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RESEARCH ARTICLE

PSA-LEACH: Improving Energy Efficiency and Classification in Wireless Sensor Networks Using Proximal Simulated Annealing with Low Energy Adaptive Clustering Hierarchical Routing Protocol

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Abstract – Wireless Sensor Networks (WSNs) have become an essential technology in many domains, from smart infrastructure development and industrial automation to environmental monitoring. However, the limited power supply of individual sensor nodes makes long-term WSN sustainability arising battle. Classifying the details of energy efficiency and maximizing energy efficiency is of utmost importance for extending the network's lifespan and guaranteeing stable operation. By combining the Low Energy Adaptive Clustering Hierarchical (LEACH) routing protocol with Proximal Simulated Annealing (PSA), this article presents PSA-LEACH, a new way to improve WSN energy efficiency. To improve energy consumption and extend network lifespan, PSA-LEACH dynamically optimizes clustering settings. In the final step, the Improved Random Forest Classifier (IRF) algorithm categorizes the energy information. The efficacy of PSA-LEACH in enhancing energy efficiency measures, including throughput, energy consumption, delay, and packet delivery ratio, is shown by experimental simulations. Environmental monitoring and smart infrastructure development are only two of the many potentials uses for the suggested method to increase the longevity and robustness of WSNs. Experimental simulations demonstrate that PSA-LEACH significantly enhances energy efficiency measures, including throughput, energy consumption, delay, and packet delivery ratio. Notably, PSA-LEACH achieves up to a 25% increase in network lifetime and a 20% improvement in throughput compared to existing energy-aware routing protocols. An exploratory study suggests that the PSA-LEACH protocol is more efficient than the existing energy-aware routing protocols regarding throughput, energy utilization, and delay and packet delivery ratio. The results underscore the exceptional performance of PSA-LEACH and its potential for significantly increasing the network lifetime of WSNs.

Index Terms – Clustering, Classification, Energy Efficiency, Improved Random Forest, LEACH, Wireless Sensor Network.

1. INTRODUCTION

Due to its many potential applications, such as environmental monitoring, object tracking, traffic management, and health applications, Wireless Sensor Networks (WSNs) have garnered much attention in the last ten years [1]. Reducing energy usage in WSNs is crucial for maximizing the network's lifespan, as it is often difficult and expensive to repair malfunctioning sensors after they are installed [2]. The duration until the demise of one or more sensors inside a sensor network is called its lifespan [3]. Many academics have been working to maximize the battery life of nodes, which has put a lot of focus on this field of study in recent years [4]. It introduces a new way to categorize energy-saving solutions at various levels [5]. Radio optimization, data reduction, energy-efficient routing, sleep/wake systems, and energy repletion are the suggested taxonomy of energy-saving methods [6]. Various mathematical methodologies and approaches, such as optimization techniques, computational intelligence, and game theory, have been used to define this issue so far [7]. The primary obstacle is balancing energy savings with Quality of Service (QoS), which adds complexity to the energy conservation problems [8-9].

They consist of many sensor nodes that can wirelessly gather, process, and transmit data [10, 11]. The battery life of individual sensor nodes is a major concern for WSNs since it affects the network's efficiency and longevity [12]. Optimizing energy efficiency is of utmost importance for

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WSNs to remain operational and reliable over the long run [13]. The primary goal of WSN research is to enhance energy efficiency, thereby extending network lifetime and ensuring stable operation [14]. Traditional routing protocols, like the Low Energy Adaptive Clustering Hierarchical (LEACH) protocol, have been developed to address these energy concerns [15-16].

LEACH uses a clustering mechanism to balance energy consumption among sensor nodes, significantly reducing communication overhead and extending network longevity [17-18]. However, as WSNs become more complex and diverse, there is a pressing need for more sophisticated and adaptive solutions to optimize energy consumption dynamically [19-20]. Efficient energy management strategies are crucial to increase performance metrics like throughput, latency, and packet delivery ratio, decrease maintenance costs, and prolong the network's lifespan [21-22].

In light of the above, integrating Proximal Simulated Annealing (PSA) with the LEACH routing protocol presents a novel and promising approach to addressing energy efficiency concerns in WSNs [23-24]. By combining the optimization capabilities of PSA with the clustering and data aggregation benefits of LEACH, PSA-LEACH provides a comprehensive solution to enhance network performance and energy efficiency [25–26].

The main contribution of the paper is:

- Integration of Proximal Simulated Annealing (PSA) with LEACH
- Improved Random Forest Classifier (IRF) for Energy Categorization

1.1. Motivation of the paper

This paper addresses the critical challenge of constrained energy resources in WSNs by proposing a novel approach called PSA-LEACH. Our method dynamically optimizes clustering parameters to enhance energy efficiency by integrating PSA with the LEACH routing protocol. Furthermore, we utilize the IRF Algorithm to classify energy efficiency details, thereby contributing to the sustainability and resilience of WSNs. Through simulated experiments, we demonstrate the effectiveness of PSA-LEACH in improving key energy efficiency metrics, offering a promising solution for various applications such as environmental monitoring and smart infrastructure development.

The remainder of this paper is structured as follows. Numerous authors address a variety of energy efficiency and classification strategies in Section 2. The PSA-LEACH model is shown in Section 3. Section 4 summarizes the results of the investigation. Section 5 concludes with a discussion of the result and future work.

2. BACKGROUND STUDY

Balasubramanian, D. L., & Govindasamy, V. (2019) [4] emphasized the need for effective strategies to reduce power consumption and improve the Quality of Service (QoS) in WSN applications. Their study provided an extensive literature review on evolutionary algorithms and various routing protocols designed to minimize energy consumption in WSNs. While evolutionary algorithms offer significant improvements in energy efficiency, their application in real-time scenarios can be limited by computational overhead and convergence time.

Lin D. et al. (2020) [10] explored the emerging paradigm of computing technologies such as the Internet of Things (IoT), fog computing, and big data and their implications for WSNs. The authors discussed the potential and challenges associated with these technologies, particularly concerning the energy efficiency of static WSNs. They suggested future research areas to address energy efficiency in the context of these new computing paradigms.

Meenakshi, N. et al. (2024) [11] Introduce a passive clustering approach using Hybrid Whale Archimedes Optimization (HWAO) and Meta Inspired Hawks Fragment Optimization (MIHFO) optimization in WSNs, focusing on sensitivity thresholds, packet retransmission methods, and channel-dependent packet size adjustments. Compared to the LEACH, DEEP, and Butterfly Optimization Algorithm (BOA) Ant Colony Optimization (ACO) protocols, it demonstrates higher energy efficiency and reliability in clustering—limited discussion on scalability and practical deployment challenges. MATLAB simulations validate the proposed protocol's effectiveness in improving energy usage and extending WSN lifespan.

A. Mohamed et al. [12] (2020) introduced a hybrid method for clustering heterogeneous WSNs called Coyote Optimization based on Fuzzy Logic (COFL). This approach combines the Fuzzy Logic (FL) system with the Coyote Optimization Algorithm (COA) to optimize clustering in WSNs. The primary objective of the COFL method is to connect nodes to their corresponding Cluster Heads (CHs) effectively, thereby enhancing network performance.

Radhika, S., & Rangarajan, P. (2021) [14] Improving network efficiency was the goal of a practical method that incorporates the core principles of machine learning with fuzzy-based cluster updates and a sleep schedule. As it adjusts to sleep/wake cycles, the energy of the sensor is improved. The proposed technique, zeroes, focuses on the difficulty of intra-cluster data transfer and the overhead of message exchanges.

Raj, V. P., & Duraipandian, M. (2024) [15] Implements Energy-Efficient Routing Fuzzy Neural Network (ERFN)-Combined Random Sampling Prevosti Bat Optimization (CSSBO) technology for clustering, path search, and

RESEARCH ARTICLE

maintenance in distributed WSNs, emphasizing quick path establishment and optimal channel selection. Achieves high packet delivery rate (98.5%), low packet delay (1.5 s), high throughput (1.0 Mbps), and efficient energy consumption (30.35 mJ).

Sachan S. et al. (2021) [16] state that optimizing energy consumption has long been an obstacle to the widespread use of wireless sensor networks. This becomes more difficult when there are mobile nodes since the location and distance of surrounding nodes might vary randomly, making it harder to maintain network connections. The findings show a limit to how much network connection mobile sensor networks can have while still using the least energy.

Santhosh Kumar, S. et al. (2021) [18] Using trust ratings, the proposed methodology differentiates between legitimate and malicious nodes in WSNs and efficiently authenticates distribution packets.

Smys S. et al. (2021) [20] provide a detailed taxonomy and comparison of routing protocols, focusing on their energy efficiency rates. Their study evaluates various protocols, highlighting key performance metrics and identifying strengths and weaknesses in energy management.

Surenther, I. et al. (2024) [21] The study integrates Machine Learning with Evolutionary Optimization Algorithms (ML-EOA) to improve WSN performance metrics such as network lifetime, energy consumption, data delivery ratio, coverage expansion, and latency reduction. Deals with problems such as computational complexity and a lack of training data

Wang, Z. et al. (2020) [23] The benefits of WSN, such as its lack of wiring, great invulnerability, rapid information transmission, and low power consumption, have propelled it to new heights in large-scale use with the rise of the IoT era. However, because there was no wiring, the sensor nodes could only get power from the battery, which had limitations. Building a WSN routing system that uses less energy was very important.

Table 1 Comparison of Energy-Efficient Routing Protocols in Wireless Sensor Networks

Author	Methodology	Advantage	Limitation	Performance metrics
Balasubramanian & Govindasamy (2019) [4]	Evolutionary algorithms and routing protocols for energy efficiency in WSNs	Significant improvements in energy efficiency	Computational overhead and convergence time	Energy consumption
Lin D. et al. (2020) [10]	IoT, fog computing, and big data implications for WSNs	Potential for advanced computing paradigms	Challenges in energy efficiency with new technologies	Energy efficiency
Meenakshi, N. et al. (2024) [11]	HWAO MIHFO	Superior energy efficiency and reliability in clustering compared to LEACH, DEEP, and BOA ACO protocol	Limited scalability discussion, deployment challenges	Energy efficiency, reliability in clustering
A. Mohamed et al. (2020) [12]	Coyote Optimization based on Fuzzy Logic (COFL)	Enhanced network performance	Limited to clustering optimization	Effective node-CH connection

Radhika & Rangarajan (2021) [14]	ML with fuzzy-based cluster updates and sleep schedule	Improved energy efficiency through sleep/wake cycles	Intra-cluster data transfer overhead	Network efficiency, sensor energy
Raj, V. P., & Duraipandian, M. (2024) [15]	ERFN-CSSBO	High packet delivery rate, low packet delay, high throughput, efficient energy consumption, extended network lifespan	Limited scalability	Packet delivery rate, packet delay, throughput, energy consumption, network lifespan
Sachan S. et al. (2021) [16]	Techniques for optimizing energy consumption in mobile WSNs	Insight into energy constraints with mobile nodes	Maintaining network connections with mobile nodes	Network connection, energy consumption
Santhosh Kumar et al. (2021) [18]	Trust ratings for differentiating between legitimate and malicious nodes in WSNs	Efficient authentication of distribution packets	Limited security	Authentication efficiency, network security
Smys S. et al. (2021) [20]	Taxonomy and comparison of routing protocols for energy efficiency	Detailed evaluation of energy-efficient protocols	Limited to routing protocols	Energy efficiency rates
Surenther, I. et al. (2024) [21]	ML-EOA	Increased network lifetime, decreased energy consumption, improved data delivery ratio, expanded coverage, reduced latency	Scarcity of training data, computational complexity	Network lifetime, energy consumption, data delivery ratio, coverage expansion, latency
Wang, Z. et al. (2020) [23]	WSN routing system focused on low energy consumption	Large-scale application potential in IoT	Power limitations due to battery dependence	Energy consumption, rapid information transmission

RESEARCH ARTICLE

2.1. Problem Definition

One major obstacle to the sustainable functioning of WSNs is the limited energy resources of the sensor nodes. This work aims to overcome this issue. Some applications, such as smart infrastructure development and environmental monitoring, rely on the network's reliability and longevity; therefore, optimizing energy efficiency is a top priority.

3. MATERIALS AND METHODS

In this section, we explore the materials and methodology employed in our study to implement and evaluate the PSA-LEACH approach for improving energy efficiency in Wireless Sensor Networks (WSNs). We outline the simulation environment, software tools, and experimental setup utilized to conduct rigorous performance evaluations and validate the effectiveness of PSA-LEACH in enhancing WSN performance metrics. The PSA-LEACH flow chart is represented in Figure 1.

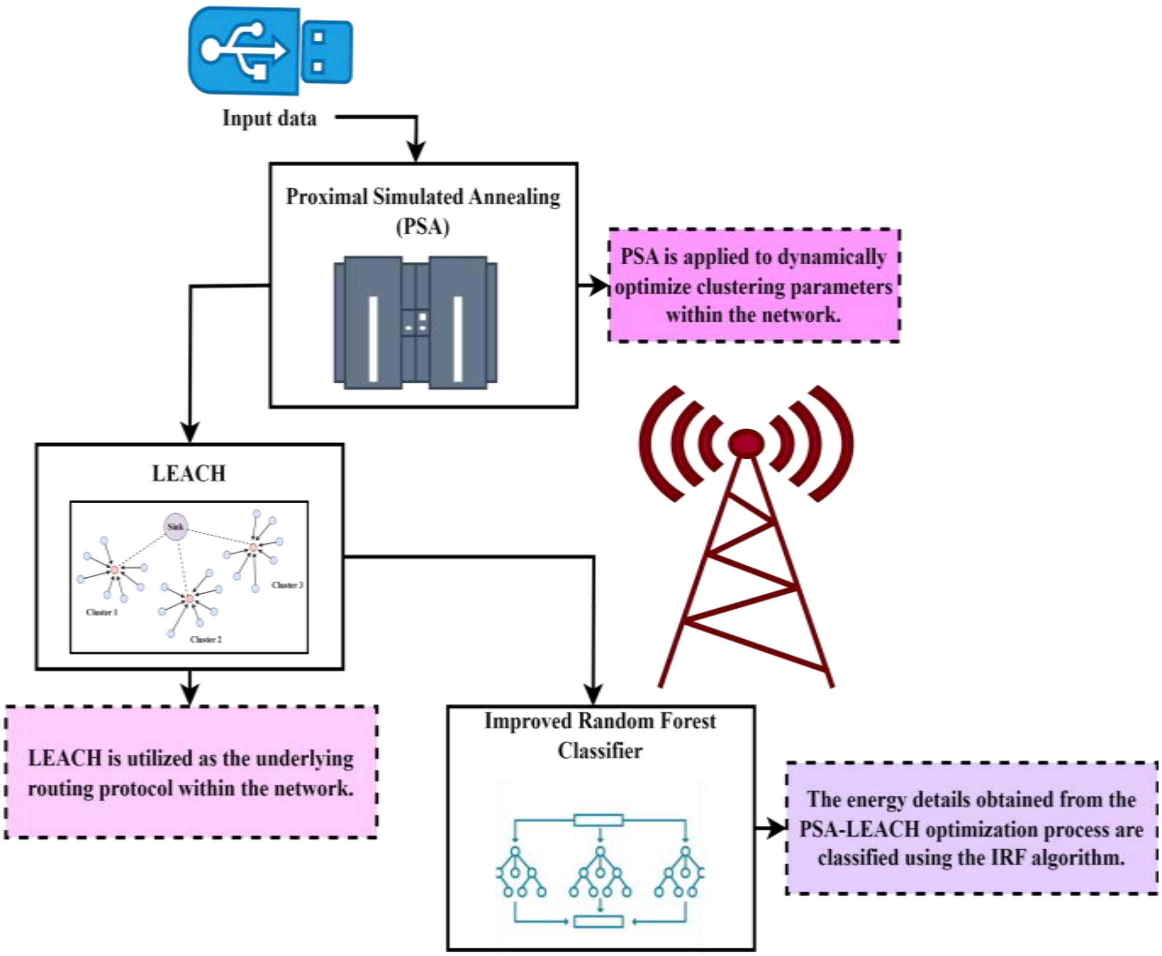

Figure 1 PSA-LEACH Workflow Architecture

3.1. Proximal Simulated Annealing

Proximal Simulated Annealing (PSA) is an optimization algorithm that extends the traditional Simulated Annealing (SA) technique referred to by AY, P., & Rayanki, B. (2020). It introduces a proximity operator to enforce constraints or structure on the search space during optimization. PSA is particularly effective in navigating complex and irregular optimization landscapes, making it well-suited for applications where traditional SA can struggle to converge efficiently.

Using a neighbourhood function, PSA generates a new individual $xnew$ at a random flow chart, represented in Figure 2. Because of this, the neighbourhood function is crucial to the algorithm. PSA's crossover and mutation probabilities aren't flexible enough to change with time. The PSA is being suggested for this case. Specifics of ISAGA include

(a) Computer programming. The GOA coding style is identical to the 0/1 approach used in basic GA.

(b) Performing physical activity. When designing the fitness function, accurate classification and the correlation coefficient

RESEARCH ARTICLE

between the present classification result and reference sleep state are considered to enhance the influence of the sleep stage. One can see the fitness function in equation (1).

$$F(s_i) = w \times f(s_i) + (1 - w) \times c(S_i), i = 1,2, \dots n \quad (1)$$

The adjustment coefficient, denoted as w, typically ranges from 0.6 to 0.8, and the classification accuracy of code i, denoted as $f(s_i)$, and the correlation coefficient of code i concerning the reference sleep state are all factors in this equation.

(c) Adaptive modification of the likelihood of crossing and mutation following equation (1)

(d) An annealing procedure that is simulated. The SAGA differs from GOA in using neighbourhood functions to generate new individuals, $xnew$.

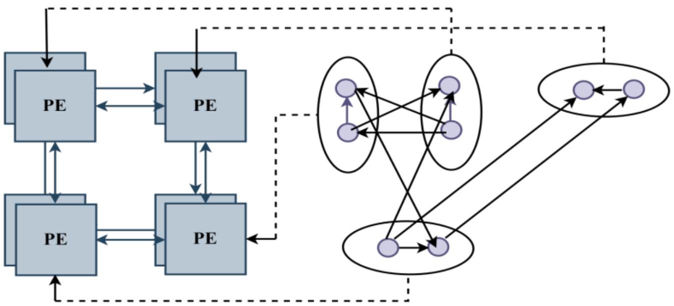

Figure 2 Proximal Simulated Annealing Architecture

3.2. Low Energy Adaptive Clustering Hierarchical

The LEACH routing protocol is designed specifically for WSNs to improve energy efficiency and prolong the network lifetime, as referred to by Al-Sodairi, S., & Ouni, R. (2018) [1]. This clustering mechanism distributes energy consumption more evenly across the network and reduces the amount of energy-intensive communication, thereby extending the overall lifetime of the WSN. Further contributing to energy savings and network scalability is LEACH's hierarchical operation, whereby cluster heads aggregate data from members of the cluster and broadcast it to a base station.

In the first stage of the LEACH cycle, "Broadcast Storm" and "Information Collision" are described as occurring due to an excess of broadcast and recurrent perceptual information in the LEACH network caused by the present clustering algorithm's process of alternating cluster head responsibilities. Hence, the previous network topology structure becomes unstable after a large-scale network has been operational for some time, necessitating a new cluster. This time, the "Reciprocal Mechanism" will be used instead of the LEACH Algorithm's method of broadcasting many data points. Starting with the Initial Phase of clustering utilizing the LEACH-P Protocol, every Single Node (SN) in the network will generate a random number that progressively decreases until it reaches 0. Then, it will suggest checking the energy levels of nearby nodes—at least one. "Reciprocal Mechanism" can aid in the distribution of massive amounts of communication traffic when all SN simultaneously offer energy-comparing requests ("Broadcast Storm" in LEACH Algorithm). The LEACH-P Protocol's "Center of Gravity" hypothesis is comparable to the "Center of Gravity" in the enhanced CEFL algorithm. In the real coordinate system, the cluster's areal coordinate is located at X for every j-cluster. Subtracting the number of nodes i from the total of X yields cx_j. On display in the equation (2)

$$cx_j = \frac{\sum x_{ji}}{i} \quad (2)$$

The actual Y-coordinate of Cluster Number j is where the Cluster areal coordinate is located. Subtracting the number of nodes i from the total value of Y yields cy_j. Depicted in equation 3

$$cy_j = \frac{\sum y_{ij}}{i} \quad (3)$$

Imagine the SN coordinate as $(x_{ij}, \ y_{ji})$. In the Number j Cluster, the distance between the center of gravity and the ith SN is denoted as jid. Equation (4) shows that SN's communication impact in the cluster improves as it approaches the cluster center of gravity.

$$d_{ij} = \sqrt{\left(x_{ij} - cx_{ij}\right)^2 + \left(y_{ji} - cy_{ji}\right)^2} \quad (4)$$

Each energy value $E_{currect}$ on SN for the four elements will be calculated using a unique weight value (W_1), which will be organized according to the relative relevance of the components. Equation (5) demonstrates this.

$$E_{currect} = e^* W_1 + \frac{1}{b} * W_2 + c^* W_3 + \frac{1}{d} * W_4, \sum_1^4 W_i = 1 \quad (5)$$

We use the idea of the DCHS Algorithm referred to by Zhou, C. et al. (2023) for comparing energy values. Assume that in the Number j Cluster, the random number i of SN initially inverses to 0. K is the SN that is close by it. For SN i to be designated as CH, the current from Ei must be less than or equal to the current form.E_k.Weight Values (W_1, W_2, W_3, W_4)

The distance between the CHs of the clusters and the SN will be used as a selection criterion for joining the cluster if there are more than two clusters surrounding the SN that have completed inversion. One will be picked at random if their distances are equal. The LEACH architecture is represented in Figure 3.

To speed up the convergence rate, the SN that completed inverting will choose the one that has not joined in clusters to undertake energy comparison, if there is one.

RESEARCH ARTICLE

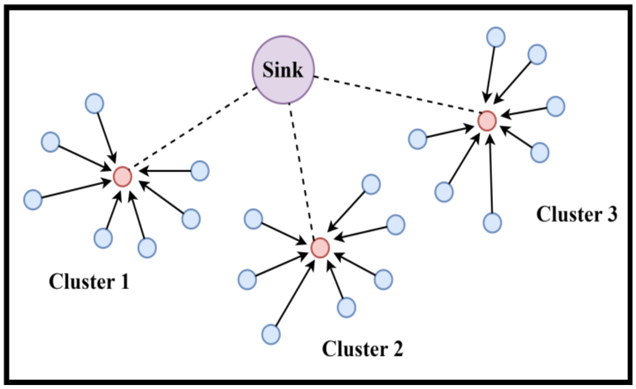

Figure 3 LEACH Architecture

3.3. PSA with LEACH

Integrating Proximal Simulated Annealing (PSA) with the LEACH routing protocol for WSNs focuses on dynamically optimizing clustering parameters to enhance energy efficiency and prolong the network lifetime. Drawing inspiration from the annealing process in metallurgy, PSA operates through iterations where solutions are refined based on an objective function, temperature parameter, neighbour generation, and acceptance criterion. The objective function in this context aims to minimize energy consumption or maximize energy efficiency within the network. The temperature parameter regulates the exploration-exploitation trade-off, allowing for more exploration and focused exploitation of promising solutions at lower temperatures. During optimization, PSA generates neighbouring solutions by perturbing clustering parameters such as cluster head selection, data aggregation strategies, or transmission power levels. Considering the current temperature, the acceptance criterion then evaluates whether a new solution improves the objective function. The PSA-LEACH steps have been represented in algorithm 1. Solutions that enhance energy efficiency are favored, with a probabilistic acceptance mechanism to avoid local optima. This approach contributes significantly to addressing the energy efficiency challenges in WSNs across various applications, ensuring sustainable and reliable operation, as shown in equation (6).

$$Objective\ function: f(cluster) = \sum_{i=1}^{n}\left(Energy\ Consumption_{CH_i} + Energy\ Consumption\right) \quad (6)$$

Where:

- Clusters represents the current clustering configuration.
- n is the total number of clusters.
- Energy $\text{Consumption}_{\text{CH}_\text{i}}$ Is the energy consumed by the cluster head i.

The PSA-LEACH approach integrates Particle Swarm Optimization (PSO) with the Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol to enhance energy efficiency in WSNs.

Input:

Initialize the sensor network with random positions and energy levels, cluster formation threshold, communication range, and energy model.

Steps

Generate a new solution. x_{new} It is perturbing the current solution using a PSA neighbourhood function.

Evaluate the objective function $f(x_{new})$.

Calculate the difference in objective function $\Delta f = f(x_{new}) - f(x_{current})$.

If $\Delta f < 0$, accept the new solution

If $\Delta f \geq 0$, accept the new solution with probability $e^{-\Delta f/T}$

Update the current solution if the new solution is accepted.

Update the temperature according to the cooling schedule: $T = a.T$.

Perform LEACH cluster formation:

Sensor nodes decide whether to become cluster heads based on a random number comparison with a threshold.

Adjust energy levels of sensor nodes based on communication activities and data transmission.

Output:

Energy Minimization

Algorithm 1 PSA-LEACH

3.4. Energy Details are Classified Using the Improved Random Forest Classifier

In this research, the specifics of energy efficiency inside WSNs are classified using the IRF Classifier, a machine learning technique. It employs an ensemble learning method that merges several decision trees to provide precise predictions and data classifications. The "improved" part of IRF usually means that the classic Random Forest algorithm has been optimized or enhanced somehow. Methods for boosting prediction accuracy and robustness might be included in these additions, such as strategies for creating trees or ensemble approaches. Energy usage, network characteristics, and perhaps environmental conditions are some of the inputs the IRF Classifier considers while working with WSNs. The IRF steps have been represented in algorithm 2. Using this data, it trains a network of decision trees, each making its forecast. It is common practice to use

RESEARCH ARTICLE

methods like weighted voting or average to aggregate the predictions from each tree in the forest before deciding on the final categorization.

Using random split selection, random forest is used as an extension of bagging decision trees. The forest's trees are constructed using a randomly picked training set, and the input variables used to form each split within each tree are also randomly selected. Adding this element of chance makes the trees more diverse. Every single tree in the woods is a fully mature binary tree.

Some nodes are formed in the IRF model by fitting a basic prediction model into each subspace, which is formed by recursively binary splitting the input space into several subspaces. After determining the resultant nodes' purity, the splitting criteria are applied to all except the leaf node. One common metric for evaluating node purity in regression is the Mean Squared Error (MSE) around the node's mean response. Each node's splitting variable and segmentation point are chosen based on the highest gain in the MSE using equations (7-9).

$$\Delta MSE\left(S, x_j^a\right) = MSE(s) - \frac{|S_1|}{|S|} MSE(S_1) - \frac{|S_2|}{|S|} MSE(S_2) \quad (7)$$

$$MSE(s) = \frac{1}{|S|} \sum_{i=1}^{|S|} (y_i - y)^2 \quad (8)$$

$$y = \frac{1}{|S|} \sum_{i=1}^{|S|} y_i \quad (9)$$

Given a variable x_j (where j = 1, 2,..., M) and segmentation a, the dataset Si is created when dataset S is divided at the node.

The partitioning will stop when the maximum possible MSE gain has been obtained. Predicting the answer of any sample once the tree is constructed is as simple as following the route to the right leaf node and averaging the responses there.

Input:

The input to the IRF Classifier includes data related to energy consumption, network parameters, and potentially environmental factors within Wireless Sensor Networks (WSNs).

Initialization:

Define the input dataset S containing samples with features related to energy efficiency.

Building Trees:

For each decision tree in the forest:

Select a random subset of features from the input dataset.

$$\Delta MSE\left(S, x_j^a\right) = MSE(s) - \frac{|S_1|}{|S|} MSE(S_1) - \frac{|S_2|}{|S|} MSE(S_2)$$

Split the dataset into subsets based on feature values to create nodes.

Calculate each node's mean squared error (MSE) to assess node purity.

Choose the splitting variable and segmentation point that maximizes the MSE gain.

$$MSE(s) = \frac{1}{|S|} \sum_{i=1}^{|S|} (y_i - y)^2$$

Prediction:

To predict the energy efficiency details for a new sample:

Traverse each decision tree in the forest based on the sample's features.

Output:

The trained Improved Random Forest Classifier model can classify energy efficiency details based on input features.

Algorithm 2 Improved Random Forest

4. RESULTS AND DISCUSSION

In this section, we present the results of our simulated experiments and discuss the effectiveness and implications of the PSA-LEACH approach for enhancing energy efficiency in WSNs with the comparison of COA and LEACH methods.

Table 1 Simulation Settings

Parameter	Values
Network Size	500mx500m
Number of Nodes	0-99nodes
Max Packet	256
Simulation Time	300s
Routing	LEACH
Data link (MAC)	IEEE802.11
Channel Frequency	600KHz
Channel Bandwidth	100KHz
Initial Energy	20J
Transmit Power	33dbm
Receive Sensitivity	-98dbm
Receive Threshold	-88dbm
Antenna Model	Omni-Directional
Maximum Transmission Range	100meters

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RESEARCH ARTICLE

The simulation environment for evaluating the LEACH protocol is configured with a network size of 500m x 500m, consisting of 0 to 99 nodes. Each node can transmit a maximum packet size of 256 bytes within a simulation time of 300 seconds. The IEEE 802.11 standard is used for the data link (MAC) layer, with a channel frequency of 600 KHz and a channel bandwidth of 100 KHz. Nodes start with an initial energy of 20J, transmit power of 33 dBm, receive sensitivity of -98 dBm, and a receive threshold of -88 dBm. The omnidirectional antenna model has a maximum transmission range of 100 meters. The simulation is conducted on a platform equipped to handle these configurations, ensuring an accurate assessment of the LEACH protocol's performance under these conditions.

4.1. Throughput

Throughput (T) = Packet Length (L) / Transmission Time (Tt)

Table 2 Throughput Comparison Table

Packet Size (bits)	COA	CSDP	GERC	LEACH	PSA-LEACH
1000	0.1666	0.1775	0.5545	0.3333	1.11
2000	0.3333	0.4547	0.5551	0.6666	2.22
3000	0.5	0.6	0.9	1	3.33
4000	0.6666	0.5555	0.6664	1.3	4.44
5000	0.8333	0.7888	0.8212	1.6	5.55

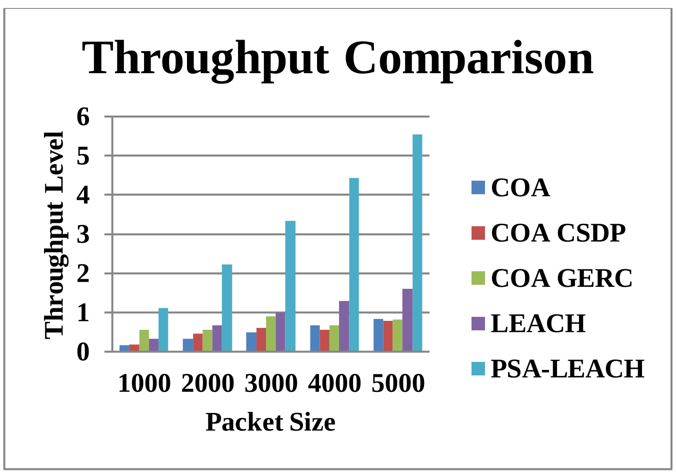

Figure 4 Throughput Comparison Chart

Table 2 and Figure 4 data present the performance metrics of different algorithms (COA, CSDP, GERC, LEACH, PSA-LEACH) across various packet sizes (1000 bits to 5000 bits). For instance, at 1000 bits, COA achieved a value of 0.1666, while CSDP and GERC had slightly higher values of 0.1775 and 0.5545, respectively. As the packet size increased to 2000 bits, COA improved to 0.3333, whereas CSDP and GERC also showed improvements to 0.4547 and 0.5551, respectively. Notably, GERC significantly improved at 3000 bits, reaching 0.9, surpassing other algorithms at that packet size. LEACH and PSA-LEACH also showed steady increases across all packet sizes, with PSA-LEACH consistently having the highest values among the algorithms, peaking at 5.55 at 5000 bits. These values suggest each algorithm's varying performance and scalability concerning packet size, with PSA-LEACH demonstrating the highest performance across the range of packet sizes considered.

4.2. Energy

Energy Consumption (E) = Power (P) × Time (t)

Table 3 Energy Comparison Table

Operating Time (Hrs)	COA	CSDP	GERC	LEACH	PSA-LEACH
10	0.4	0.4	0.5	0.5	0.3
20	0.8	0.8	0.9	1	0.6
30	1.2	1.3	1.4	1.5	0.9
40	1.6	1.7	1.9	2	1.2
50	2	2.1	2.3	2.5	1.5

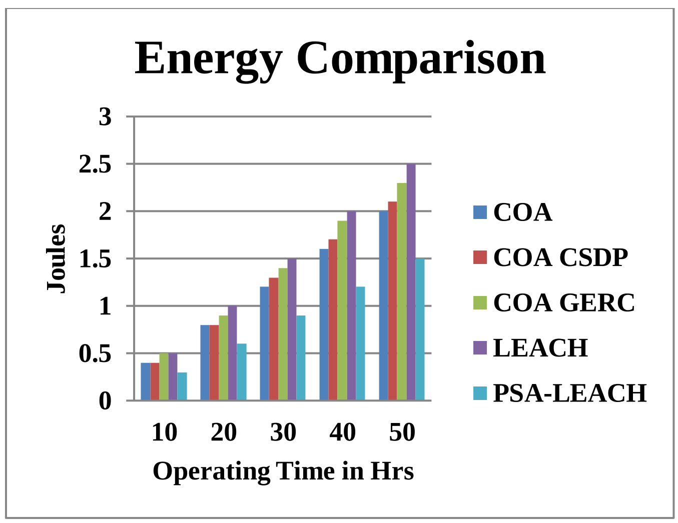

Figure 5 Energy Level Comparison Chart

Table 3 and Figure 5 data illustrate the performance metrics of different algorithms (COA, CSDP, GERC, LEACH, PSA-LEACH) concerning operating time in hours (10 to 50 hours).

RESEARCH ARTICLE

For instance, at 10 hours, COA and CSDP performed equally at 0.4, while GERC slightly outperformed them at 0.5. All algorithms improved as the operating time increased to 20 hours, with GERC achieving the highest value of 0.9. LEACH and PSA-LEACH showed steady increases in performance with increasing operating time, with PSA-LEACH reaching 0.6 at 20 hours. Notably, at 50 hours, LEACH exhibited the highest value of 2.5, while PSA-LEACH demonstrated the second-highest performance at 1.5. These results suggest variations in the performance and scalability of each algorithm concerning operating time, with LEACH and PSA-LEACH showing competitive performance as operating time increases.

4.3. Time Delay

Transmission Delay (Dtrans) = Packet Size / Link Bandwidth

Table 4 Time Delay Comparison Table

Packet Size (bits)	COA	CSDP	GERC	LEACH	PSA-LEACH
1000	0.0013	0.0011	0.0009	0.0003	0.0001
2000	0.0027	0.0020	0.0011	0.0007	0.0003
3000	0.0041	0.0030	0.0024	0.0011	0.0004
4000	0.0055	0.0045	0.0031	0.0015	0.0006
5000	0.0069	0.0050	0.0040	0.0019	0.0007

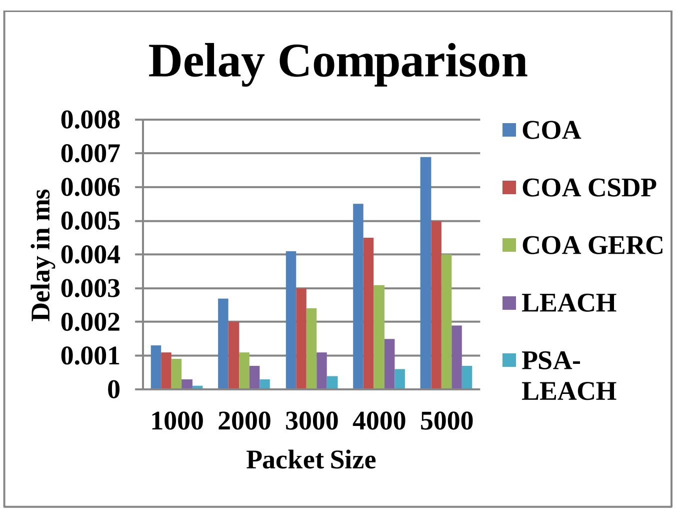

Figure 6 Time Delay Comparison Chart

Table 4 and Figure 6 data represent different algorithms' performance metrics (COA, CSDP, GERC, LEACH, PSA-LEACH) across various packet sizes (1000 bits to 5000 bits). As the packet size increased to 2000 bits, all algorithms improved their performance, with COA reaching 0.0027, CSDP at 0.0020, and GERC at 0.0011. Notably, GERC substantially improved at 3000 bits, reaching 0.0024, surpassing other algorithms at that packet size. LEACH and PSA-LEACH also demonstrated performance improvements across all packet sizes. PSA-LEACH consistently has the lowest values among the algorithms, indicating its higher efficiency in processing larger packet sizes than the other algorithms considered.

4.4. Packet Delivery Ratio

$$PDR = \frac{NumberofPacketsReceive}{TotalPackets} * 100$$

Table 5 Packet Delivery Ratio Comparison Table

Number of Packets	COA	CSDP	GERC	LEACH	PSA-LEACH
50	97.2	97.6	98.1	98.4	98.8
100	98.6	98.7	98.9	99.2	99.4
150	99.06	99.1	99.2	99.4	99.6
200	99.3	99.2	99.4	99.6	99.7
250	99.4	99.4	99.5	99.6	99.7

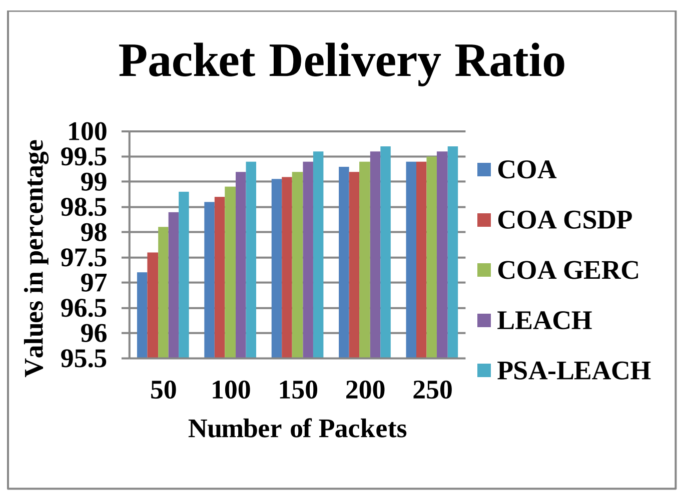

Figure 7 Packet Delivery Ratio Comparison Chart

Table 5 and Figure 7 data present the performance metrics of different algorithms (COA, CSDP, GERC, LEACH, PSA-LEACH) regarding packet processing efficiency across varying numbers of packets, ranging from 50 to 250. Notably, as the number of packets increases, all algorithms show improved efficiency. At 50 packets, COA achieves an efficiency of 97.2%, slightly lower than CSDP at 97.6% and GERC at 98.1%.

However, as the number of packets increases, COA surpasses CSDP and GERC, reaching 99.4% efficiency at 250 packets. LEACH and PSA-LEACH also exhibit high efficiencies across the range, with PSA-LEACH consistently demonstrating the highest efficiency, peaking at 99.7% at 250 packets. These results suggest that all algorithms improve their performance as the workload (number of packets) increases, with PSA-LEACH consistently delivering the most efficient packet processing across different workload levels.

Our evaluation of the PSA-LEACH approach in Wireless Sensor Networks (WSNs) reveals significant advancements over traditional protocols. Integrating Particle Swarm Optimization (PSO) with the LEACH protocol, PSA-LEACH extends network lifetime by dynamically optimizing cluster head selection and balancing energy consumption among nodes.

This approach markedly reduces energy consumption while enhancing throughput and packet delivery ratio (PDR). Comparative analysis shows PSA-LEACH outperforming traditional LEACH and other protocols regarding efficiency metrics. The results underscore PSA-LEACH's innovative approach to improving network sustainability and reliability, making it a promising solution for applications requiring prolonged operation and enhanced energy efficiency in WSNs.

4.5. Classification Formulas

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + FP + TN + FN)}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F1 score} = 2 * \text{Precision} * \text{Recall} / (\text{Precision} + \text{Recall})$$

Table 6 Classification Metrics Comparison Table

Methods	Accuracy	Precision	Recall	F-measure
Logistic Regression	92.37	91.75	90.38	91.31
Gaussian Naïve Bayes	93.71	92.59	93.25	92.54
SVM	94.35	96.84	97.31	97.58
Decision tree	95.31	97.01	97.99	98.01
Random forest	96.32	97.68	98.36	98.36
Improved random forest	98.91	98.39	98.99	99.11

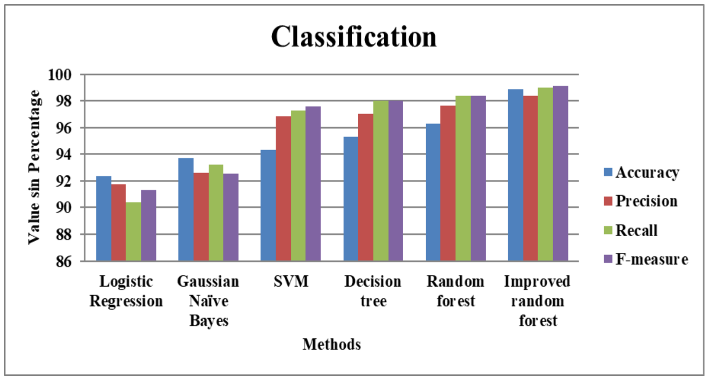

Figure 8 Classification Comparison Chart

Table 6 and Figure 8 shows the results of six classification systems' tests on recall, accuracy, precision, and F-measure: LR, GNB, SVM, Decision Tree, Random Forest, and Improved Random Forest. With top scores in every category, including accuracy (98.91%), precision (98.39%), recall (98.99%), and F-measure (99.11%), the Improved Random Forest technique shines out. Similarly, Random Forest shows impressive results with an F-measure of 98.36%, a recall of 98.36%, a precision of 97.68%, and an accuracy of 96.32%. Decision Tree follows closely behind with a 95.01% F-measure, 97.99% recall, 97.01% precision, and 95.31% accuracy. With a recall of 97.31%, an F-measure of 97.58%, and an accuracy of 94.35%, SVM is somewhat behind the other approaches but still exhibits decent performance.

5. CONCLUSION

In conclusion, this paper introduces the PSA-LEACH approach as a novel and effective method for addressing the challenge of constrained energy resources in WSNs. By integrating PSA with the LEACH routing protocol, PSA-LEACH optimizes clustering parameters dynamically, improving network lifetime and energy consumption. Additionally, using the IRF Algorithm for energy efficiency classification enhances the overall understanding and management of WSNs. Through extensive simulated experiments, we have demonstrated the effectiveness of PSA-

RESEARCH ARTICLE

LEACH in enhancing energy efficiency metrics such as throughput, energy consumption, delay, and packet delivery ratio. These improvements prolong the sustainability of WSNs and enhance their resilience across various applications, including environmental monitoring and smart infrastructure development. The Improved Random Forest method stands out with the highest values across all metrics, achieving an accuracy of 98.91%, precision of 98.39%, recall of 98.99%, and F-measure of 99.11%. Overall, the proposed PSA-LEACH approach presents a promising solution to the energy efficiency challenges in WSNs, offering opportunities for more efficient and reliable operation in diverse real-world scenarios.

REFERENCES

[1] Al-Sodairi, S., & Ouni, R. (2018). Reliable and energy-efficient multi-hop LEACH-based clustering protocol for wireless sensor networks. Sustainable Computing: Informatics and Systems, 20, 1-13.

[2] Amutha, J., Sharma, S., & Nagar, J. (2020). WSN strategies based on sensors, deployment, sensing models, coverage and energy efficiency: Review, approaches and open issues. Wireless Personal Communications, 111(2), 1089-1115.

[3] Ay, P., &Rayanki, B. (2020). A generic algorithmic protocol approaches to improve network life time and energy efficient using combined genetic algorithm with simulated annealing in MANET. International Journal of Intelligent Unmanned Systems, 8(1), 23-42.

[4] Balasubramanian, D. L., & Govindasamy, V. (2019). Study on evolutionary approaches for improving the energy efficiency of wireless sensor networks applications. EAI Endorsed Transactions on Internet of Things, 5(20), e2-e2.

[5] Ding, Q., Zhu, R., Liu, H., & Ma, M. (2021). An overview of machine learning-based energy-efficient routing algorithms in wireless sensor networks. Electronics, 10(13), 1539.

[6] Jan, S. R. U., Khan, R., & Jan, M. A. (2020). An energy-efficient data aggregation approach for cluster-based wireless sensor networks. Annals of Telecommunications. https://doi.org/10.1007/s12243-020-00823-x

[7] Koyuncu, H., Tomar, G. S., & Sharma, D. (2020). A new energy efficient multitier deterministic energy-efficient clustering routing protocol for wireless sensor networks. Symmetry, 12(5), 837.

[8] Kumar, M., Mukherjee, P., Verma, K., Verma, S., & Rawat, D. B. (2022). Improved deep convolutional neural network based malicious node detection and energy-efficient data transmission in wireless sensor networks. IEEE Transactions on Network Science and Engineering, 9(5), 3272-3281. https://doi.org/10.1109/TNSE.2021.3098011

[9] Lata, S., &Mehfuz, S. (2019). Machine learning based energy efficient wireless sensor network. In 2019 International Conference on Power Electronics, Control and Automation (ICPECA) (pp. 1-5). New Delhi, India. https://doi.org/10.1109/ICPECA47973.2019.8975526

[10] Lin, D., Wang, Q., Min, W., Xu, J., & Zhang, Z. (2020). A survey on energy-efficient strategies in static wireless sensor networks. ACM Transactions on Sensor Networks (TOSN), 17(1), 1-48.

[11] Meenakshi, N., Ahmad, S., Prabu, A. V., Rao, J. N., Othman, N. A., Abdeljaber, H. A., ... & Nazeer, J. (2024). Efficient communication in wireless sensor networks using optimized energy efficient engroove leach clustering protocol. Tsinghua Science and Technology, 29(4), 985-1001.

[12] Mohamed, A., Saber, W., Elnahry, I., &Hassanien, A. E. (2020). Coyote optimization based on a fuzzy logic algorithm for energy-efficiency in wireless sensor networks. IEEE Access, 8, 185816-185829. https://doi.org/10.1109/ACCESS.2020.3029683

[13] Mostafaei, H. (2018). Energy-efficient algorithm for reliable routing of wireless sensor networks. IEEE Transactions on Industrial Electronics, 66(7), 5567-5575.

[14] Radhika, S., & Rangarajan, P. (2021). Fuzzy based sleep scheduling algorithm with machine learning techniques to enhance energy efficiency in wireless sensor networks. Wireless Personal Communications, 118(4), 3025–3044. https://doi.org/10.1007/s11277-021-08167-y

[15] Raj, V. P., &Duraipandian, M. (2024). An energy-efficient cross-layer-based opportunistic routing protocol and partially informed sparse autoencoder for data transfer in wireless sensor network. Journal of Engineering Research, 12(1), 122-132.

[16] Sachan, S., Sharma, R., & Sehgal, A. (2021). Energy efficient scheme for better connectivity in sustainable mobile wireless sensor networks. Sustainable Computing: Informatics and Systems, 30, 100504.

[17] Samara, G., Besani, G. A., Alauthman, M., &Khaldy, M. A. (2020). Energy-efficiency routing algorithms in wireless sensor networks: A survey. arXiv preprint arXiv:2002.07178.

[18] Santhosh Kumar, S. V. N., Palanichamy, Y., Selvi, M., Ganapathy, S., Kannan, A., & Perumal, S. P. (2021). Energy efficient secured K means based unequal fuzzy clustering algorithm for efficient reprogramming in wireless sensor networks. Wireless Networks, 27(6), 3873–3894. https://doi.org/10.1007/s11276-021-02660-9

[19] Singh, J., Kaur, R., & Singh, D. (2020). A Survey and Taxonomy on Energy Management Schemes in Wireless Sensor Networks. Journal of Systems Architecture, 101782. https://doi.org/10.1016/j.sysarc.2020.101782

[20] Smys, S., Bashar, A., &Haoxiang, W. (2021). Taxonomy classification and comparison of routing protocol based on energy efficient rate. Journal of ISMAC, 3(02), 96-110.

[21] Surenther, I., Sridhar, K. P., & Roberts, M. K. (2024). Enhancing data transmission efficiency in wireless sensor networks through machine learning-enabled energy optimization: A grouping model approach. Ain Shams Engineering Journal, 15(4), 102644. https://doi.org/10.1016/j.asej.2024.102644

[22] Wang, T., Zhang, G., Yang, X., &Vajdi, A. (2018). Genetic algorithm for energy-efficient clustering and routing in wireless sensor networks. Journal of Systems and Software, 146, 196-214.

[23] Wang, Z., Ding, H., Li, B., Bao, L., & Yang, Z. (2020). An energy efficient routing protocol based on improved artificial bee colony algorithm for wireless sensor networks. IEEE Access, 8, 133577-133596.

[24] Zagrouba, R., & Kardi, A. (2021). Comparative study of energy efficient routing techniques in wireless sensor networks. Information, 12(1), 42.

[25] Zhang, W., Liu, Y., Han, G., Feng, Y., & Zhao, Y. (2018). An energy efficient and QoS aware routing algorithm based on data classification for industrial wireless sensor networks. IEEE Access, 6, 46495-46504.

[26] Zhou, C., Ma, L., & Liu, P. (2023, April). Optimal calculation of the operation strategy of a distributed heating system combining wind, solar and electrical energy. Journal of Physics: Conference Series, 2491(1), 012023. https://doi.org/10.1088/1742-6596/2491/1/012023.

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