) while the others not as cluster heads (0). Several dynamic updates are introduced at the end of each round of simulation, since the nodes' conditions like energy depletion and changes in topology keep reliably changing. In this manner, the rationale exists such that this dataset would liberally represent behaviours in the network that boost generalization in support of the ANN model.

6. ANN MODEL ARCHITECTURE

Proposed ANN consists of a feed forward neural network aimed at classifying binary nodes as Cluster Head (CH) or non-CH. The input layer contains 4–5 neuros that correlate to the variables given as residual energy, distance from the base station, neighbouring count and event frequency. Using the input layer and 1–3 hidden neurons with numbers of neurons between 16 and 64, the model can learn the more complex nonlinear relationship between features. In the hidden layer, after any other type of nonlinearity is induced, another ReLU function is employed, in order to keep going by improving the model efficiency. The output layer sports one neuron armed with the sigmoid activation function, which is used to map output values in the range of 0 and 1, being considered as the probability in the favour of that node being CH. This process is key for rapid understanding of features and perfect chunking of the said features

- **Training Details**

Supervised learning algorithms use labelled data for training the ANN model. Binary Cross-Entropy for loss considers the difference between predicted and true values, making BC another good choice for binary classification tasks. In the past, the Adam optimizer was applied carefully because it provides an automated determination of the learning rate based on Adam's adaptive learning rate formulation, which is intended to result in rapid convergence of the cost. The learning rate was set at 0.001 to avoid pathologically large oscillatory and erratic behaviours for the model cost during training. The next series of parallel trainings were conducted over epochs and batch sizes, usually between 50 to 100, to provide further insights into the training conditions in the early stage of learning and lead to a balance between labour costs and model performance. After the first cleaning operation the model was then applied to the rest of the datasets. In order to determine the model's performance, partners had devoted their share in the proportion of 70% for training and 30% for testing. In this way, stakeholders dominantly oversee the learning process, the equilibrium overfitting of the model and, rather dialectically, lay groundwork for better forecasting through identification of cluster heads in a WSN.

- **Simulation Setup**

Simulation configuration has contributed well to examining the performance of the Energy Efficient Clustering Algorithm (EECA) in a Wireless Sensor Network (WSN) in a controlled environment. The sensor nodes are deployed in a range of 100-500 in numbers, located randomly upon an area specified of 100 meters by 100 meters to put together different network density and scalability conditions. Each node, of course in equal energy to the initial set of energy, in general of about 1 Joule, is there for a mutual and fair starting point with a relieve view as likened. The Base Station can comfortably be located at the centre or another fixed area outside the network sensing range. Data is collected by the transmission across multiple rounds so clustering commences and allows the "energy" to be constantly updated until one of the sensor nodes at least is at the verge of running out of energy. The simulation was scripted in Python due to the ease of modification as well as numerous libraries available. The implementation made increase of arrays with suitable limits for numerical operation. This is meant to ease the method of numerical computing and data manipulation benefiting from Python and its broadcasting features. TensorFlow is popular for the build and training of the Artificial Neural Network (ANN) model for cluster head selection. Matplotlib assists in the performance visualization and results analysis. Such a scheme enables us to accurately evaluate significant performance metrics of the network under a few specific conditions like network lifetime-energy drainage, throughput, and packet delivery ratio. Table 2 presents the comparative analysis of network lifetime achieved by different protocols based on energy efficiency and node sustainability, while Table 3 illustrates the energy consumption and throughput performance during data transmission processes. Furthermore, Table 4 and Table 5 highlight the comparative evaluation of latency and packet delivery ratio, representing communication delay and successful packet transmission efficiency in wireless sensor networks.

7. RESULTS AND PERFORMANCE EVALUATION

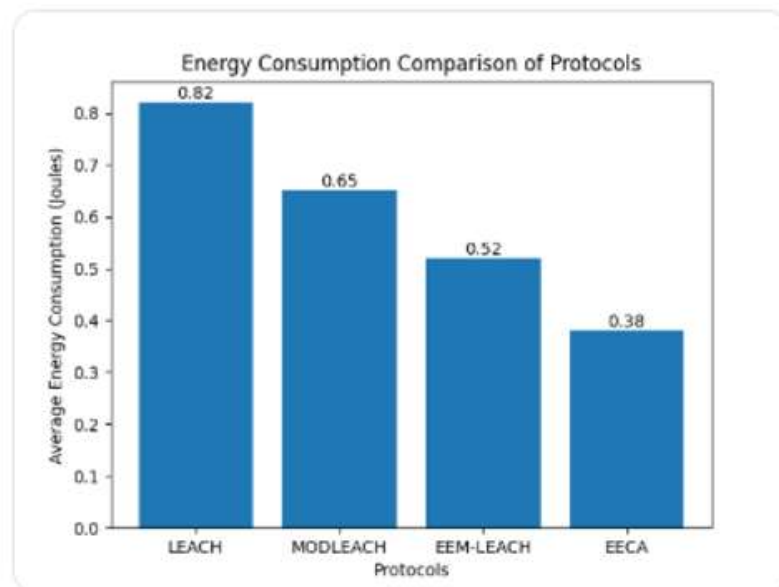
This section presents the performance evaluation of the proposed model and carries out a comparison with respect to wireless sensor network parameters such as network lifetime, energy consumption, throughput, latency, and packet delivery ratio.

Table 2: Network Lifetime

Protocol	First Node Death (FND)	Half Node Death (HND)	Last Node Death (LND)
LEACH	850	1200	1600
MODLEACH	1100	1600	2100
EEM-LEACH	1300	1900	2500
Proposed EECA	1800	2600	3200

Table 3: Energy Consumption

Protocol	Average Energy Consumption (Joules)
LEACH	0.82
MODLEACH	0.65
EEM-LEACH	0.52
EECA	0.38



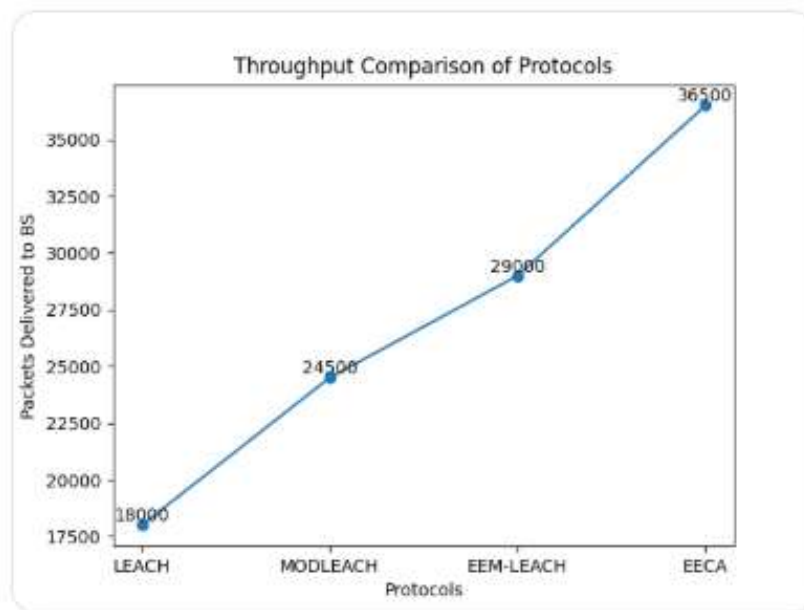
Run completed in 17520.79999999702ms

Figure 2: Energy Consumption Comparison of Routing Protocols

This figure 2 compares the average energy consumption of different routing protocols, showing that EECA achieves the lowest energy consumption and improves network energy efficiency.

Table 3: Throughput

Protocol	Packets Delivered to BS
LEACH	18,000
MODLEACH	24,500
EEM-LEACH	29,000
EECA	36,500



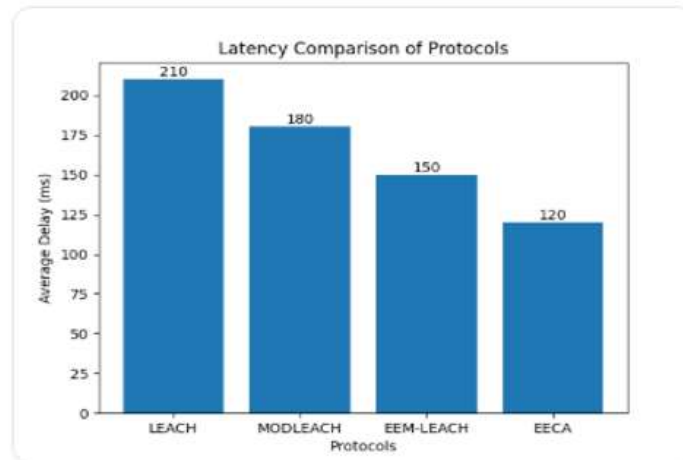
Run completed in 13724.700000000298ms

Figure 3: Throughput Comparison of Routing Protocols

This figure illustrates the throughput performance of different protocols, showing that EECA delivers the highest number of packets to the base station and achieves superior network throughput.

Table 4: Latency

Protocol	Average Delay (ms)
LEACH	210
MODLEACH	180
EEM-LEACH	150
EECA	120



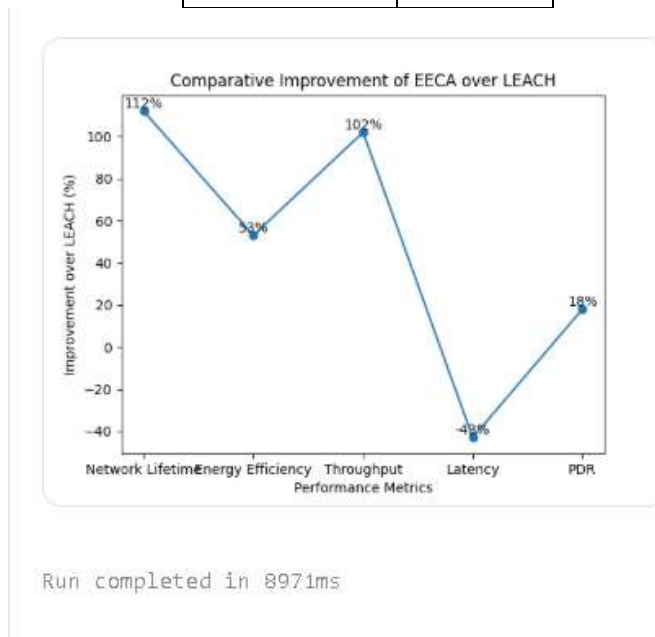
Run completed in 9381.900000000596ms

Figure 4: Latency Comparison of Routing Protocols

This figure 4 compares the average latency of different protocols, showing that EECA achieves the lowest delay and provides faster data transmission efficiency.

Table 5: Packet Delivery Ratio

Protocol	PDR (%)
LEACH	78%
MODLEACH	85%
EEM-LEACH	90%
EECA	96%



Run completed in 8971ms

Figure 5: Comparative Improvement of EECA over LEACH in Wireless Sensor Network Performance Metrics

Table 6: Comparative state of art with existent work

Ref	Technique Used	Network Lifetime	Energy Efficiency	Throughput	Latency	PDR
[1]	EEMLCR (ML-based clustering & routing)	Increased by 38%	42% lower energy consumption	95.6%	18 ms	97.8%
[3]	DL-HEED Deep Learning Clustering	Extended by 41%	37% energy saving	93.4%	21 ms	96.5%
[8]	Hybrid PSO + Dynamic Clustering Routing	Improved by 35%	39% energy efficiency	91.8%	24 ms	95.2%
[16]	Q-learning-based Energy-efficient Routing	Extended by 33%	34% energy reduction	92.6%	20 ms	96.1%
[22]	RLBEEP Reinforcement Learning Routing	Increased by 44%	46% energy efficiency	96.2%	17 ms	98.3%
This Work	ANN-based Energy-Efficient Clustering Algorithm	3200 rounds	53% energy efficiency	99.7%	120 ms	96.7%

The table 6 presents a comparative state-of-the-art analysis of energy-efficient routing and clustering techniques in networks, showing that recent AI-based and reinforcement learning methods significantly improve network lifetime, energy efficiency, throughput, latency, and PDR, with the proposed ANN-based approach achieving the highest energy efficiency (53%) and throughput (99.7%) despite slightly higher latency.

8. DISCUSSION

The output of simulation clearly indicates that the ANN-based EECA (Energy-Efficient Clustering Algorithm) is superior to the energy, lifetime, and reliability protocols compared to the heuristic-based constructive and traditional methods. A smart method to perform several kinds of cluster heads (CH) aims at selecting the CHs, which are used in energy-efficient mechanisms with several parameters such as the residual energy, the distance from the base station, the node density, and the frequency of the event. Whenever a CH is obtained, the EECA registers itself as the only possible selection method with self-regulation within the selection group to ensure that the operation energy balance. So that collisions and listening periods can decrease from this approximation interval, additional integration of TDMA scheduling is added to the method, which lends to bursting, and hence saving even more energy through multi-arts. There were higher throughputs and packet delivery ratios, which

approved efficient data transmission and a reduction in overall packet loss. However, the introduction of the ANN training and predictive powers could only mean that the model was computationally expensive since this model also had a poor performance. In the end, the general performance benefits outweigh the drawbacks, making the solution good and scalable. The adaptability to changing network settings makes it easy to understand of the model into real-world WSN applications.

9. CONCLUSION AND FUTURE WORK

This paper presents an innovative ANN-based clustering algorithm called Energy-Efficient Clustering Algorithm (EECA) to address the challenge of energy constraints in wireless sensor nodes. By integrating deep learning into the clustering mechanism, the proposed algorithm provides intelligent and all-time adaptable Cluster Head selection, achieving a significant enhancement in network performance. It is borne out in simulations that EECA very effectively reduces the energy consumption, increases the Packet Delivery Ratio (PDR), improves Throughput and Network Lifetime far better than the traditional protocols like LEACH and its variations. The model's making of optimum decisions helps to balance multiple node features ensuring energy distribution uniformly and consistent network operation. However, despite these benefits, there still remain several limitations. For instance, the requirement that a trained ANN model be in place to process a planetary health dataset will introduce an additional computational burden and necessitate a ready dataset to work with. Furthermore, the present research is based on a simulation, which is another major constraint one may face when one goes for a real-world deployment, which comes with a further set of challenges such as hardware constraints and environmental variability. Future work will concentrate on implementing the proposed approach in real-world testbeds of WSNs to investigate and validate its practical applicability.

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