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FLOWER POLLINATION OPTIMIZATION APPLICATION IN WSN CLUSTERING AND COMPRESSION-AWARE TRANSMISSION FOR IOT-DRIVEN ENVIRONMENTAL MONITORING

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ABSTRACT

Wireless Sensor Networks (WSNs) are the components that lie at the fundamental part of Internet of Things (IoT). They are used in systems of environmental monitoring applications. The deployment in practical situations is limited within the constraints of limited battery life and excessive overhead of data communication. This paper presented a research work that focus on addressing these challenges by integrating a framework of optimization process that is associated for consideration of energy-aware selection of mechanism of sets of CH and data compression prior to data transmission towards base station (BS). The Flower Pollination Algorithm (FPA) as optimization method is followed for finding optimal set of CHs. FPA use multiple network parameters that include characteristics like node distribution, residual energy, divergence, convergence, centrality, and distance to the BS. The data compression is applied after the aggregation at CHs by applying simple hence fast compression methods to add on higher efficiency. Two data compression algorithms are applied known as ASWDR and Zstandard (ZSTD). Under the compression part the data size is reduced prior to the transmission to BS from CHs. The simulation model developed on MATLAB software is executed to generate results that are demonstrate the performance enhancement observed by proposed optimal CHs set selection by FPA associated with ASWDR or ZSTD based compression of data that results in reducing the consumption of energy significantly. In this way the proposed work in this article is introducing the performance enhancement respective to fast convergence, network stability, load balancing, and higher network lifetime compared to conventional methods like LEACH, SEP, DEEC and recent optimization methods like GA, PSO based routing protocols for efficient WSN-based IoT applications.

Research Gap: Existing literature focus either optimization-based cluster head selection or data compression independently in WSN. The existing routing protocols emphasize energy-efficient clustering but ignore the large communication overhead caused by transmission of aggregated environmental data. Similarly, compression techniques are rarely integrated with routing frameworks for weather-monitoring applications.

Problem Addressed: This study is addressing problem of high energy consumption that reduces network lifetime in IoT-based WSNs system. It basically occurs due to inefficient CH selection and data transmission overhead. The proposed work integrates FPA for optimal CH selection with ASWDR and ZSTD data compression techniques prior to transmission towards BS.

Rational: IoT-based WSN has limited energy of node and communication overhead is due to continuous environmental data transmission. Existing methods mainly focus on either routing optimization or data compression separately, which limits overall network efficiency and lifetime.

Keywords: *IoT, WSN, Data compression, Clustering, Optimization*

1. INTRODUCTION

By continuously extracting and monitoring sensor-generated data, modern IoT-enabled infrastructures have dramatically changed information technology applications across several fields. Numerous applications, such as agriculture, predictive analytics, climate forecasting, and crop production monitoring, are supported by such IoT-driven systems. Additionally, the controlled use of pesticides and fertilisers has decreased operating costs [1, 2]. The integration of many devices with real-time information exchange capabilities across internet-based systems led to the development of the Internet of Things (IoT). Electronic circuits, sensor components, mechanical modules, and radio frequency identification (RFID) tags are some of these coupled devices [3, 4].

Sensors are used in these systems to produce information focused on specific applications. A Wireless Sensor Network (WSN), which serves as the core infrastructure for IoT-based services, is naturally established by interaction between such devices [3]. A WSN is made up of several sensor nodes that are dispersed either purposefully or at random throughout a monitoring area. By sending gathered data to a Base Station (BS), these sensor nodes' main function is environmental observation [4]. However, because to limited battery resources, sensor nodes have a limited operational lifetime, which presents significant issues for WSNs [5]. Cluster-based routing techniques have been extensively investigated to get around these limitations. These clustering techniques are very successful in extending the lifetime of networks [6–9].

Nodes are arranged into several clusters in a clustering-oriented communication architecture. The remaining nodes serve as cluster members, with a cluster head (CH) at the center of each cluster [10–12]. Information aggregation is carried out by cluster leaders, who then send processed data to the BS. Because of these extra duties, CHs use significantly more energy than regular cluster members [13–15]. As a result, choosing CHs necessitates closely examining nodes with favorable operational traits. Network conditions like residual energy, node distribution, geographical position, and distance from the base station are represented by these attributes. Making decisions based on these factors helps ensure dependable and energy-efficient network performance [9].

For the best CH selection in WSNs, several methods have been put forth. These techniques range from sophisticated optimization-driven mechanisms to simple fitness-function and weighted-decision approaches [16, 17]. However, CH selection is not the only way to achieve increased efficiency in WSNs. Additionally, it mostly depends on technology developments in data transmission and aggregation procedures. When compared to multi-hop communication techniques, single-hop or direct communication toward the BS is used by CHs in many clustering protocols, which leads to much higher energy dissipation [18–20]. As a result, recent research has made minimising energy use during the transmission stage a top priority.

Effective management of enormous sensed datasets at the CH presents another crucial difficulty after data aggregation and prior to information forwarding to the BS [5]. Large-scale sensed data transmission raises communication bandwidth occupancy and energy usage. Data compression techniques that lower storage needs and transmission costs can help to mitigate this problem [6]. For application-specific requirements, a variety of compression algorithms have been developed, many of which use lossy compression strategies. These techniques successfully reduce the quantity of the data, but they also produce reconstruction errors that could raise reliability issues [7]. A number of newly suggested methods concentrate on locating and measuring mistakes related to lossy compression strategies in order to address these problems [8–10].

Time-series weather data is very important in big data analytics. When depicting temporal environmental fluctuations related to temperature, atmospheric pressure, humidity, rainfall, solar radiation, and wind speed, these datasets are very helpful. Applications involving long-term forecasting and climate analysis depend on these factors. Despite the importance of these applications, little research has been done on combining optimization-driven CH selection with aggregated data compression prior to transmission to the BS. While lossy compression techniques are crucial for effective meteorological data retention, the breadth of current research is still constrained. For example, compression was only taken into account for temperature and humidity observations in the system described in [9], leaving several other weather-related factors untouched (Figure 1).

In order to assure energy-efficient transmission of meteorological information in WSN environments, this study proposes an optimization-based methodology for choosing the best cluster heads, followed by data compression utilising two different compression methods following the aggregation stage. To evaluate performance improvement, network lifetime, energy usage, and total transmitted data during the entire operational duration are assessed. In addition to compression techniques that ensure minimal energy consumption during sensor-to-cluster head (S2CH) and cluster head-to-base station (CH2BS) transmission, the primary goal is to use significant network features as fitness metrics for CH selection.

Background: Recent advancements in IoT and WSN technologies have enabled their application in several real-world environmental and smart monitoring systems. Nature-inspired optimization algorithms like Bat Algorithm, PSO, Sparrow Search, and Ant Colony Optimization applied widely for energy-efficient routing and selection of CH in IoT-enabled WSNs. Cai et al. and Cui et al. applied Bat Algorithm-based LEACH protocols for improving network lifetime and energy balancing in IoT application, while Ghawy et al. applied PSO assisted routing for efficient packet delivery in WSNs.

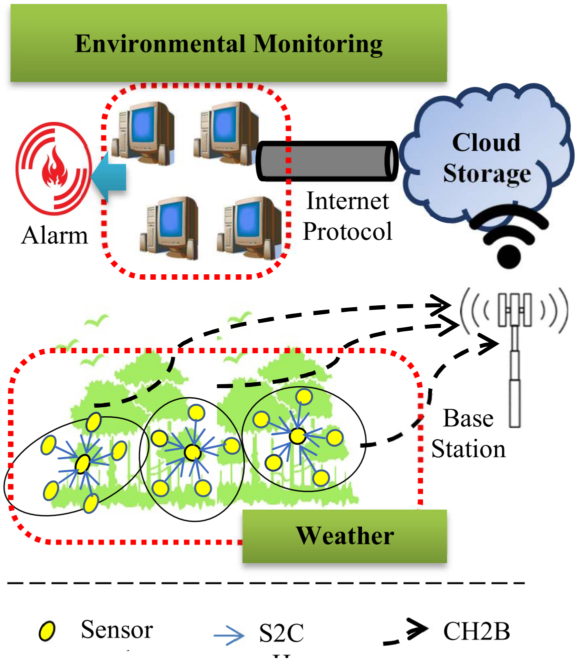

Figure 1: Application of WSN in weather monitoring.

Similarly, optimization for routing frameworks is explored in industrial IoT, FANETs, and smart communication systems. Dev et al. implemented Harris Hawks Optimization for green IoT communication, whereas Kumar et al. proposed the WAOA hybrid whale-ant optimization for energy-efficient WSN routing. In environmental and healthcare monitoring applications, data compression methods like wavelet-based compression, TinyML-assisted adaptive compression, and sparse reconstruction techniques are investigated for reduction of communication overhead and transmission energy. Khafaga et al. applied Haar wavelet-based compression in IoMT systems. Signoretti et al. introduced TinyML-based adaptive compression for IoT environments.

Applications: Recent studies demonstrated the increasing application of IoT and WSN in weather and environmental monitoring systems. Cai et al. [1] and Cui et al. [2] applied optimization-assisted LEACH protocols for environmental sensing applications for improving network lifetime and energy balancing during fast speed weather data. Similarly, Khan et al. [10] also applied nature-inspired algorithms for routing in IoT for efficient environmental data transmission in dynamic monitoring scenarios. In environmental monitoring applications, WSNs are used widely to collect temperature, humidity, pressure, rainfall level, wind speed, and atmospheric data from remote regions. Dai et al. [3] proposed an IoT application for weather data based environmental monitoring, while Dev et al. [4] applied Harris Hawks Optimization for energy-efficient IoT environmental systems. Signoretti et al. [26] introduced TinyML-assisted adaptive compression techniques for IoT based environmental monitoring for reducing transmission overhead and improving long-term efficiency.

WSN has major role in IoT-driven environmental monitoring applications due to need of continuous transmission of sensor data records. Such excessive amount of communication needs high energy consumption. The inefficient selection of CH significantly reduces network lifetime. For addressing these issues, this work proposed to integrate FPA-based optimal set of CH selection scheme with compression-aware transmission using ASWDR and ZSTD techniques. The proposed framework helps to improve energy efficiency, load balancing, packet delivery, and overall network stability with fast converging optimum search for environmental data records.

The layout of this article next follows the section 2nd names as literature review. It covers the recent research and developments under optimization approach based WSN enable IoT application. In the section 3rd the details of methodology and simulation scheme is presented in to systematically describe the proposed framework. Under the section 4th discussions are incorporated regarding the results analysis to explain the performance evaluation and validation Finally the 5th section is covering the conclusion drawn and future scopes.

2. LITRATURE REVIEW

Because sensor devices have limited energy resources, computing power, and communication bandwidth, the quick growth of IoT and WSN applications has greatly raised the need for energy-efficient communication and efficient data handling.

In order to address these issues, a lot of research has concentrated on data compression algorithms, optimisation methods, and intelligent routing strategies with the goal of increasing scalability, extending network lifetime, and improving Quality of Service (QoS).

2.1 Methods Based on Routing

In order to optimise cluster head selection and routing path planning, modern routing strategies primarily use algorithms inspired by biology and nature. Although computational overhead rose, Cai et al. [1] and Cui et al. [2] upgraded the traditional LEACH protocol utilising modified Bat Algorithms to achieve better energy balance and a longer network lifetime. Although Ghawy et al.'s PSO-based routing method [7] showed quick convergence and effective packet delivery, premature convergence happened in constantly changing network conditions. Similar to this, the optimal search capability of the Sparrow Search Algorithm-based routing mechanism developed by Kathiroli and Selvadurai [8] increased energy efficiency; nevertheless, resilience was impacted by parameter sensitivity. Hybrid routing strategies further enhanced throughput and energy utilization while introducing additional control overhead [9]. Khan et al. [10] used optimisation techniques inspired by nature to study mobility-aware routing in FANETs. In order to reduce redundant transmissions, Ma et al. [13] used Ant Colony Optimisation to optimise hierarchical APTEEN routing. In a different study, Rani and Sharma [17] combined optical communication concepts with nature-inspired routing to increase data transmission speeds at the cost of implementation complexity.

2.2 Methods Based on Optimisation

Studies focused on optimisation have moved beyond routing to include resource management, green communication, and node deployment. Although long-term energy impacts were not examined, Dai et al. [3] optimised node deployment in industrial IoT networks to increase coverage efficiency. While relying on centralised processing, Dev et al. [4] used Harris Hawks Optimisation to lower communication energy and achieve significant energy savings. While Bat Algorithm variations enhanced cluster head selection and routing stability in IoT and NoC systems [15], [16], Mnasri and Alrashidi [14] suggested a lightweight optimisation framework for energy-efficient routing with faster convergence. Although computational complexity rose, hybrid optimisation frameworks like GREPHRO and WAOA showed improved convergence and robustness [11], [12]. Although they produced more control traffic, improved Ant Colony Optimisation techniques further improved load balancing and energy efficiency [20].

2.3 Methods Based on Compression

By lowering the amount of information communicated, data compression techniques primarily aim to minimise communication energy. For IoT data reduction, Dhou and Cruzen [5] developed biologically inspired chain coding, which reduced energy consumption at the expense of increased processing complexity. In microcontroller-based systems, mild compression dramatically reduces transmission energy, as proved experimentally by Piłtkowski et al. [21]. In IoMT and IoT contexts, wavelet-based compression approaches supported by optimisation algorithms were used to balance data quality and compression efficiency [22]. While reducing data size without sacrificing reconstruction accuracy, learning-based compression and sparse reconstruction techniques were shown to need more processing power and memory [23], [25]. Adaptability for dynamic data patterns was brought about using TinyML-assisted adaptive compression, however training overhead became a constraint [26]. Although efficient transmission with reduced complexity is made possible by lightweight data reduction techniques, adaptation problems still exist for varied data environments.

All things considered, routing, optimisation, and compression techniques have separately shown significant gains in effectiveness and performance for Internet of Things applications. However, the lack of integrated frameworks, growing computational overhead, and reliance on centralised processing continue to be major obstacles. As a result, there is still a great need for unified, lightweight, and scalable frameworks that can work together to solve problems with data compression, routing, and optimisation.

3. METHODOLOGY

This study assumes that a square shape area of region is covered by sensor nodes that are dispersed at random. The base station is thought to be in the middle of the network field. Sensor nodes send data packets to the CH, which then forwards them to the base station. Using two different optimisation techniques, the best set of sensor nodes is found in order to pick CH sets. To ascertain if randomly chosen node groups are suitable to serve as cluster heads, the CH selection criterion assesses their fitness. Numerous factors, including neighbouring node distance, distance from the base station, and CH participation eligibility, are influenced by node placement and residual energy. As a result, these basic factors are used to create higher-level functions that accurately indicate the collective suitability of node sets for CH involvement while also representing network and node characteristics. The optimisation approach in this work first generates many candidate node sets as potential CH solutions.

3.1 Network Parameters Considered for Selection of CH

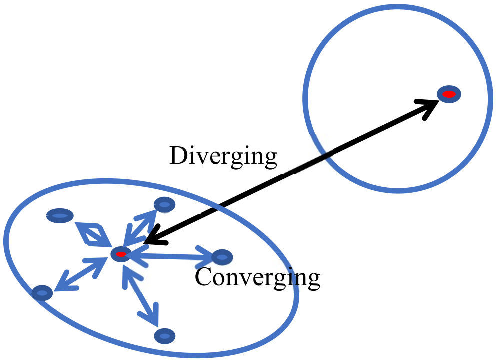

Figure 2: Converging and diverging function illustration.

The fitness function is created by proportionally combining network parameters. The Converging Function (F_{conv}), Diverging Function (F_{Diverg}), Centrality, Node Degree (N_{degree}), Distance to Base Station (D_{S2BS}), and Residual Energy (E_{Res}) are some of these factors. The cumulative distance between cluster members and their matching CH within a cluster is known as F_{conv} (Figure 2). The bulk of nodes in an optimum cluster are located near the corresponding CH. Improved cluster shape and lower energy usage are indicated by a lower F_{conv} value. The cumulative distance between several cluster centers is represented by F_{Diverg}. The degree of inter-cluster separation is represented by this parameter. More distance between clusters means that more sensor nodes may be efficiently covered by fewer CHs. Centrality quantifies how close the CH is to the cluster's geometric center. Sensor nodes can communicate with less energy expenditure thanks to a CH close to the cluster center, which balances energy consumption across the cluster. The ratio of nodes in a cluster to all nodes in the network is known as node degree. If count of CH in a solution set = C then count of cluster is also C, the count of nodes in a cluster=N_c, $D_{cluster}$= sum of distance between nodes and CH.

$$D_{cluster} = \sum_{i=1}^{Nc} D_{Si-CH} \quad (1a)$$

$$F_{converging} = \sum_{j=1}^{C} D_{cluster}^{j} \quad (1b)$$

Distance between CHs=$D_{CHi\ to\ CHj}$

$$F_{diverging} = \sum_{i=1}^{C} \sum_{j=1}^{C} D_{CHi\ to\ CHj} \quad (2)$$

$$\text{Centerality}_{CHi} = \sqrt{\frac{\Sigma dis^2}{n}} \quad (3)$$

$\sum dis^2$: sum of squared distances of nodes to cluster heads i.

$$N_{degree} = \text{var}\left\{\frac{\text{(number of nodes in Ckuster i)}}{\text{total number od nodes in network}}\right\} \quad (4)$$

3.2 Fitness Function

Six parameters in all are taken into account, but not all of them contribute equally to the fitness evaluation criterion for choosing the best CH set. While some parameters are supposed to stay lower, others must show greater levels. When both $F_{diverge}$ and E_{resch} have larger values, a node set's fitness value rises. This suggests that the chosen cluster head nodes have more remaining energy and are widely dispersed. As a result, F_{diverg} and E_{resch} are directly proportional to the fitness function. On the other hand, F_{conv}, Centrality, Dch2bs, and N_{degree} have an inverse relationship with the fitness value. Equation (5) shows how the six network fitness parameters are combined based on their direct and inverse proportional relationships to produce the overall fitness function F_{total}.

$F_{total}=(a_1*F_{Diverg}+a_2*E_{res}^{ch})+(a_3/F_{conv}+a_4/centrality+a_5 / Dis_{ch2bs}+a_6/N_{degree})$ (5)

$F_{total}= f (f_1, f_2, 1/f_3, 1/f_4, 1/f_5, 1/f_6)$ (6)

The set of {a1 to a6} represents scaling factor that multiplied individually to f_1 to f_6 parameters to maintains them within the same range for ensuring the uniform weightage of parameter in the value of fitness function i.e. F_{total}. In this way the final fitness function expression is obtained as (eq. 7):

$fitness\ value = \sum_{i-1}^{6} F_i * a_i =$
$f_1*a_1+f_2*a_2+1/f_3*a_3+1/f_4*a_4+1/f_5*a_5+1/f_6*a_6$ (7)

3.3 Data transmission and compression

The optimisation algorithms provide several candidate sets that reflect potential CH solutions and choose various node IDs. The most ideal set is found by evaluating the fitness value of each potential solution in the CH population. In order to get a better solution, node IDs are updated during the next iteration (generation) utilising neighbouring node information in accordance with the displacement and movement rules of PSO or FPA. Until the candidate solution is no longer improved, the optimisation process is repeated several times. Clusters are created in accordance with the ideal cluster head set, and the energy used to transmit k-bit data packets from sensor nodes to the CH is computed depending on transmission distance.

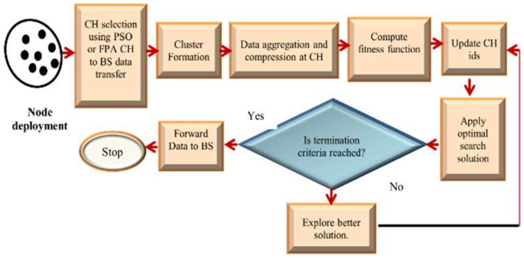

Figure 3: Block diagram illustrating the steps involved in execution of proposed protocol.

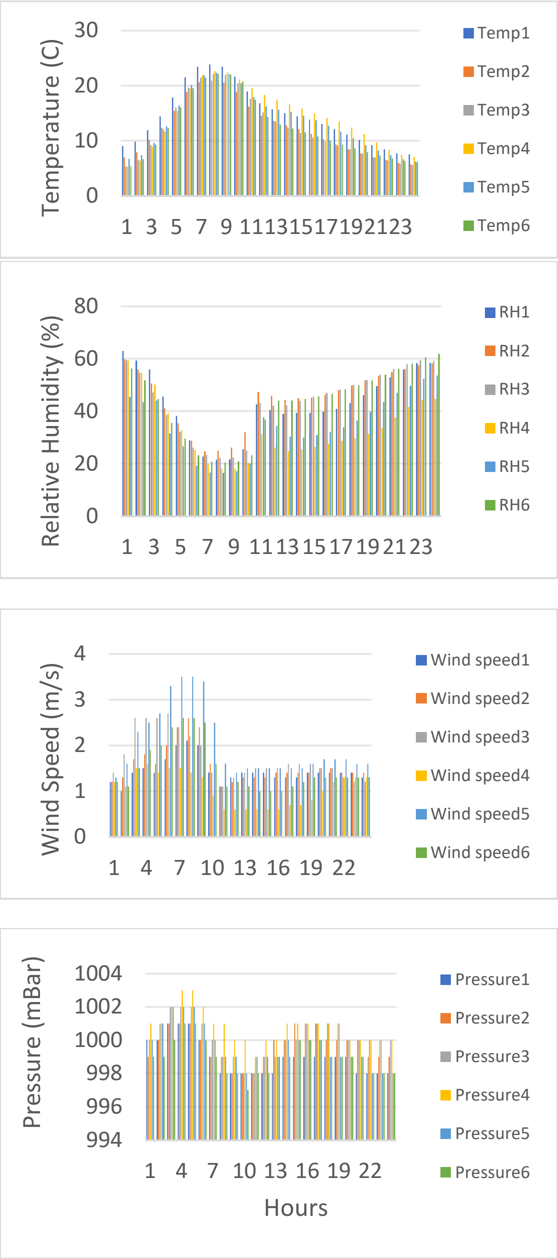

Figure 3: Representation of data records used to simulate the WSN based transmission of weather data.

The collected data is combined at the cluster head after the first-hop transmission from sensor nodes to the CH. Before the CH-to-BS transmission phase, two different data compression algorithms—ASWDR and ZSTD—are used to reduce the amount of the data. The energy needed for packet transmission from the CH to the BS is calculated when the compression stage is finished. The flowchart shown in Figure 4 depicts the general operational framework of the suggested system.

3.4 Data set

The National Solar Radiation Database (NSRDB) internet service provided the dataset. Temperature (°C), relative humidity (%), pressure (mBar), and wind speed (m/s) are all recorded in the Excel dataset using the geographic coordinates [26.93, 80.98]. These coordinates match weather sensor readings from the Kukrail forest area near Lucknow, Uttar Pradesh, India. High-quality datasets with precise temporal and spatial resolution that include observations of sun radiation and other meteorological data are available from NSRDB. The NSRDB framework was created particularly for aviation and airport-related applications employing cloud and weather-based models. Once a user has registered on the NSRDB platform, these datasets are freely available.

Hourly plots of sensor data for four sensor parameters—temperature, relative humidity, pressure, and wind speed—that were gathered from six distinct locations are shown in Figure 4. For the purpose of presentation and visualisation, the figure shows sample observations from 24 sensors (four sensor categories spread over six sites) throughout a 24-hour period. Nonetheless, the full database is vast and includes ongoing records that were gathered all year long.

Figure 6a shows the process for updating the present optimal solution in the direction of the next improved option. Similarly, the Flower Pollination Algorithm (FPA) is also used in the cluster head (CH) selection process. This method treats each sensor node as a flower. Self-pollination is the search for new cluster heads among nodes in the same cluster region, while cross-pollination is the investigation of nodes in adjacent clusters, as shown in Figure 6b.

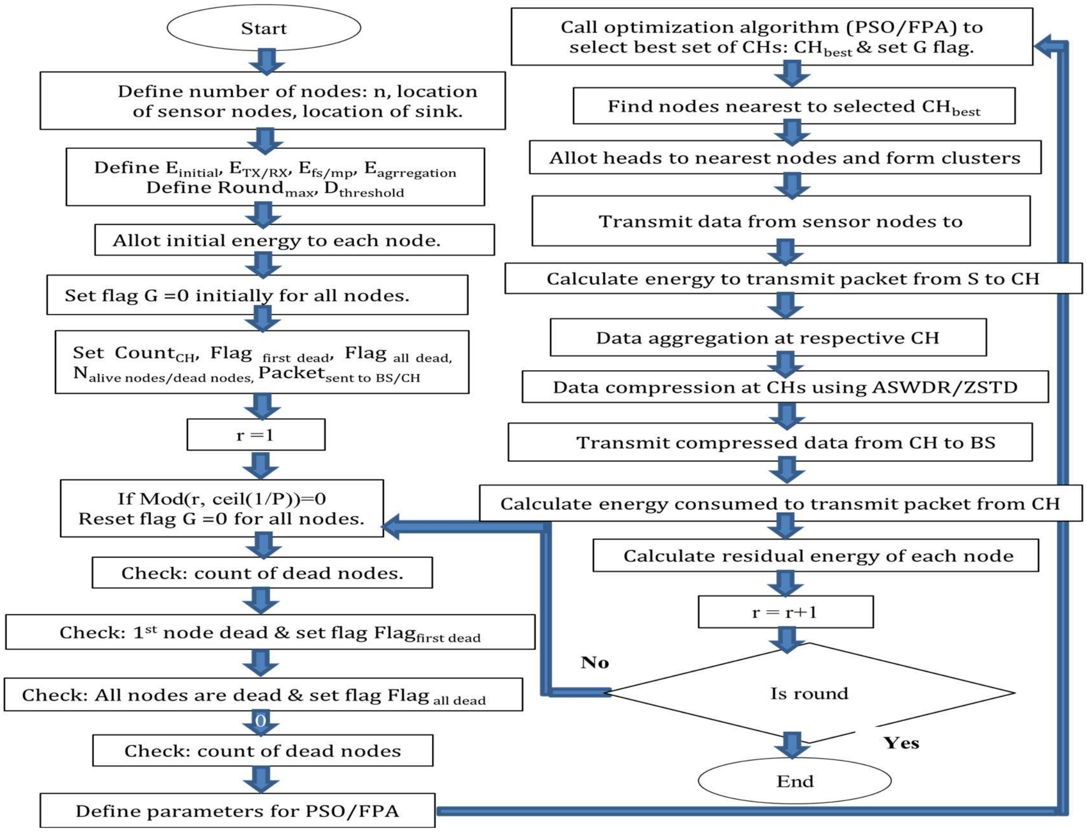

Figure 5 Flowchart of proposed framework for CG id set selection with optimization scheme.

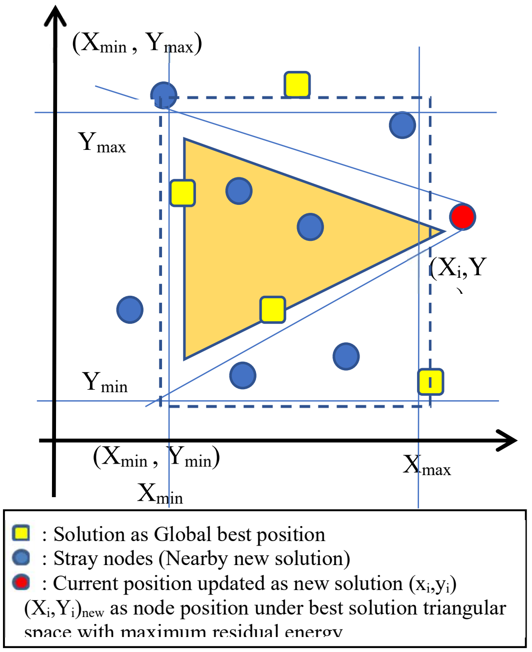

Fig. 6a Updated CH id from current solution to best solution using PSO.

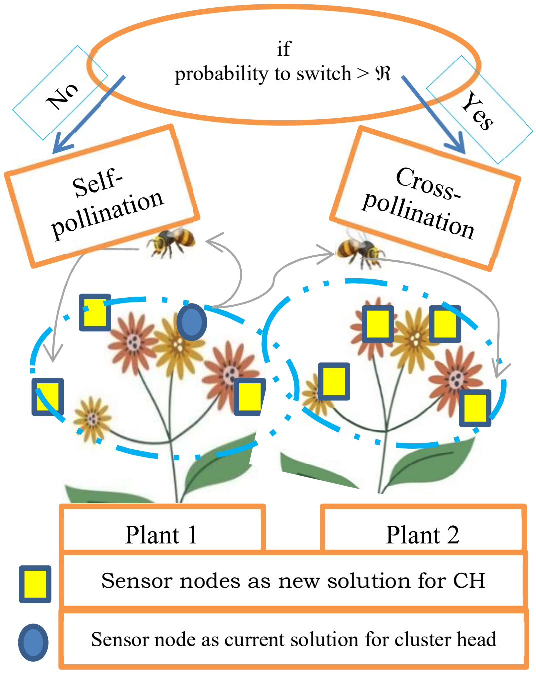

Fig. 6b Updated position of CH from current solution to best solution with FPA.

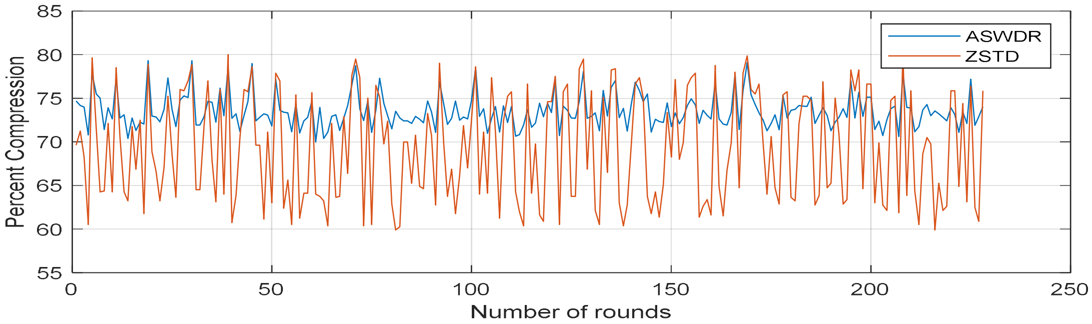

Fig. 7 Percent compression ratio at different rounds for ASWDR and ZSTD data compression

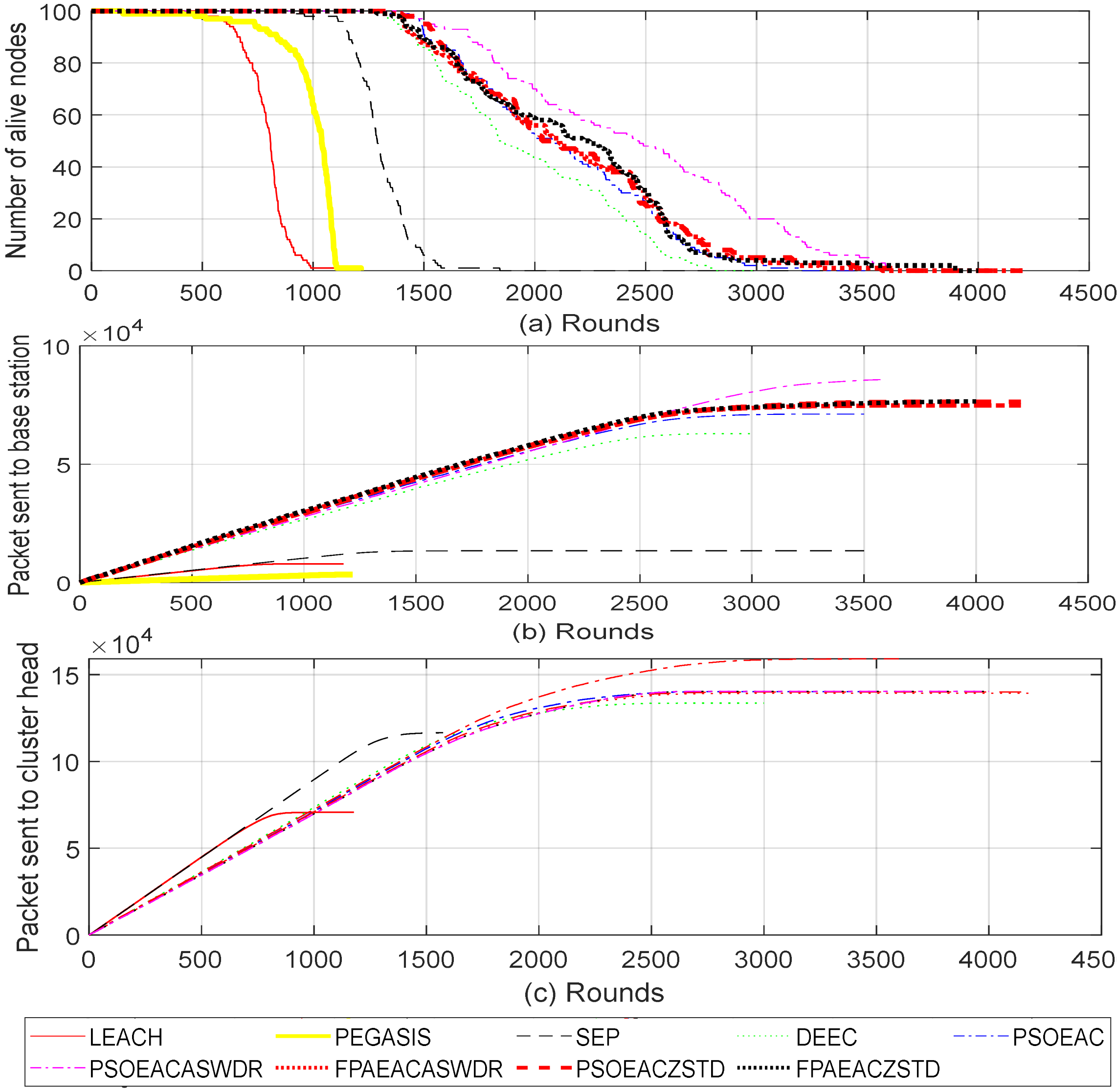

Figure 8. Number of alive nodes, Packet sent from CH to BS and sensor node to CH w.r.t. number of rounds.

4. RESULTS

The simulation code was executed in the MATLAB programming environment utilising common network parameters such as starting energy, free-space and multipath propagation losses, data aggregation energy, and transmitter/receiver electrical energy. The upper limit for transmission cycles was established at 4000 for data packet transfer. To corroborate the acquired results, standard protocols such as LEACH, EGASIS, SEP, and DEEC were also implemented for comparison. Simulations conducted without data compression were also executed and labelled as PSO Energy-Aware Clustering (PSO-EAC) and FPA-EAC.

The optimised CH selection architecture was then constructed, incorporating ASWDR and ZSTD compression algorithms. The proposed schemes are designated as PSO-EAC-ASWDR, FPA-EAC-ASWDR, PSO-EAC-ZSTD, and FPA-EAC-ZSTD. Figure 7 depicts the fluctuation in compression ratio over many transmission rounds for packets sent from CHs to the BS. In the case of ASWDR the compression ratio lies in between 70% to 80% range and for the ZSTD this ration shows a broader range, varying from 60% to 80%. In this way the on average compression ratio for ASWDR is 0.73 and in the ZSTD it is 0.69. It validates that the ASWDR is offering relatively higher compression of agregated data.

Furthermore, the performance is shownn for network in terms of network lfetime indicates count of alive nodes w.r.t. round (Figure 8a), the packets sent from CH to the BS (Figure 8b), and packets transmitted from sensor nodes to CH. Figure 8a is employed to ascertain network longevity based on the transmission rounds associated with the demise of the first node, half of the nodes, and all nodes, designated as First Dead, Half Dead, and All Dead circumstances, respectively.

The aggregate number of transmitted packets across all algorithms was computed and presented in Table 1. The findings reveal that FPA-EAC-ASWDR attained the maximum packet transmission count, with 4.40x108 packets sent from sensor nodes to CHs and 2.11x108 packets sent from CHs to the BS. Consequently, FPA-EAC-ASWDR was recognised as the most efficacious method due to its optimal CH selection capability via FPA and enhanced compression efficiency attained through ASWDR, culminating in higher overall network performance. Due to the implementation of compression techniques, the packet size at the cluster heads (CHs) is diminished by around 60–70%. As a result, reduced energy is utilised during the CH-to-BS transmission phase. Furthermore, CH selection predicated on minimal convergence, elevated centrality, appropriate node degree, and increased divergence distance aids in reducing transmission distance. Consequently, the integration of optimised routing and compression techniques collectively decreases total network energy usage. Figure 9 illustrates the boxplot comparison of energy consumption across all implemented algorithms.

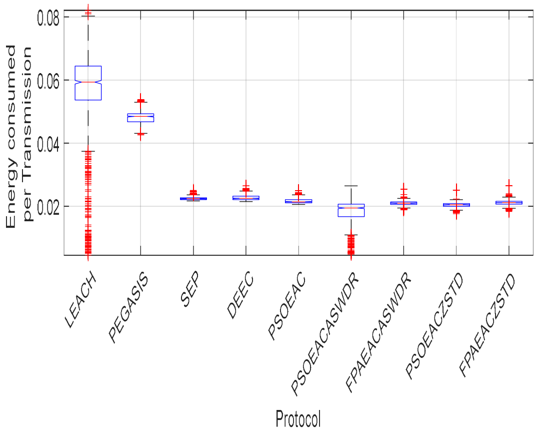

Figure 9 Boxplot diagram representing energy consumption under conventional and proposed scheme.

Table1. Performance evaluation in terms of total packet sent

Packet Sent	PSOEAC ASWDR	FPAEAC ASWDR	PSOEAC ZSTD	FPAEAC ZSTD
Sensor to CH	3.84x 10^8	**4.41** x10^8	3.83 x10^8	4.16 x10^8
CH to BS	1.75 x10^8	**2.12** x10^8	1.71 x10^8	2.04 x10^8

The values of energy consumed are shown in table 2 for all the algorithms and the minimum, maximum, average and standard deviation value are shown. It is observed that FPAEACASWDR consumes on average 0.0178 J energy per transmission that is lowest one.

Table2. Summary of statists showing energy consumption

Technique	Minimum Energy Consumed (J)	Maximum Energy Consumed (J)	Average Energy Consumed (J)	Standard Deviation (J)
LEACH	0.0033	0.1208	0.0555	0.0178
PEGASIS	0.0426	0.0538	0.0484	0.0025
SEP	0.0217	0.0251	0.0225	0.0005
DEEC	0.0215	0.0264	0.0228	0.0009
PSO-EAC-ASWDR	0.0035	0.0265	0.0182	0.0037
FPA-EAC-ASWDR	0.0020	0.0255	0.0178	0.0039
PSO-EAC-ZSTD	0.0033	0.0255	0.0179	0.0036
FPA-EAC-ZSTD	0.0184	0.0265	0.0212	0.0010

To enhance the validation of the results acquired, the simulation environment was altered by adjusting the quantity of sensor nodes and the dimensions of the network region. The quantity of sensor nodes was set at 100 and 200, while the network dimensions were designated as 100×100 m² and 200×200 m². Consequently, four distinct simulation scenarios were created as follows: [nodes, area]: [100, 100×100m²], [100, 200×200m²], [200, 100×100m²], and [200, 200×200m²]. The simulation results are depicted in relation to transmission rounds for the First Dead, Half Dead, and All Dead node states, as outlined in Table 3.

Following data aggregation at each cluster head (CH), the consolidated packets are compressed via ASWDR before being transmitted to the base station (BS). The results indicate that the compression technique reduces packet size by around 40–50%. Decreased packet size results in less energy consumption during transmission. Moreover, bandwidth utilisation is optimised, enabling the network to accommodate a greater number of nodes and facilitate more frequent communication. ASWDR effectively compresses consolidated data, therefore diminishing total communication expenses. The compressed packets are ultimately transmitted to the base station utilising DEEC-based routing.

Simulation results are indicating that ASWDR is decreased the average energy consumption to 0.018 J. The proposed work gives a network lifetime of 3620 rounds i.e. higher than DEEC and LEACH, which obtained 2811 and 1175 rounds, respectively. The compression ratio is approximately 42% that is quite higher as reported by other litratures, that range from 15% to 25%. In this work ASWDR is not applied independently; rather, it is intergrated as a compression layer within the routing protocol. This helps in mitigating high transmission costs by decreasing packet data size, hence conserves the energy and enhance the overall communication efficiency.

Table 4 is showing the validity of the proposed method by showing the comparision with recently methods of the IoT system related data compression and routing. The innovation of the proposed framework is in the amalgamation of optimisation approaches with data compression to improve IoT applications in WSN environments, a topic that has not been thoroughly explored in current research. Comparisons of IoT-based compression approaches to other methods of Khafaga et al., Hosny et al., and Bencherqui et al., is performed in terms of compression ratio (CR) as the evaluation metric. The proposed ASWDR compression gives CR of 42% and existing methods are providing CR in between 15% and 25%.

Table 3 Network lifetime as number of dead nodes for different schemes at varying number of total nodes and deployment area

Nodes	**Field Length**		**First Dead**	**Half Dead**	**All Dead**
100	100	PSO ASWDR	**1456**	2147	3804
200	100		**1278**	1965	3788
100	200		841	**1748**	3387
200	200		**1056**	1694	3562
100	100	PSO ZSTD	1362	2079	3688
200	100		1057	1978	3651
100	200		797	1701	**3434**
200	200		1031	1677	3869
100	100	FPA ASWDR	1301	2113	3566
200	100		1054	**1995**	3537
100	200		682	1592	3325
200	200		969	1633	**3922**
100	100	FPA ZSTD	1289	**2248**	**3910**
200	100		1149	1945	**3873**
100	200		**922**	1675	3243
200	200		1010	1642	3231

Table 4. Performance comparison of FPOEACASWDR to different protocols

<table>
<tr><td colspan="3">Comparison to recent methods in terms of compression ratio</td></tr>
<tr><td>Method</td><td>Author (Year)</td><td>CR</td></tr>
<tr><td>Block based Haar DWT & COVIDOA[22]</td><td>Khafaga et.al (2023)</td><td>25.5%</td></tr>
<tr><td>Tchebichef moments and ABC [30]</td><td>Hosny et.al (2018)</td><td>18.7%</td></tr>
<tr><td>Hahn Moments and ABC [29]</td><td>Bencherqui et.al (2022)</td><td>15.4%</td></tr>
<tr><td>FPAEACASWDR</td><td>(Proposed)</td><td>42%</td></tr>
<tr><td colspan="3">*ABC: Artificial bee colony</td></tr>
<tr><td colspan="3">Comparison to recent methods in terms of average energy consumption.</td></tr>
<tr><td>Method</td><td>Author</td><td>Avg. energy consumption</td></tr>
<tr><td>PRVD [31]</td><td>Elyyan et.al. (2023)</td><td>.0211</td></tr>
<tr><td>EGRPM [27]</td><td>Naghibi et.al (2020)</td><td>.284</td></tr>
<tr><td>RRP [28]</td><td>Zomaya et.al. (2017)</td><td>.313</td></tr>
<tr><td>FPAEACASWDR</td><td>(Proposed)</td><td>.0178</td></tr>
</table>

In similar manner comparisons are performed with literature that covers energy-efficient data routing protocols. The Energy Efficient Geographic Routing Protocol (EGRPM), Rendezvous-Based Routing Protocol (RRP), and PRVD are considered in the comparative analysis. It is observed that the proposed framework gives the minimum average energy consumption relative to the other methods. The proposed protocol demonstrates higher energy efficiency, with an average energy usage of merely 0.018 Joules. This figure is inferior to the 0.021 Joules documented by Elyyan et al. (2023) and markedly lower than the average energy consumption estimates of 0.285 and 0.315 Joules cited by Naghibi et al. (2020) and Zomaya et al. (2017), respectively.

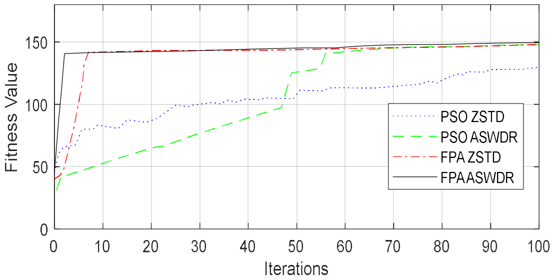

Figure 10. Convergence plot for PSO and FPA based optimal cluster heads set selection scheme.

The on average number of rounds are recorded for converging of optimization algorithms for finding out optimal solution that finds the best set of CHs. The fitness value directed towards maximum value as the iteration moves forward under each round to produce best solution. Each optimization algorithm takes different number of iterations to reach maximum fitness value. Figure 9 is demonstrating the convergence plot for PSO and FPA ZSTD/ASWDR algorithm. It has been observed that the FPA ASWDR converging rate is fastest.

5. CONCLUSION

This study presented an energy-efficient clustering and communication framework for wireless sensor networks to tackle the difficulties of constrained node energy and high communication overhead in IoT-based weather monitoring applications. The proposed method is different from traditional clustering methods because instead of focusing on CH selection or direct communication to the BS, it is integrating optimization-based CH selection with compression of data prior to transfer to improve overall network energy efficiency.

The FPA is applied to find the ideal set of CH by using several network and node-specific parameters. It is resulting in balanced cluster and equal energy usage. During the aggregation phase, lightweight data compression techniques were employed to significantly decrease the volume of data carried from Cluster Heads to the Base Station, hence reducing transmission energy consumption. A comparative analysis with traditional protocols such as LEACH, PEGASIS, SEP, and DEEC revealed that the proposed FPA-based framework offers improved network stability, extended lifespan, superior packet delivery performance, and reduced average energy consumption across diverse deployment scenarios and network sizes.

The suggested framework effectively combining optimization approach with data compression to enhance the scalability and sustainability of WSN. The research may incorporate adaptive compression thresholds, diverse sensor architectures, and real-time deployment to improve robustness and applicability across extensive IoT systems. Future work may focus on the implementation of the proposed framework for real-time hardware environments for validating the practical implementation under dynamic network conditions. Further it may include adaptive compression techniques, mobile sink system, hybrid optimization.

Findings

The proposed FPA assisted clustering integrated with ASWDR and ZSTD compression reduced energy consumption hence increase network lifetime. The framework enhances packet transmission efficiency and gives better load balancing for environmental monitoring application with higher convergence speed.

Limitations

The study was validated only through MATLAB simulations and did not include real-time hardware implementation or dynamic network scenarios. However, the FPA has introduced higher convergence due to low computational complexity but it may increase for large-scale heterogeneous WSN systems.

Abbv.	Full Form
IoT	Internet of Things
WSN	Wireless Sensor Network
CH	Cluster Head
BS	Base Station
FPA	Flower Pollination Algorithm
PSO	Particle Swarm Optimization
ABC	Artificial Bee Colony
SEP	Stable Election Protocol
DEEC	Distributed Energy Efficient Clustering
LZ77	Lempel–Ziv 1977
FSE	Finite State Entropy
ZSTD	Zstandard
QoS	Quality of Service
FANET	Flying Ad Hoc n/w
RFID	Radio Frequency Identification
APTEEN	Adaptive Periodic Threshold-sensitive Energy Efficient Sensor Network Protocol

EGRPM	Energy Efficient Geographic Routing Protocol using Mobile Sink
RRP	Rendezvous-Based Routing Protocol
CR	Compression Ratio
DWT	Discrete Wavelet Transform
LEACH	Low Energy Adaptive Clustering Hierarchy
IoMT	Internet of Medical Things
NSRDB	National Solar Radiation Database
ASWDR	Adaptive Scanning Wavelet Difference Reduction
S2CH	Sensor-to-Cluster Head
CH2BS	Cluster Head-to-Base Station
PEGASIS	Power-Efficient Gathering in Sensor Information Systems
RFID	Radio Frequency Identification

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REFERENCES

[1]. X. Cai, Y. Sun, Z. Cui, W. Zhang, and J. Chen, “Optimal LEACH protocol with improved bat algorithm in wireless sensor networks”, KSII Transactions on Internet and Information Systems, vol. 13, no. 5, 2019.

[2]. Z. Cui, Y. Cao, X. Cai, J. Cai, and J. Chen, “Optimal LEACH protocol with modified bat algorithm for big data sensing systems in internet of things”, Journal of Parallel and Distributed Computing, vol. 132, 2019, pp. 217–229.

[3]. L. Dai, B. Wang, L. T. Yang, X. Deng, and L. Yi, “A nature-inspired node deployment strategy for connected confident information coverage in industrial internet of things”, IEEE Internet of Things Journal, vol. 6, no. 6, 2019, pp. 9217–9225.

[4]. K. Dev, P. K. R. Maddikunta, T. R. Gadekallu, S. Bhattacharya, P. Hegde, and S. Singh, “Energy optimization for green communication in IoT using Harris hawks optimization”, IEEE Transactions on Green Communications and Networking, vol. 6, no. 2, 2022, pp. 685–694.

[5]. K. Dhou and C. Cruzen, “An innovative chain coding technique for compression based on the concept of biological reproduction: An agent-based modeling approach”, IEEE Internet of Things Journal, vol. 6, no. 6, 2019, pp. 9308–9315.

[6]. U. Draz, T. Ali, S. Yasin, et al., “Hybridization and optimization of bio and nature-inspired metaheuristic techniques of beacon nodes scheduling for localization in underwater IoT networks”, Mathematics, vol. 12, no. 22, 2024, p. 3447.

[7]. M. Z. Ghawy, G. A. Amran, H. AlSalman, et al., “An effective wireless sensor network routing protocol based on particle swarm optimization algorithm”, Wireless Communications and Mobile Computing, vol. 2022, 2022, pp. 1–13.

[8]. P. Kathiroli and K. Selvadurai, “Energy efficient cluster head selection using improved sparrow search algorithm in wireless sensor networks”, Journal of King Saud University - Computer and Information Sciences, vol. 34, no. 10, 2022, pp. 8564–8575.

[9]. K. Kaur and S. Kaur, “Hybrid bio-inspired optimization-based routing protocol for enhancing data transmission in clustered network”, Array, vol. 27, 2025, p. 100481.

[10]. I. U. Khan, I. M. Qureshi, M. A. Aziz, T. A. Cheema, and S. B. H. Shah, “Smart IoT control-based nature inspired energy efficient routing protocol for flying ad hoc network (FANET)”, IEEE Access, vol. 8, 2020, pp. 56371–56378.

[11]. G. Kumar, R. Saha, M. Conti, T. Devgun, and R. Thomas, “GREPHRO: Nature-inspired optimization duo for internet-of-things”, Internet of Things, vol. 25, 2024, p. 101067.

[12]. N. Kumar, K. Singh, and J. Lloret, “WAOA: A hybrid whale-ant optimization algorithm for energy-efficient routing in wireless sensor networks”, Computer Networks, vol. 254, 2024, p. 110845.

[13]. J. Ma, S. Wang, C. Meng, Y. Ge, and J. Du, “Hybrid energy-efficient APTEEN protocol based on ant colony algorithm in wireless sensor network”, EURASIP Journal on Wireless Communications and Networking, no. 1, 2018, p. 102.

[14]. S. Mnasri and M. Alrashidi, “Energy-efficient IoT routing based on a new optimizer”, Simulation Modelling Practice and Theory, vol. 119, 2022, p. 102591.

[15]. B. N. K. Reddy and A. S. Kumar, “Evaluating the effectiveness of bat optimization in an adaptive and energy-efficient network-on-chip routing framework”, Journal of Parallel and Distributed Computing, vol. 188, 2024, p. 104853.

[16]. M. P. K. Reddy, “Cluster head selection in IoT using enhanced self adaptive bat algorithm”, Journal of Networking and Communication Systems, vol. 2, no. 4, 2019.

[17]. R. Rani and S. Sharma, "Nature-inspired routing and optical communication for next-generation IoT systems", Journal of Optical Communications, 2025.

[18]. M. Raval, S. Bhardwaj, A. Aravelli, J. Dofe, and H. Gohel, "Smart energy optimization for massive IoT using artificial intelligence", Internet of Things, vol. 13, 2021, p. 100354.

[19]. G. Santhosh and K. V. Prasad, "Energy optimization routing for hierarchical cluster based WSN using artificial bee colony", Measurement: Sensors, vol. 29, 2023, p. 100848.

[20]. L. Wang, Y. Luo, and H. Yan, "Optimization analysis of node energy consumption in wireless sensor networks based on improved ant colony algorithm", Sustainable Energy Technologies and Assessments, vol. 64, 2024, p. 103680.

[21]. D. Piątkowski, T. Puślecki, and K. Walkowiak, "Study of the impact of data compression on the energy consumption required for data transmission in a microcontroller-based system", Sensors, vol. 24, no. 1, 2023, p. 224.

[22]. D. S. Khafaga, E. A. Aldakheel, A. M. Khalid, H. M. Hamza, and K. M. Hosny, "Compression of bio-signals using block-based Haar wavelet transform and COVIDOA for IoMT systems", Bioengineering, vol. 10, no. 4, 2023, p. 406.

[23]. J. Azar, G. B. Tayeh, A. Makhoul, and R. Couturier, "Efficient lossy compression for IoT using SZ and reconstruction with 1D U-Net", Mobile Networks and Applications, vol. 27, no. 3, 2022, pp. 984–996.

[24]. Y. Wang, K. Yang, W. Wan, Y. Zhang, and Q. Liu, "Energy-efficient data and energy integrated management strategy for IoT devices based on RF energy harvesting", IEEE Internet of Things Journal, vol. 8, no. 17, 2021, pp. 13640–13651.

[25]. M. Zhang, H. Zhang, D. Yuan, and M. Zhang, "Learning-based sparse data reconstruction for compressed data aggregation in IoT networks", IEEE Internet of Things Journal, vol. 8, no. 14, 2021, pp. 11732–11742.

[26]. G. Signoretti, M. Silva, P. Andrade, I. Silva, E. Sisinni, and P. Ferrari, "An evolving TinyML compression algorithm for IoT environments based on data eccentricity", Sensors, vol. 21, no. 12, 2021, p. 4153.

[27]. Naghibi, M., and H. Barati. "EGRPM: Energy Efficient Geographic Routing Protocol Based on Mobile Sink in Wireless Sensor Networks." *Sustainable Computing: Informatics and Systems* 25 (2020): 100377.

[28]. Sharma, S., D. Puthal, S. K. Jena, A. Y. Zomaya, and R. Ranjan. "Rendezvous Based Routing Protocol for Wireless Sensor Networks with Mobile Sink." *Journal of Supercomputing* 73 (2017): 1168–1188.

[29]. Bencherqui, A., A. Daoui, H. Karmouni, H. Qjidaa, M. Alfidi, and M. Sayyouri. "Optimal Reconstruction and Compression of Signals and Images by Hahn Moments and Artificial Bee Colony (ABC) Algorithm." *Multimedia Tools and Applications* 81 (2022): 29753–29783.

[30]. Hosny, K. M., A. M. Khalid, and E. R. Mohamed. "Efficient Compression of Bio-Signals by Using Tchebichef Moments and Artificial Bee Colony." *Biocybernetics and Biomedical Engineering* 38 (2018): 385–398.

[31]. Elyyan, R. R., and K. A. Darabkh. "A New IoT Power-Limited Wireless Sensor Networks Routing Protocol Utilizing Computational Intelligence." *International Conference on Advanced Communication Technologies and Networking (CommNet)*, Rabat, Morocco, 1–7, 2023.