



RESEARCH ARTICLE

Load aware active low energy adaptive clustering hierarchy for IoT-WSN

R. Sridevi*, V. S. J. Prakash

Abstract

Clustering is a primary process that takes place in an IoT based wireless sensor network environment commences from the deployment phase. Due to the heterogeneity and resource constrained nature of internet of things (IoT) networks, dynamic clustering, cluster head selection, and routing are required to optimize the network and to improve the overall network performance. Load aware active low energy adaptive clustering hierarchy (LAALEACH) work is an attempt to introduce novel components to the standard LEACH protocol. The main objective of LAALEACH work is to achieve a load aware active routing in IoT based wireless sensor network environments. Rapid load estimator, load pattern tracker, and load aware active routing are the contributed modules introduced in this LAALEACH work. Most recent related works are analyzed and the proposed modules are devised in a way to overcome the issues in the existing methods. Standard network performance parameters such as throughput, packet delivery rate, communication delays, and energy consumption are measured by the OPNET based simulation during the experiments. Obtained improvements in the overall performance is the accomplishment of LAALEACH work.

Keywords: Active routing, Adaptive clustering, LEACH protocol, Load aware, Low energy, Internet-of things, Wireless sensor network.

Introduction

Wireless sensor networks are used all over the world in this modern era for plenty of purposes such as environmental monitoring, agriculture, industrial automation, healthcare, smart cities, defense, natural resource conservations, home automation, asset tracking, and structural health monitoring (Akin-Ponnle, A. E., *et al.*, 2023). The incorporation of IoT in the field of WSN yields an abundance of benefits such as data accessibility, scalability, data fusion, interoperability, energy efficiency, data analytics, cloud service integrations, real-time data monitoring and alerts (Panahi, U., & Bayılmış, C.,

2023). An IoT based WSN network deployment depends on several criteria specifically basic architecture, connectivity options, network coverage, RF range of the nodes, node compatibility, data security, regularity compliance, environmental factors, deployment costs, and maintenance. Node deployment, clustering, cluster head selection, routing, traffic analysis, load balancing, energy aware node mode selection, authentication and security measures are the crucial process in an IoT based WSN (Tyagi, H., *et al.*, 2023).

IoT is the interconnected global network of computing devices that can collect and share data over the internet in real time (Selvakumar, R., *et al.*, 2023).

The low energy adaptive clustering hierarchy (LEACH) protocol is a widely known and fundamental algorithm in wireless sensor networks (Saoud, B., *et al.*, 2023). It's designed to reduce energy consumption in WSNs by enabling nodes to efficiently organize themselves into clusters and electing cluster heads for data aggregation and transmission. Though, LEACH is a prevalent protocol in WSN, some of the limitations of LEACH such as unequal cluster head selection, single-hop communication dependency, static clustering, constrained scalability, security leaks, and data aggregation overhead makes it incongruent for IoT-WSN (Anand, S., & Sinha, S., 2023).

Load balancing distributes data processing and communication tasks evenly across sensor nodes and gateways, preventing overutilization of some nodes while

Department of Computer Science, Cauvery College for Women (Autonomous), Affiliated to Bharathidasan University, Tiruchirappalli, Tamil Nadu, India.

***Corresponding Author:** R. Sridevi, Department of Computer Science, Cauvery College for Women (Autonomous), Affiliated to Bharathidasan University, Tiruchirappalli, Tamil Nadu, India., E-Mail: sridevirajaram1981@gmail.com

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underutilizing others (Srivastava, A., & Paulus, R., 2023). This optimization ensures efficient resource utilization. In battery-powered IoT devices, energy conservation is paramount. Load balancing helps evenly distribute data transmission and processing tasks, preventing some nodes from exhausting their energy quickly, thus extending the network's overall lifespan (Rizwanullah, M., *et al.*, 2023). IoT applications often require low-latency communication, especially in real-time monitoring and control scenarios. Load balancing can reduce latency by evenly distributing data and processing tasks, ensuring that critical information reaches its destination quickly (Mershad, K., & Dahrouj, H., 2023). It allows for efficient traffic management in scenarios with heterogeneous IoT devices. For example, in a smart city application, load balancing can allocate more resources to high-traffic areas without neglecting less busy regions.

This LAALACH work is a venture to improve the load balancing ability of LEACH which is more appropriate for IoT-WSN environments.

Existing Methods

A study about most related works is carried out to find the methodologies used, their advantages and limitations in this section. Simplified LEACH protocol with superior energy efficiency for the internet of things (Sharma, A., *et al.*, 2023), Incorporating metaheuristic optimization algorithm ABO for improvement of LEACH protocol in wireless sensor networks (Malik, M., *et al.*, 2023), improving network efficiency in video traffic analysis using wireless sensor network (Gharge, A. P., & Hadia, S. K., 2023), security aware congestion management using fuzzy analytical hierarchal process for wireless sensor networks (Kushwaha, V., & Pandey, D., 2023), and idiosyncratic fuzzy low-energy adaptive clustering hierarchy (Sridevi, R., & Sinthu Janita Prakash, V., 2023) are the existing methods taken for interpretation.

In 2023 Anu Sharma *et al.*, presented a work based on alternative convergent sunflower optimization, thus abbreviated as ASCO. The motivation behind ASCO work is to simplify the standard prototype LEACH protocol to maintain an equilibrium between power and performance by introducing diversification and intensification mechanisms. Energy efficiency, network lifespan, and data transmission rate are taken as the primary concerns in ASCO work. Experiments were carried out based on MATLAB based implementation. Network lifetime, communication overhead, energy consumption, and scalability are the reviewed parameters in the results and discussions section

As per the claim, improved network lifetime is the advantage of ASCO work, whereas, compromised network performance such as throughput and packet delivery ratio are the observed limitations of ASCO work. The maximum number of nodes taken for the experiment is 400, thus the applicability of ASCO work for high density network environment is in ambiguity.

In 2023, Monika Malik *et al.*, introduced ABOLEACH work that is optimized with African buffalo metaheuristic algorithm. Low energy and High energy nodes are distinguished in ABOLEACH work for efficient routing purposes. A temporary route is created during the energy aware phase to overcome connection failures in the wireless sensor networks. A dedicated algorithm is developed to handle the low and high-power node categories. A MATLAB based implementation is used to evaluate the performance of ABOLEACH work. Throughput, energy consumption, communication delays and packet loss are measured during the MATLAB simulation. Maximum number of simulated nodes is restricted to 125 only.

Achievement of lower power consumption while comparing with other discussed methods is the advantage of ABOLEACH method. The avowed improvement is demonstrated only with 125 number of nodes. The operability with limited number of nodes is observed as the limitation of ABOLEACH work.

In 2023, Gharge *et al.*, introduced a hybrid genetic algorithm based cluster head selection anchored in LEACH to improve the performance of wireless sensor networks. It is contended that HGACHS method improves the network performance by minimizing the first node dead, half node dead, last node dead scenario. MATLAB is used to perform the network simulation for the experiments. Performance parameters such as throughput, jitter, averages number of dead nodes, and Energy consumption are measured during the experiments.

Mitigated energy consumption and progressed network lifetime are the observed advantage of HGACHS work. The performance improvement of HGALEACH is demonstrated for 200 number of nodes deployed in 200 square meters during the simulation. Narrowed simulation space with a smaller number of nodes does not comply with a typical real-world environment. Overall increase in end-to-end delay is the noted limitation of HGACHS method.

In 2023, Kushwaha, V. *et al.*, submitted a multi-criteria decision-making method to improve the wireless sensor network performance. Fuzzy analytical hierarchy process is used in SACMUF method to control the network traffic congestion. SACMUF selects the cluster heads based on the factors specifically node potential, remaining energy, traffic burst rate, and node load rank. A MATLAB simulation with 100 number of nodes deployed in 200 square meters is created for the evaluation purpose of the discussed method. Energy consumption, and number of dead nodes are measured during the experiments to evaluate the performance of the methodologies.

Improved energy saving of the proposed method causes less energy consumption and less number of dead nodes during the simulation process. More remaining energy at a specific timestamp, and lower number of dead node count are the advantages of SACMUF method. Essential network

performance metrics such as throughput, communication delays, and packet delivery rate are not accomplished in SACMUF work, which is observed as the limitation.

In 2023, the author submitted IFLEACH work to improve the overall performance of an IoT based WSN. Idiosyncratic fuzzy energy estimator, cumulative fuzzy energy hierarchy builder, and energy based cluster head exchanger are the novel contributed modules of IFLEACH work. Sensor node, relay node, idle node, computational node and cluster head are the different node labels used to systematize the network environment in IFLEACH work. The nodes are sorted based on the cumulative remaining energy and the role of the nodes are switched cautiously to prevent the nodes from draining the power source. IFLEACH work is managed to increase the network lifetime without giving more impact to the performance. OPNET based simulation is conducted for the discussed methods during the experiments. Most important network performance metrics such as throughput, latency, end-to-end delay, packet delivery rate, and energy consumption are logged during the experiments.

Achievement of better performance with lesser power consumption is the advantage of IFLEACH work. Load balance is not included in the optimization process which could be the limitation of IFLEACH work.

Research Gap

In accordance with the interpretations performed on existing methods, it is identified that there is a huge opportunity for more research works towards IoT-WSN environment betterment. Most of the IoT-WSN nodes are battery-powered devices with limited computational resources. Therefore, it is an indispensable fact that the algorithms that are going to operate in an IoT-WSN should be kept lightweight to embed in the nodes.

The resonance between the power and performance should be maintained in a streamlined manner to get the most out of the network. Clear research is necessitated to improve IoT-WSN-related tasks such as node deployment clustering, cluster head selection, routing, authentication, load balancing, and security.

Background

LAALACH protocol is backed by the traditional LEACH protocol and a multi-hop LEACH model. A coherent interpretation about the traditional LEACH and multi-hop LEACH is given in this section.

LEACH

LEACH is a popular protocol in wireless sensor networks that was developed to reduce the energy consumption of sensor nodes, thereby extending the network's lifetime. LEACH organizes sensor nodes into clusters, where one node in each cluster acts as the cluster head (CH) or the leader of that

cluster. The CH is responsible for collecting and aggregating data from its cluster members and transmitting it to a central base station or sink node (Sahu, T., & Badholia, A., 2017).

One of the key features of LEACH is its randomized algorithm for selecting cluster heads. Instead of having fixed CHs, LEACH uses a probabilistic approach. Each sensor node decides, with a certain probability, whether to become a CH for a given round. This randomness helps distribute the energy consumption across the network, as different nodes take turns being CHs (Behera, T. M., *et al.*, 2022). Cluster heads are responsible for aggregating data from their cluster members before forwarding it to the base station. This reduces the amount of data transmitted over long distances and minimizes energy consumption.

Despite its advantages, LEACH does have some limitations. For example, it doesn't consider network heterogeneity, and the random selection of CHs may lead to uneven energy consumption if nodes are not uniformly distributed or if some nodes have higher energy reserves than others (Harun, H. B., *et al.*, 2022). There are a number of researches carried out to overcome these issues till date.

Multi-hop LEACH (M-LEACH)

Mobility induced multi-hop LEACH (Mohapatra, S., *et al.*, 2022) protocol is introduced by Seli Mohapatra *et al.*, in 2022 for heterogeneous mobile networks. Due to the multifarious property of M-LEACH protocol, it is preferred to use for IoT-WSN environments. Nonetheless, creating an efficient routing protocol poses greater challenges because of the irregular energy consumption and constantly changing event patterns. The intricacy of this task escalates significantly as node mobility comes into play. In this regard, adopting a multi-hop routing strategy with a well-managed mobility pattern emerges as a promising solution to enhance energy efficiency while optimizing memory and storage utilization within the network. In light of these considerations, this research introduces a novel energy-efficient model tailored for heterogeneous networks, taking into account both node mobility and the remaining energy levels for the purpose of cluster head selection in the multi-hop-LEACH (M-LEACH) model.

Exclusive equations are provided in M-LEACH work for different IoT-WSN component models such as rapid propagation model, MAC model, routing model, congestion model, energy model, and mobility model. In accordance with the experimental outcomes, it is understood that the increased throughput and minimized communication delays are the prominent achievements of M-LEACH model, thus engaged to use in LAALACH work.

Proposed Method

Proposed LAALACH work improves the traditional LEACH by introducing a better load balancing procedure. Rapid load estimator (RLE), load pattern tracker (LPT), and load

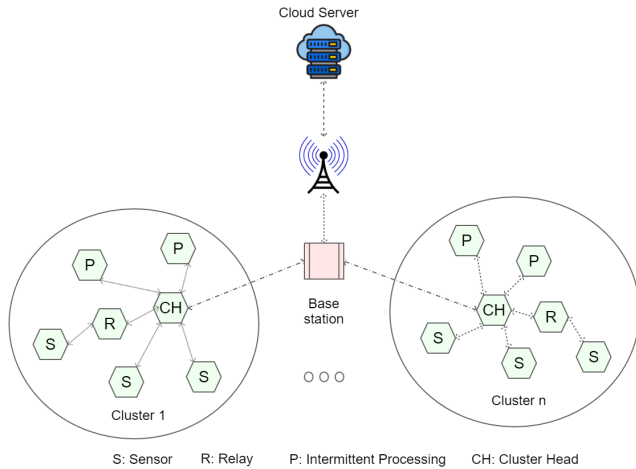


Figure 1: Typical IoT-WSN environments

aware active routing (LAAR) are the novel functional blocks of LAALEACH. A clear exposition about the methodologies, and their operative principles are provided in this section.

Rapid Load Estimator (RLE)

RLE is used to classify the load levels in each data transmission path. A typical IoT-WSN environments consists different types of nodes such as sensor, relay, intermittent processing, cluster heads and receiver node or base station. A representative IoT-WSN image is illustrated in Figure 1.

A customized path set is introduced in RLE to hold the data transfer paths and possible alternative paths. The cluster head selection procedure is inherited from the antecedent work IFLEACH. Once the cluster heads are finalized, the communication paths are aggregated by RLE in the path table. The multi-hop LEACH model is used to find the data transmission paths to update RLE path set. A typical multipath IoT-WSN communication is visualized in Figure 2 for ease of explication.

As in the diagram, the communication path p_1 between node N1 to Node N9 is $(N_1 \rightarrow N_4 \rightarrow N_8 \rightarrow N_9)$. Similarly, path p_2 is $(N_1 \rightarrow N_3 \rightarrow N_7 \rightarrow N_9)$. In RLE, the nodes are represented as a member of path sets such as $p_1 = \{N_1, N_3, N_5, N_6\}$, Similarly $p_2 = \{N_1, N_2, N_4, N_6\}$. The set of all possible paths are accumulated as the path set $P = \{p_1, p_2 \dots p_n\}$ where n is the maximum number of discovered paths between source and destination nodes. The bandwidth usage is measured periodically for every timestamp t . The average bandwidth usage βN_x is calculated for Node N_x by equation 1.

$$\beta N_x = \frac{1}{4} \sum_{i=0}^3 \beta N_{x,t-i} \tag{Equation 1}$$

Where $\beta N_{x,t-i}$ is the bandwidth usage of Node N_x at timestamp $t - i$.

The average bandwidth usage is represented as β_{p_x} is calculated for path p_x as in equation 2

$$\beta_{p_x} = \frac{1}{n} \sum_{i=1}^n \beta N_i \tag{Equation 2}$$

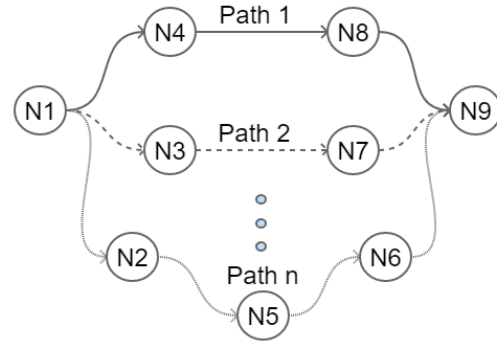


Figure 2: Multi-path communication

Where n is the number of discovered paths between the source and the destination

The load set L is composed of Load label members $\{\lambda_1, \lambda_2 \dots \lambda_3\}$ correspondingly mapped to the path set P . The load label members are determined using equation 3.

$$\lambda_x = \begin{cases} \text{Low if } \beta_{p_x} < \frac{1}{3} \beta_{max} \\ \text{Medium if } \frac{1}{3} \beta_{max} \leq \beta_{p_x} < \frac{2}{3} \beta_{max} \\ \text{High otherwise} \end{cases} \tag{Equation 3}$$

Where β_{max} is the maximum available bandwidth in the IoT-WSN network, with the constrain $\lambda_x \in L$

In this manner, the load estimation is performed by RLE module and preserved in set L .

Load Pattern Tracker (LPT)

IoT-WSN devices tend to save power by skipping transmission data where there is no significant difference in the sensor data. The purpose of this setup is to promote power saving among the network nodes. During some time of the days or days of the year, the environment changes frequently due to climate conditions. For example, during the rainy season, the temperature and humidity fluctuations are common. The sensor nodes often pickup different values during this season, that causes frequent aggregation and transmission of data which will obviously increase the network traffic. LPT takes care of these situations by prediction the load based on the past traffic data records. LPT reserves some paths and bandwidths based on the on prediction of this context. Since the load pattern tracker is a timeseries rooted one, Recurrent neural network (RNN) is used to sift through the quandary. The standard RNN model is customized in LPT to track the past network traffic load data and to predict the upcoming traffic load. The RNN architecture used in LPT is rendered in Figure 3.

The criterion equations for different layers of RNN are given below:

$$i^{(z)} = b + wh^{(z-1)} + Ux^{(z)} \tag{Equation 4}$$

$$h^{(z)} = \tanh(i^{(z)}) \tag{Equation 5}$$

$$o^{(z)} = c + vh^{(z)} \tag{Equation 6}$$

$$\hat{y}^{(z)} = \text{softmax}(o^{(z)}) \tag{Equation 7}$$

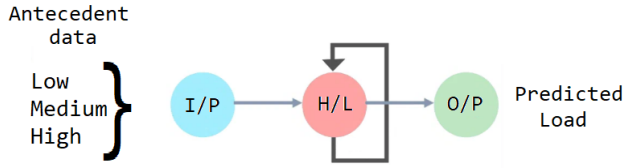


Figure 3: LPT-RNN architecture

The imminent load level is predicted by means of this LPT module, and the load predictions for all attainable paths are held in a set A with members $\{\alpha_1, \alpha_2 \dots \alpha_n\}$ mapped to every member of path set P in sequence with one-to-one perception.

Load Aware Active Routing (LAAR)

The path set P , and the traffic load set A are the input determinants for LAAR. Current load of the paths is measured in the LAAR algorithm, and the paths are switched between alternate paths in a way that ensures sensible data aggregation, and minimization of relentless path occupancy. By engaging these tasks, the overall performance and lifetime of the network is effectuated through LAAR module.

$$\text{Path selection } (p_x) = \begin{cases} \text{Switch to alternate path if } \gamma_x = \text{High} \\ \text{Retain current path } p_x \text{ if } \gamma_x = \text{Medium or low} \end{cases} \quad \text{Equation (8)}$$

$$\text{Path selection } (p_x) = \begin{cases} \text{Switch to alternate path if } \gamma_x = \text{High} \\ \text{Retain current path } p_x \text{ if } \gamma_x = \text{Medium} \\ \text{Initiate data aggregation for all Nodes } \in p_x \text{ otherwise} \end{cases} \quad \text{Equation (9)}$$

The cognizant process pursued in the LAAR module guarantees the overall performance improvements of -IoT based WSN network environments, and the same is reflected during the experiments.

Experimental Setup

LAALACH is a network framework that relies on low-level access to basic parameters. C++ programming language is used to develop network communication snippets, and network elements. Sufficient access to the machine level operations, most recent modernistic features, and the supreme performance speed are the reasons behind the selection of C++ 20.0 (<https://www.geeksforgoeks.org/features-of-c-20/>) programming language. Visual Studio IDE (<https://visualstudio.microsoft.com/vs/>) is used to create a user interface (UI), which serves as the core executable for entire simulation. OPNET (Mahmood, T. M., 2022) – the industrial standard network simulator is used to perform the evaluation process of the discussed methods. OPNET has several cutting-edge features such as loading C++ code scripts directly to memory, software defined network components reinforcement, and the ability to log data for different timestamps. A computer with i7 4.7GHz processor, 16GB RAM and 1TB SSD is used to develop the proposed method and to carryover the experiments. The network simulation parameters are given in Table 1.

Algorithm: LAAR

Input: P, A

Output: Path switching

-
- Step 1: Let $\Gamma = \{\gamma_1, \gamma_2 \dots \gamma_n\}$ be the set of current bandwidth usage of the nodes
- Step 2: Let $\Delta = \{\delta_1, \delta_2 \dots \delta_n\}$ be the set of timers to count busy duration of the paths
- Step 3: Load available paths list from Set P
- Step 4: Load Predicted Traffic Loads from A
- Step 5: Initialize timers as $\forall i = 1 \rightarrow n := \delta_i = 0$
- Step 6: $\forall i = 1 \rightarrow n := \text{Measure } \gamma_i \text{ for every } p_i$
- Step 7: For $i = 1 \rightarrow n$
- Step 8: if $\alpha_i = \text{High}$
- Step 9: Apply path selection strategy as in Equation 8
- Step 10: if $\alpha_i = \text{Medium}$
- Step 11: Apply path selection strategy as in Equation 9
- Step 12: if $\alpha_i = \text{Low}$
- Step 13: Free up bandwidth of path p_i
- Step 14: Set $\delta_i = 0$
- Step 15: Initiate data aggregation for all $N_x \in p_i$
- Step 16: End for (Step 7)
- Step 17: $\forall i = i \rightarrow n := \text{Increment } \delta_i \text{ by } 1$
- Step 18: For $i = 1 \rightarrow n$
- Step 19: If $\delta_i > \delta_{max}$
- Step 20: Allocate alternate path for p_i
- Step 21: Initiate data aggregation for all $N_x \in p_i$
- Step 22: Free up Bandwidth of p_i
- Step 23: Set $\delta_i = 0$
- Step 24: End for (Step 18)
-

Table 1: Network simulation parameters

Element	Details
Simulation area	5000 x 5000 square meters
Simulation time	1 hour real-world
Evaluation time stamp	6 minutes
Number of nodes	1000 in step 100
Type of nodes	Heterogeneous
Communication mode	Wireless
Number of Wi-fi routers	30
Node placement	Random distribution
Traffic type	Random real-world replica
Node movement	Random real-world replica

Results and Analysis

Pivotal network performance measurement parameters such as throughput end-to-end delay, latency, packet delivery ratio, energy consumption and security levels are analyzed during the experiments conducted. The simulation is performed for 100 to 1000 number nodes and the performance parameters are logged for every 100 number of nodes during the simulation. A comprehensive exposition of the acquired results, and the improvement achievement is given in this section.

Throughput

Throughput is an important parameter in the context of IoT-based wireless sensor networks since several factors are depending on it such as data reliability, real-time applicability, energy efficiency, network scalability, effective spectrum utilization, and quality of service. Throughput is represented in bits-per-second ((bps) units, which is calculated using the formula $Throughput = \frac{\text{transferred data volume}}{\text{transfer time duration}}$. Measured throughput values for the discussed methods are enumerated in Table 2 and comparison graph is provided in Figure 4.

In accordance with the experiment outcomes, it is observed that LAALEACH method scored highest throughput of 36402 kbps during the simulation with 100 number of nodes. Performance rank of discussed methods based on the throughput average is LAALEACH, IFLEACH, SACMUF, ACSO, ABOLEACH, and HGACHS with the values 31364, 30309, 24879, 22723, 20607, and 20308 kbps. An achievement of 4.3% is achieved by LAALEACH than the nearest achiever IFLEACH.

Table 2: Throughput

Throughput (kbps)						
Nodes	HGACHS	ABOLEACH	SACMUF	ACSO	IFLEACH	LAALEACH
100	31582	31033	34625	34932	34906	36402
200	28437	29936	33944	30797	33373	35361
300	26189	26387	31361	29011	33092	34446
400	24581	25423	28980	25538	32305	32465
500	21587	22657	26078	24789	30287	32077
600	19811	19452	24150	20879	29366	31368
700	16444	16387	21472	19221	29139	29413
800	14922	13904	18135	15943	28215	28093
900	11247	11536	16878	14544	27066	27893
1000	8279	9353	13171	11572	25344	26125

End-to-End Delay

End-to-end delay is a specific type of latency that measures the total time it takes for a data packet or signal to travel from the source to the destination in a network, considering all delays along the entire path. It specifically refers to the cumulative delay experienced by data as it traverses the entire network from sender to receiver. End-to-end delay is often used to assess the overall performance of a communication system and is important in applications where the total time from sending a packet to receiving a response matters. End-to-end delay is used to be measured in milli second units. End-to-end delay is calculated by applying the formula

$$\text{End to End Delay} = \text{Transmission delay} + \text{Propagation delay} + \text{Queueing delay} + \text{Processing Delay} + \text{Jitter}$$

The following Table 3 summarizes the measured end-to-end delay values for the discussed methods.

As indicated by the results, it is discovered that LAALEACH undergoes lesser end-to-end delay values than the other methods. The lesser end-to-end delay value

Table 3: End-to-end delay

End-to-end delay (mS)						
Nodes	HGACHS	ABOLEACH	SACMUF	ACSO	IFLEACH	LAALEACH
100	185	156	203	144	105	90
200	206	177	220	160	109	98
300	227	201	248	185	111	99
400	253	216	270	204	108	105
500	266	238	282	230	115	102
600	294	257	305	246	115	113
700	313	280	330	271	124	114
800	329	299	345	287	124	116
900	352	326	372	310	128	121
1000	373	344	392	329	125	125

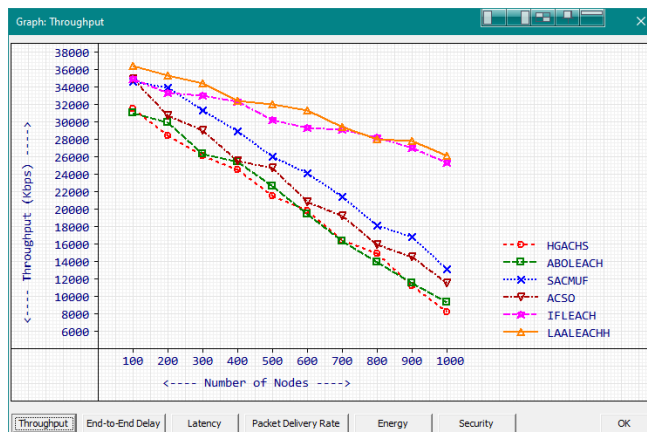


Figure 4: Throughput

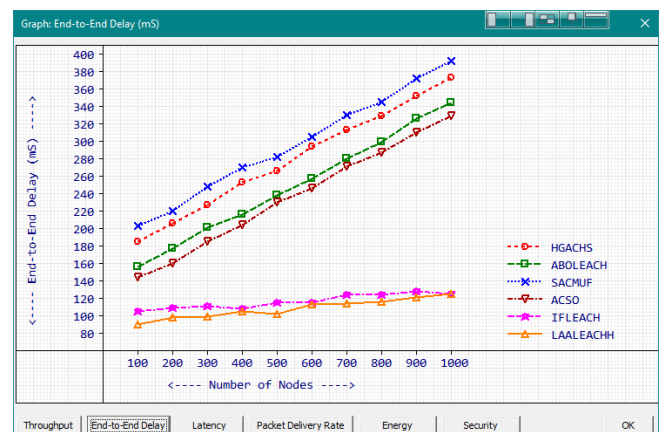


Figure 5: End-to-end delay

Table 4: Latency

Latency (mS)						
Nodes	HGACHS	ABOLEACH	SACMUF	ACSO	IFLEACH	LAALEACH
100	45	30	51	23	21	22
200	44	31	45	31	22	21
300	40	34	47	26	23	21
400	51	35	55	30	27	20
500	47	40	55	34	23	24
600	46	44	58	34	27	25
700	52	43	56	35	24	21
800	57	49	63	42	33	23
900	54	43	63	40	33	31
1000	63	49	69	45	33	28

Table 5: Packet delivery ratio

Packet delivery ratio (%)						
Nodes	HGACHS	ABOLEACH	SACMUF	ACSO	IFLEACH	LAALEACH
100	94	93	91	96	100	99
200	92	91	87	94	98	98
300	90	90	85	93	97	97
400	88	86	85	90	96	97
500	84	86	81	89	95	97
600	82	84	79	86	94	96
700	81	82	77	85	94	94
800	78	80	75	83	93	94
900	78	77	74	80	91	94
1000	74	76	72	79	91	93

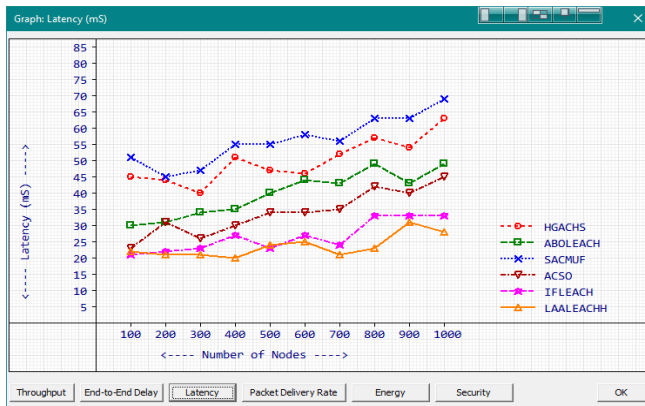


Figure 6: Latency

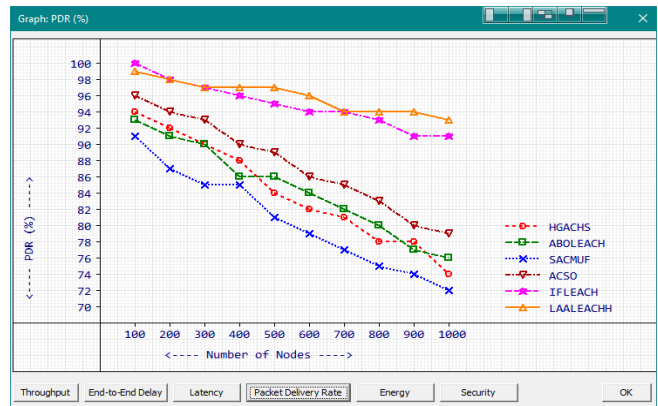


Figure 7: Packet delivery ratio

refers the higher performance of the methodology in the stipulated environment. The performance rank based on end-to-end delay averages is LAALEACH, IFLEACH, ACSO, ABOLEACH, HGACHS, and SACMUF with the values 108, 116, 237, 249, 280, and 297 mS respectively ordered from the best.

The comparison graphs for end-to-end delay parameter is given in Figure 5.

Latency

Latency, in the context of IoT-WSN, refers to the time delay between the initiation of a data transfer or communication event and the moment when the data is received or processed at its destination. It encompasses various components of delay within the network. Gauged latency values are given in Table 4.

As per the consonance with the experimental results, it is realized that the performance of LAALEACH is advantageous. The performance rank towards latency readings is LAALEACH, IFLEACH, ACSO, ABOLEACH, HGACHS, and SACMUF with the values 24, 27, 34, 40, 50, and 56 mS given in order started from the best. The latency comparison chart is given in Figure 6.

Packet Delivery Ratio

Packet delivery ratio (PDR) in IoT-WSN is a metric used to measure the efficiency of data packet transmission within the network. It represents the ratio of successfully delivered data packets to the total number of data packets sent by a node or the network as a whole. PDR is a critical performance metric in IoT-WSN and provides insights into the network’s reliability and quality of service. PDR is used to assess how effectively data packets are transmitted from source nodes (such as sensors or devices) to their intended destinations (such as data sinks or gateways) within the wireless sensor network. DR is an important QoS metric. Applications with strict QoS requirements, such as real-time monitoring or control, may require a high PDR to ensure data integrity and timeliness. PDR is calculated using the following formula.

$$PDR = \frac{\text{Number of packets successfully delivered}}{\text{Total numberr of transmitted packets}} \times 100\%$$

The experimental outcomes for PDR have been documented in Table 5.

IFLEACH secured 100% PDR during the simulation with 100 number of nodes. But while taking the average for all the readings, proposed LAALEACH secured the PDR score of

Table 6: Average energy

Nodes	Avg. energy (J)					
	HGACHS	ABOLEACH	SACMUF	ACSO	IFLEACH	LAALEACH
100	713	607	737	507	389	342
200	733	617	763	503	375	341
300	762	639	762	545	413	361
400	805	662	805	567	414	362
500	801	707	811	586	415	419
600	825	743	835	596	414	412
700	846	734	858	628	439	445
800	892	776	889	675	450	417
900	894	801	915	675	484	460
1000	920	834	926	695	481	466

Table 7: Security level

Nodes	Security (%)					
	HGACHS	ABOLEACH	SACMUF	ACSO	IFLEACH	LAALEACH
100	91	92	91	96	98	99
200	91	93	90	96	98	98
300	91	92	90	96	98	98
400	90	92	90	97	98	99
500	90	92	91	96	98	99
600	90	93	91	96	99	98
700	90	93	91	97	99	99
800	91	92	91	97	98	99
900	91	92	90	97	98	99
1000	90	92	91	96	98	98

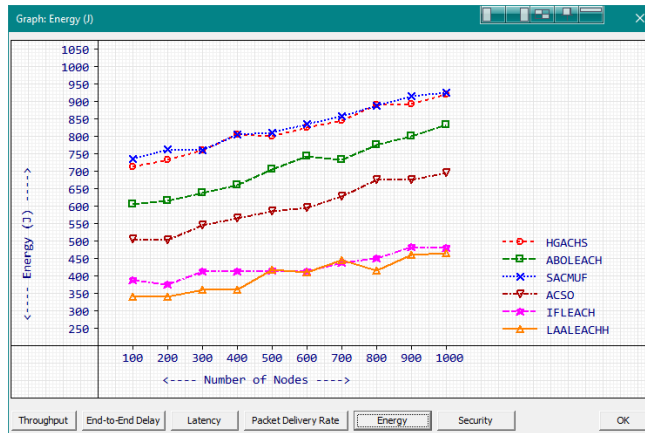


Figure 8: Average energy consumption

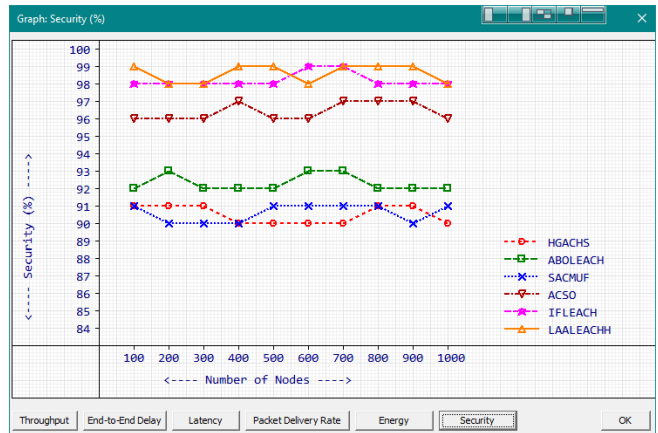


Figure 9: Security level

95.9% whereas the score of IFLEACH is 94.9%. The findings show that LAALEACH can acquire higher PDR in higher density network environments. The performance rank sequence concerning PDR average is LAALEACH, IFLEACH, ACSO, ABOLEACH, HGACHS, and SACMUF with the acquired values 95.9, 94.5, 87.5, 84.5, 84.1 and 80.6% respectively listed from the best.

PDR comparison graph is provided in Figure 7 for visual representation.

Energy Consumption

Many of the IoT devices, especially sensors and actuators in WSNs, are powered by batteries. Energy efficiency is crucial to extend the operational lifespan of these devices. Prolonging battery life reduces the need for frequent battery replacements, which can be costly and logistically challenging, especially for remote or inaccessible deployments. Energy is measured in Joules (J). Observed experimental results for average energy consumptions of the discussed methodologies are recorded in Table 6.

The comparison graph is given in Figure 8.

LAALEACH consumed lesser amount of energy during the experiments carried out. Improvement in the network

lifetime is ensured by this lesser energy consumption. The performance degree sequence in accordance with energy consumption is LAALEACH, IFLEACH, ACSO, ABOLEACH, HGACHS, and SACMUF with the data points of 402.5, 427.4, 597.7, 712, 819.1, and 830.1 J given in order listed from the best.

Security

Security is of paramount importance in IoT-WSN due to the critical role these networks play in gathering, transmitting, and managing data in a wide range of applications. Ensuring the confidentiality, integrity, and availability of data is essential to safeguard sensitive information, protect user privacy, and maintain the reliability of real-time monitoring and control systems. Security measures are imperative in defending against unauthorized access, data breaches, and cyberattacks, which can have significant consequences, particularly in industries like healthcare, critical infrastructure, and industrial automation.

In an increasingly connected world, where IoT-WSN deployments continue to expand, robust security not only builds trust among users but also mitigates risks, enhances resilience, and ensures the long-term viability of these

transformative technologies. Measured security values are tabulated in Table 7.

The performance rank based on measured security average is LAALEACH, IFLEACH, ACSO, ABOLEACH, SACMUF, and HGACHS with the numeric data 98.6, 98.2, 96.4, 92.3, 90.6, and 90.5%.

The security level graph is provided in Figure 9.

The experimental shows that LAALEACH improves the overall network lifetime by cautiously switching the paths, and improve the overall performance without having any impact on other performance parameters.

Conclusion

A load sharing framework is designed over the traditional LEACH algorithm to improve the overall lifetime of the network. The implementation inherits standard flexibility of the traditional LEACH, and the Idiosyncratic fuzzy energy estimation property of preceding IFLEACH under one roof as LAALEACH. The accomplishment of load level classification and the introduction of customized path sets in RLE ensures a smooth load balancing between the nodes. The LPT modules prevents unexpected overloads during the regular operations. The integration of functional modules RLE, LPT, and LAAR is the novelty of this work that ensures the overall performance improvements in a typical IoT based wireless sensor network environments. Submitted LAALEACH model provide better affirmation for efficient resource management, and intelligent shared network traffic load distribution without compromising any other performance parameter. Due to the reduced communication delays such as end-to-end delay and latency, proposed LAALEACH work can be suggested to operate in real-time IoT-WSN environments. Optimizations based on bioinspired algorithms with the proposed modules may improve the results which is not yet attempted. It is stated as the limitation of the work, which could be unraveled in the future works.

Code Availability

Available in GitHub, like will be provided on request

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