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RESEARCH ARTICLE - ENGINEERING

Minimizing Energy Consumption Based on Clustering & Data Aggregation Technique in WSN (MECCLADA)

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Abstract

Wireless sensor networks WSNs have expanded in popularity in recent years and are now being utilized for many different operational tasks including tracking, monitoring, transportation, military operations, and healthcare. Therefore, it's essential for WSNs to prolong the sensor node's lifespan. The most crucial component in the sensor nodes is the energy from the battery, determining how long the WSN will last. Energy saving is essential since there is a limited battery powering the sensor nodes. Energy is needed at sensor nodes for a variety of operations, including data receipt and transmission, data processing, sensing, and other operations. However, data processing uses substantially less energy than data transmission, which has the highest energy consumption of all of them. As a result, reducing the spacing between the base station (BS) and the sensor node will result in reducing the distance that the data travels on its way to the BS, which will help conserve energy and increase the lifespan of WSNs. In this research, two methods that operate at the sensor node level are proposed: clustering and data aggregation. K-means clustering and Extrema Point (EP) data aggregation. The proposed approaches operate in three steps periodically: data collection, data aggregation, and data transmission. By aggregating duplicated data before transmitting, it to the base station (BS), these methods aim to shorten the distance between sensor nodes and the base station as well as the amount of transmitted data, while maintaining a reasonable level of accuracy for the data received at the BS or Cluster Head (CH). The efficiency of the proposed strategies is evaluated by extensive simulated experiments. The simulation outcomes demonstrate that the proposed methodology outperforms the current strategies and yields energy savings of over 90% when compared to the PIP-DA and ATP strategies.

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Keywords: Energy Saving; K-Means; Clustering; Elbow; WSN; Data Reduction; Extrema Points.

1. Introduction

Powerful, inexpensive multifunction sensors that can sense the environment, analyze data and link with one another have been made possible by recent developments in communications, mechanical, and electrical systems. The efficiency of data collection and communication by sensors are constrained by their computing, memory, networking, battery, and sensing range capabilities. Therefore, a single sensor could only be able to acquire a very tiny area. They are all connected by the wireless network known as the wireless sensor network (WSN) [1]. WSNs are growing rapidly, and new applications are always being formed. Due to the wide range of functions that WSNs may perform, including military surveillance, data collection, industrial monitoring, disaster management, emergency relief, health monitoring, habitat monitoring, and environmental monitoring, they are now widely employed. WSNs are often widely dispersed in an attempt to cover more land or interesting geographic region. The main goals of WSNs are to monitor and collect environmental and physical data for a specific region, such as traffic flow, pollution, humidity, light, temperature, and motion. The data is then transmitted to a manufacturing plant (base station or sink), where it performs additional processing to provide the data needed for various applications [2]. It's feasible that additional nodes will record and transmit the same data because of how widely and densely sensor nodes have been deployed in WSN. As a result, there's a lot of redundant sensor data. Such duplicate data transmission depletes the networks and individual nodes' resources. Data transmission is one of the main reasons why sensors in WSNs lose power. Most sensor energy is used for radio wireless communication, which includes transmitting and receiving, rather than for sensing or processing [3]. Because of this, the data aggregation approach has become a potential choice in WSNs for managing duplicate data and reducing usage of energy. Data aggregation in wireless sensor networks (WSNs) refers to the act of combining data from several sensors on intermediate nodes in order to eliminate duplicate transmission and communicate unified data only to the base station (sink). Every system that generates or analyzes a significant amount of the data must be involved in aggregation of data. For data analysis and decision-making, it is one of the most crucial WSN techniques. WSNs require data aggregation for two key reasons. The first is that there is a lot of data to analyze and comprehend since there are many nodes in each network and each node creates a lot of data. It is essential to translate this data

Nomenclature & Symbols			
ATP	Aggregation And Transmission Protocol	C_i	Set of Clusters
BS	Base Station	K	Number of Clusters
CH	Cluster Head	SSE	Sum of Squared Errors
CM	Cluster Member	n	Number of Sensors
D	Distance	$\overline{M_i}$	Mean of Set M_i
DABOEP	Data Aggregation Based on Extrema Point	r_i	Time Series Point
DABOEP-All	Data Aggregation Based on All Extrema Point	E_{amp}	Amplified Use of Energy
DABOEP-Max	Data Aggregation Based on Maximum Extrema Point	E_{tx}	Exhausted Energy for Transmitting a Packet
DABOEP-Min	Data Aggregation Based on Minimum Extrema Point	Gp	Connected Graph
EP	Extrema Point	EG	Edge Set
K-means	Clustering Algorithm	ND	Node
L	Number of Bit	R_i	Sensor Data Readings Time Series
Mea	Data Sensing Measurement Number Values	ρ	Period
Mica2Dot	Sensor Used in Intel Lap	E_{elec}	The Energy Used by The Radio's Circuits
PIP-DA	Perceptually Important Points Data Aggregation	X_i	Sensor Found in Clusters
QoS	Quality of Service	M_i	Set of Sensor Coordinate
SN	Sensor Node	C_k	K_{th} Cluster
WSN	Wireless Sensor Network	Gp	Connected Graph
Ɛ	Energy Threshold	τ	Transmitted Collected Data Set

into knowledge that the data consumer will find interesting and relevant. The importance of energy saving in WSNs is the second reason. Data aggregation reduces the volume of data transferred, processed, and energy consumed. Data aggregation on sensor networks reduces network traffic, reduces energy usage, and extends the lifetime of sensors [4]. In WSNs, data is collected in two different ways: event-driven and time-driven. Periodic data collection from sensor nodes that is gathered at a BS (sink) is known as "time-driven data collection". Contrarily, with event-driven data collection, sensors remain idle until a critical event occurs, at which point the data is immediately sent to the BS (sink) [5]. This study uses a time-driven data-gathering methodology. Periodic data collection is employed in time-driven systems when it's important to continuously monitor particular variables, such as temperature or pressure. In addition to the presumption that the network is homogenous and that the same kinds of sensors are being utilized; the temperature will be monitored in this study.

2. Related Work

The redundancy of data in WSNs is one of the most significant and challenging problems. This is due to the data that the widely dispersed sensor nodes collect being geographically and temporally similar. Due to congestion and energy consumption brought on by this highly correlated data, the underlying network's quality of service (QoS) worsens. Several approaches for prolonging the network's lifespan have been proposed so far. To enhance network lifespan, the researchers used a variety of strategies from the literature, including topology optimizations, sleep–wake cycles, energy-efficient routing, energy-efficient clustering, and so on. Data aggregation is a fundamental technique for extending a network's lifespan by reducing the energy consumption of sensor nodes. Redundancy may be reduced with the use of data aggregation, saving energy and extending the network's lifespan. Transmission is the main energy consumer factor. Data aggregation assists in this attempt by lowering sensor node battery consumption [1].

[6] This work proposes an energy-efficient data aggregation approach for clustered WSNs (EEDAC-WSN). By enabling cluster member nodes to transmit brief control frames followed by relatively in-depth messages from nodes chosen by the cluster head node, it minimizes intra-cluster communication.[7] The grid clustering-based FRS-RL system is suggested in this paper. In order to gather data more effectively, grid clustering is used for cluster creation and CH selection in highly scattered WSNs. Through the use of a fuzzy rule system-based reinforcement learning technique, the data aggregator node is also selected according to parameters including distance, neighborhood overlap, and algebraic connectedness.[8] This recommended method proposes the Cluster Head (CH) algorithm with the Integration of Distributed Autonomous Fashion with Fuzzy If-then Rules (IDAFFIT) algorithm for clustering. The optimum path is then chosen to transmit the packet from the source to the target node using the routing principle. In this situation, an adaptive source location privacy preservation mechanism called ASLPP-RR is suggested for routing. Furthermore, while employing the Secure Data Aggregation based on Principle Component Analysis (SDA-PCA) technique, end-to-end confidentiality and integrity are preserved. [9] This research proposed a new data aggregation method using an extreme learning machine (ELM), which efficiently eliminates duplicate and inaccurate data. To lessen the instability of the training process, Mahalanobis' distance-based radial basis function is used in the ELM's projection step Each sensor node's data additionally performs a Kalman filtering process before being delivered to the cluster head. [10] Distinctive Threshold It has the ability to remove WSN delays and considerably minimize duplicate data routing by configuring a combined Optimal Relay Selection based Data Aggregation (DTC-ORS-DA) scheme and a priority-based relay selection method.[11] The efficiency of the sensor type-dependent data aggregation, communication energy, and node residual energy are measured in this paper to propose a novel Q-learning-based data-aggregation-aware energy-efficient routing (Q-DAEER) algorithm. This algorithm uses reinforcement learning to find the best path by maximizing rewards at each sensor node.[12] The secure hybrid structure data aggregation (SHSDA) method is suggested in this study, in which a parent node is assigned to each node for data transfer. By distributing a key across each parent node and its progeny, the lightweight symmetric encryption method is employed to increase the security of the data.[13] This research proposes an optimal security model employing improved fully homomorphic encryption (OSM-EFHE). The network is divided into clusters, and in order to save energy, the cluster head—which acts as an aggregator—is selected using a fuzzy if-then logic.[14], The Perceptually Important Points (PIP-DA) approach for WSN is recommended in this research as a way to reduce unnecessary data before transmitting it to the BS.[15] The aggregation and transmission protocol (ATP), a two-phase adaptive protocol that operates on each sensor node individually to reduce data transmission and conserve energy, is the solution we suggest in this study. Fig. 1 depicts several aggregation techniques.

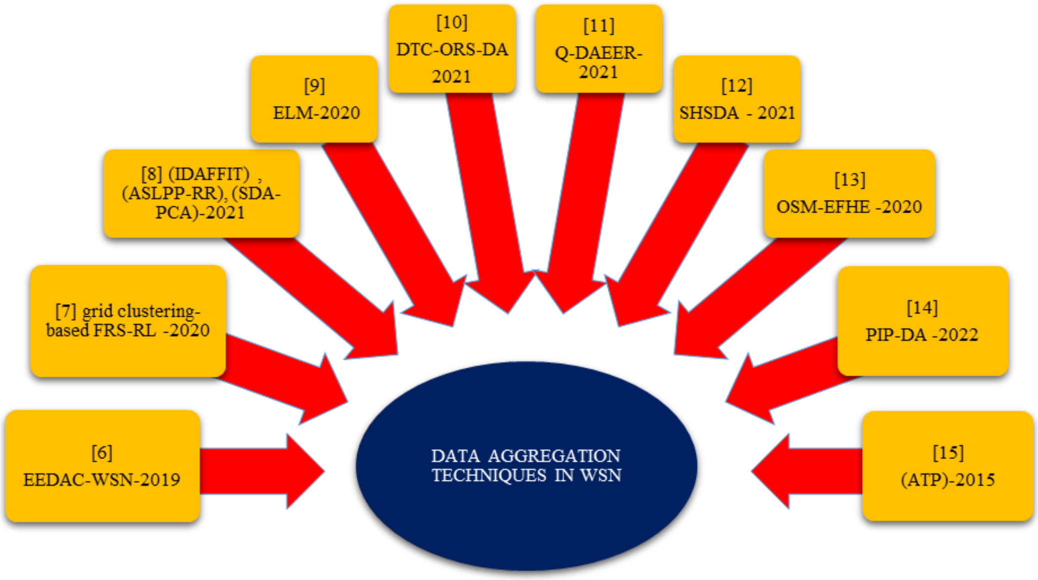

Fig. 1. Aggregation techniques

3. Methodology

This section aims to provide an overview of the methods that will be applied in this article. A detailed depiction of the overall architecture, all the algorithms used to build the system, and the suggested methods for data aggregation are also included. Fig. 2 depicts the proposed work's flowchart, which uses two phases to make it easier to understand the approaches being suggested.

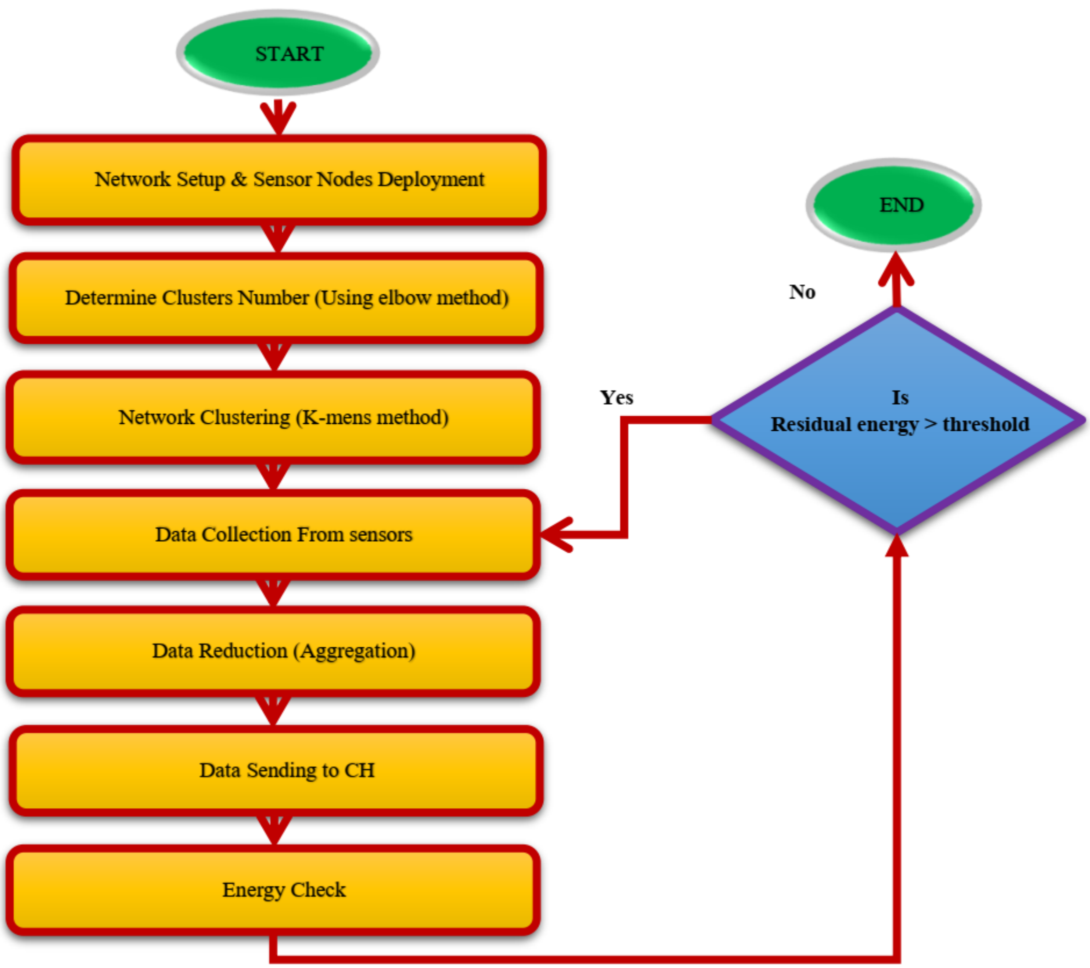

Fig. 2. Flowchart of the proposed work

3.1. Phase 1: Network clustering

This section uses the K-mean clustering approach to improve energy efficiency. Reducing the communication distance between the SNs and the BS might be regarded as the goal. After that, the SNs' lifespan was extended and the network as a whole was enhanced.

3.1.1. Sensor deployment & network setup

A Wireless Sensor Network can be exemplified as a connected graph Gp = (ND, EG). ND = {ND1, ND2,…,NDn} can be considered as n sensor node set, EG is an edge set EG = {EG1, EG2,…,EGn}. Data is collected by ND for a long time and afterwards transmitted every sensed information towards the hierarchy of CH's [16].

3.1.2. Number of clusters

A clustering strategy has been used in several studies to minimize the distance (D) between both the sensor nodes and the base station. An easier and more lightweight method is the K-means algorithm. One of the next methods must be used in conjunction with the optimal or effective number of clusters, K. Gap statistic, Average Silhouette, and Elbow. In this section, the elbow technique is a useful strategy. This technique is given in Equation 1. This displays the distances between each cluster's sample points and the centroid [17]:

$$SSE = \sum_{k=1}^{k} \sum_{xi \in sk} \| xi - ck \|^2 \tag{1}$$

SSE Represent the sum of squared errors, where x the sensor found in clusters, and Ck is the K_{th} cluster. The value of SSE is used to identify the K's ideal number. drops significantly throughout the curve and produces a lesser angle [18].

3.1.3. Algorithms of clustering

K-mean clustering is a process that uses the mean of each cluster to group or classify a few sets of data into more than one K cluster. The K-mean's main goal is to reduce the overall Euclidean distance D from CH to cluster member CM. The K-mean clustering algorithm is a well-researched mechanism of exploratory data analysis. K is represented by a total number of clusters which is positive. The major notion of K-Means can be considered as defining the K centroid for all clusters. All of the points from n data sets can be taken and associated with the nearest centroid. This is the first step. If there are no new points, this step completes and the grouping finishes. Each novel K centroid needs to re-calculate as a cluster that results from the prior move. Then, a novel binding should finish between the data set points themselves and the closest novel centroid. There can be a loop. This means that the location of the K centroid is updated gradually to the extent that there are no extra finished updates.[20], K-mean clustering steps illustrated in Algorithm 1.

Algorithm 1: K-means
Require: Set of sensors' coordinate sets $M = \{M1, M2 \dots Mn\}, K =$ total no. of cluster
Ensure: Set of clusters $C = \{C1, C2 \dots CK\}$.
1: for $j \leftarrow 1\ to\ K\ do$
2: $Cj \leftarrow \emptyset$
3: end for
4: $for\ j \leftarrow 1\ to\ K\ do$
5: randomly choose centroid x_j among $\overline{Mi}$ belongs to Cj
6: end for
7: $repeat$
8: $for\ each\ set\ Mi \in M\ do$
9: assign Mi to the cluster C_j with nearest X_j
10: end for
11: for each cluster C_j $, where\ j \in \{1, \dots K\} do$
12: update the centroid X_j to be the centroid of all sets currently in

C_j , so that $x_j = \frac{1}{|C_j|} \sum_{j \in Cj} \overline{Mi}$

13: end for
14: until clusters memberships no longer change
15: return C

3.2. Phase 2: Data reduction

The major goal of this article is to create methods for clustered networks that can aggregate data while using less energy. These methods seek to prolong the network lifetime by aggregating sensed data at the sensor node level. The purpose of aggregation at the sensor node level is to reduce the volume of detected data communicated to the CH by deleting redundant data at each interval. Thus, while maintaining the precision of the measurements obtained at the base station, communication costs are reduced, energy is conserved, and the network's lifetime is prolonged. Fig. 3 shows the flowchart of phase two.

3.2.1. Initialization

The energy threshold is initially established. The limit is 10% of total sensor energy. 20, 50, and 100 are the data sensing measurement number Mea values. Each sensor's remaining energy is evaluated when the data transmission process has been completed. If the remaining energy is higher than or equal to the threshold, continue the procedure until it is the sensor is excluded, and after that, the processing stops [21].

3.2.2 Data Collection and Transmission

The approach of time-driven data collection can be used in this situation. Periodic refers to it. SNi Records a novel reading for every time slot separately S. Next, a new vector is created by SNi. In Fig. 4, the periodic sensing is displayed [22].

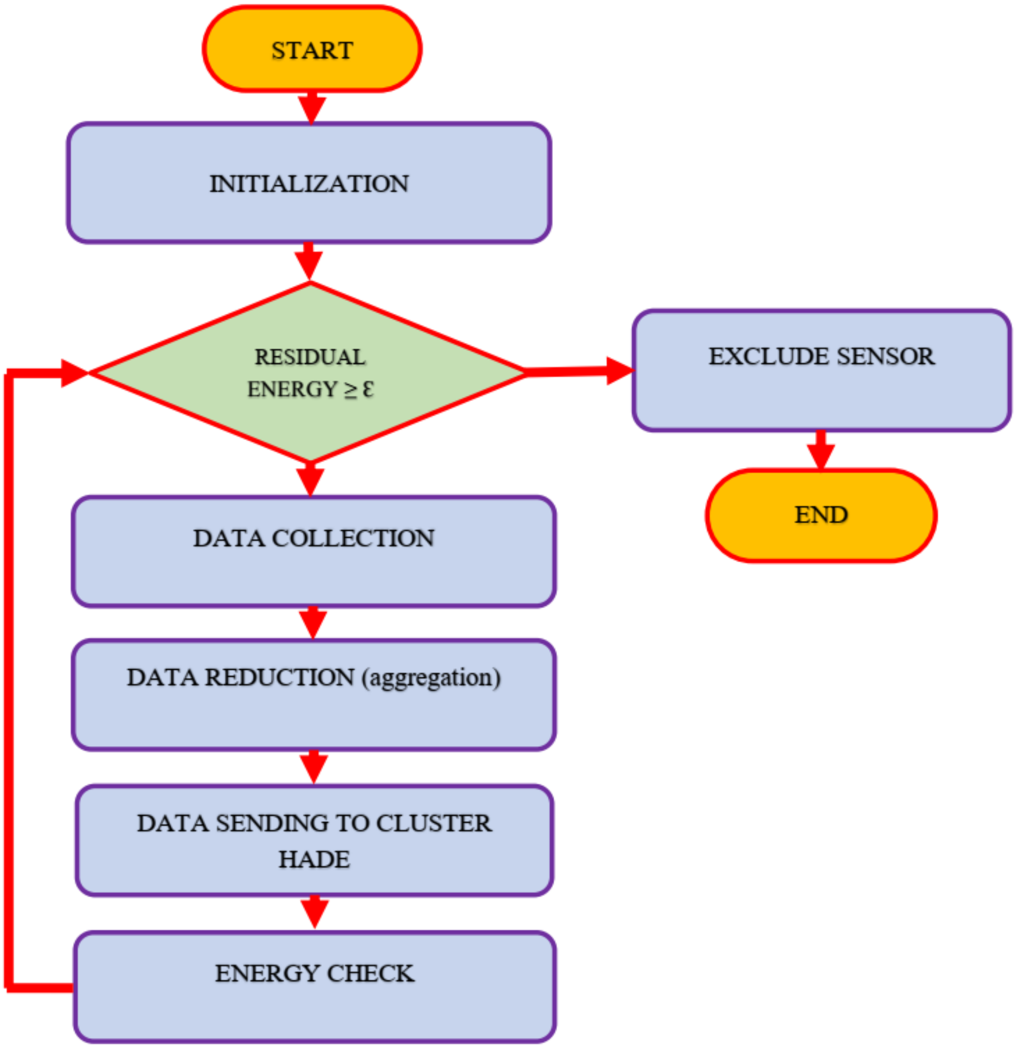

Fig. 3. Flowchart of phase two

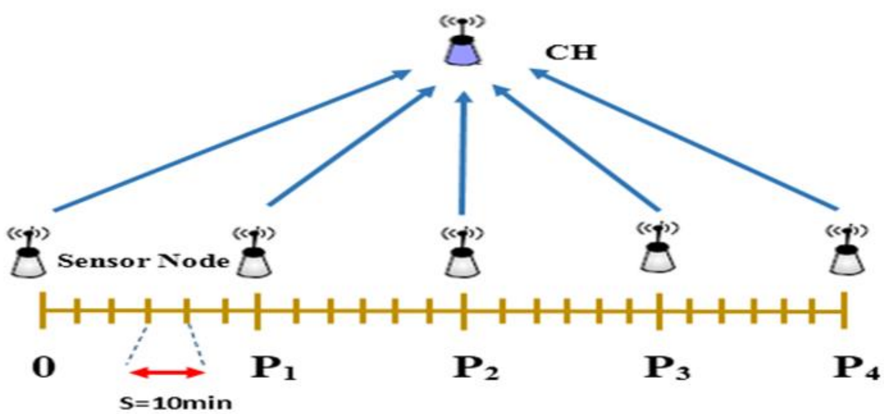

Fig. 4. Periodic sensing

3.2.3. Data aggregation based on extrema points

In this section, the "Data Aggregation based on Extrema Points (DABOEP)" approach for sensor data readings is discussed. The extrema points are extracted, and the other point is discarded. The algorithm for identifying all extrema should then be presented after defining the main types of extrema (i.e., minimum and maximum extrema points). The strict, left, right, and flat extrema are the four major types of extrema that we distinguish.

Suppose that $\mathcal{R}_i = [r_1, r_2, \ldots, r_{\tau-1}, r_\tau]$ is a sensor node with time-series data readings, r_i is a data reading in this series. The definitions of strict, left, right and flat minima are as follows:

- r_i is a $strict\ minimum$ if $r_\mathrm{i} < r_{\mathrm{i}-1}$ and $r_\mathrm{i} < r_{\mathrm{i}+1}$.
- r_i is a $left\ minimum$ if $r_\mathrm{i} < r_{i-1}$ and an index exists $right > i$ in which $r_\mathrm{i} = r_{\mathrm{i}+1} = \cdots = r_{\mathrm{right}} < r_{\mathrm{right}+1}$.
- r_i is a $right\ minimum$ if $r_\mathrm{i} < r_{\mathrm{i}+1}$ and an index exists $left < i$ is which $r_{\mathrm{left}-1} > r_{\mathrm{left}} = \cdots = r_{\mathrm{i}-1} = r_\mathrm{i}$.
- r_i is a $flat\ minimum$ if indices are existing $left < i$ and $right > i$ in which $r_{\mathrm{left}-1} > r_{\mathrm{left}} = \cdots = r_\mathrm{i} = \cdots = r_{\mathrm{right}} < r_{\mathrm{right}+1}$.
- The definitions for maxima extrema are similar.
- The suggested data aggregation approach states that a gathered sensor time-series data reading $\mathcal{R}_i = [r_1, r_2, \ldots, r_{\tau-1}, r_\tau]$ can be aggregated by choosing the two endpoints, left, right and strict extrema, and discarding the flat extrema. Algorithm 2. Demonstrates the mechanism that defines all extremes and describes their kinds, that demanding linear time and constant memory.

```
Algorithm 2: Extrema Points
  Input: Sensor node data readings R= [r1,r2,…,r (τ-1) ,rτ]
  Output: Extrema_Points   output vector of all extrema
for i←1 to τ Do
      R←Collect sensor data reading every s second
end for
Set Extrema_Points←r_1    //insert in output vector the first endpoint
first_point=2
while ((first_point <(τ-1)) & (r_i=r_1))
         first_point=first_point+1
end while
if ((first_point < (τ-1)) & (r (first_point) < r_1)) then
         first_point=FIND_MIN (first_point)
end if
while (first_point<(τ-1))
         first_point=FIND_MAX (first_point)
         first_point=FIND_MIN (first_point)
end while
Set Extrema_Points←r_τ     //insert in output vector the last endpoint
Return Extrema_Points
```

```
Algorithm 3: FIND_MIN (index) ----- After the ith point detect the first minimum
left=index
while ((index<(τ-1)) & (r_index ≥ r_(index+1))) do
          index=index+1
           if (r_left > r_index) then
                  left=index
          end if
end while
if (index<(τ-1)) then
     OUTPUT (left, index,"min")
end if
Return index+1
```

```
Algorithm 4: FIND_MAX (index) -----After the ith point detect the first maximum
left=index
while ((index<(τ-1)) & (r_index≤r_(index+1))) do
          index=index+1
           if (r_left<r_index) then
                  left=index
          end if
end while
if (index<(τ-1)) then
     OUTPUT (left, index,"max")
end if
Return index+1
```

3.2.4. Energy consumption

Communication uses the most energy, as was already mentioned. After data has been sent, each sensor's energy level must be updated; if it is higher than the threshold, the sensor must be kept; otherwise, it must be excluded. The radio unit model of the sensor node is illustrated in Fig. 5. The energy can be consumed in two parts: the components of transmission and reception. Depending on the distance D from its starting point, In order to amplify the signal during transmission, more power is needed. Therefore, the exhausted energy for transmitting a packet of L bits to a location at a distance equal to D can be calculated as illustrated in Equation 2.

$$E_{tx}(L,D) = (E_{elec} \times L) + (E_{amp} \times L \times D^2) \quad (2)$$

Where E_{elec}: The energy used by the radio's circuits; E_{amp}: amplified use of energy [22].

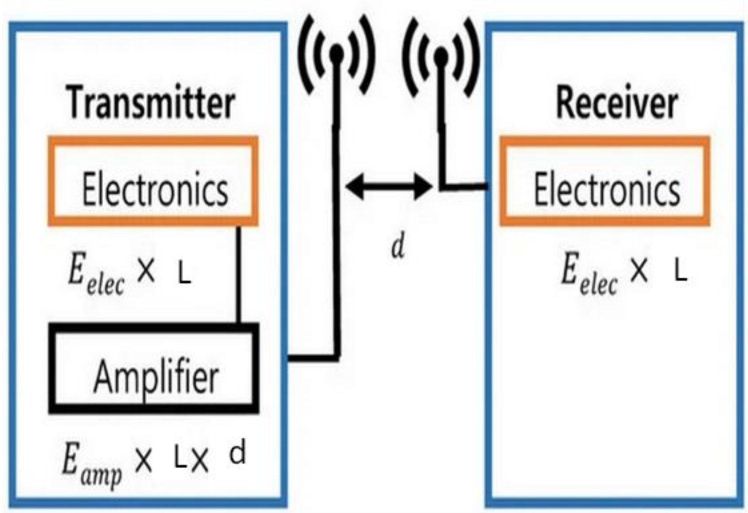

Fig. 5. Radio unit of sensor node

4. Results

In this section, graphs representing the simulation and performance evaluation results for the suggested approaches stated in Section Four are displayed and analyzed. First, real sensor data will be used to assess methodology performance using a variety of performance metrics. Second, the same category includes comparing the suggested approaches to the established protocols.

4.1. The Environment of simulation

The Python programming language, often referred to as a customized Python simulator, was employed in our method's experiment to evaluate this work. In this project, sensors from the Intel Berkeley Research Center are used to acquire a collection of online temperature data. Numerous articles that have been published that deal with WSN employ this kind of data.The network utilized In this laboratory, there are x sensors. distributed across a single-hop design.The lab is made up of 54 Mica2Dot sensors, which are fitted in a (35*45m) dimension and utilized for a variety of environmental monitoring tasks like measuring low levels, humidity, temperature, and voltage. Just for simplicity, temperature is used in our research. Every 31 s, sensors in the lab record temperature data.The log file created from the sensed data, which contains 2.3 million measurements, is used in the suggested experiment. Through a sensor, IEEE 802.15.4 can be used, similar to the MAC protocol. In this situation, it's possible that the protocol will be in charge of managing sensor interference. several sensor nodes with a yellow sign inside them denotes the fact that the data from those sensors is destroyed, resulting in only 47 sensors being selected and their data being used in [23, 24] .

4.2. Performance metrics

First, the effectiveness of the suggested approaches in experimental simulations is assessed utilizing the following conditions: the ratio of residual data after aggregation, the transmitted amount of data to CH, the quantity of energy used, and the accuracy of data. Second, it would be useful to compare the suggested strategies with some comparable study in the same area.

4.3. *Evaluation of performance*

The techniques' findings—obtained through thorough tests using a customized Python simulator—will be examined and analyzed in this section. We conducted several experiments to measure the efficiency of our suggested methods. These studies' main goal is to demonstrate that our methods may successfully result in energy-saving impacts at WSN sensor nodes. The performance is evaluated using the metrics listed, as indicated in Table 1.

Table 1. values for the experiment's variables

Variables Name	Value
WSN lap size	35×45 m
Sensors No.	47 sensors
BS No.	1
BS. Location	17.5 x 22.5
M	20, 50 and 100 times data sensing
$\mathbf{E_{elec}}$	50 nJ/bit
$\boldsymbol{\beta_{amp}}$	100 pJ/bit/m2
No. of cluster.**k**	4
Sensor's initial energy	0.2 Joule

The positioning of the sensor nodes in the lap is in [24] By segmenting the network into four clusters, the clustering technique is used to reduce the distance between the lap sensor nodes. The experiments that were carried out using the DABOEP approach utilized three scenarios. The experiment refers to the first scenario as DABOEP-All and obtains all of the extreme points of the sensor data vector. In the trials, the second scenario, also known as DABOEP-Min, simply extracts the smallest extrema points of the sensor data vector. The third scenario, known in the experiments as DABOEP-Max, exclusively uses the sensor data vector's maximum extreme points.

4.3.1. Remaining data after aggregation

This experiment's goal is to illustrate how sensor nodes can aggregate the obtained data readings using the provided method (i.e., to eliminate duplicate data readings every period). Fig. 6 illustrates the percentage of remaining data readings after the DABOEP approach has been used to minimize redundancy. In all simulation studies with varied parameters, the findings show that the suggested technique outperforms the PIP-DA and ATP methods in terms of the amount of data remaining. in comparison to PIP-DA and ATP, the suggested technique reduces the quantity of data left by 56–81% with PIP except (10% and 5%), and 79–89%, respectively.

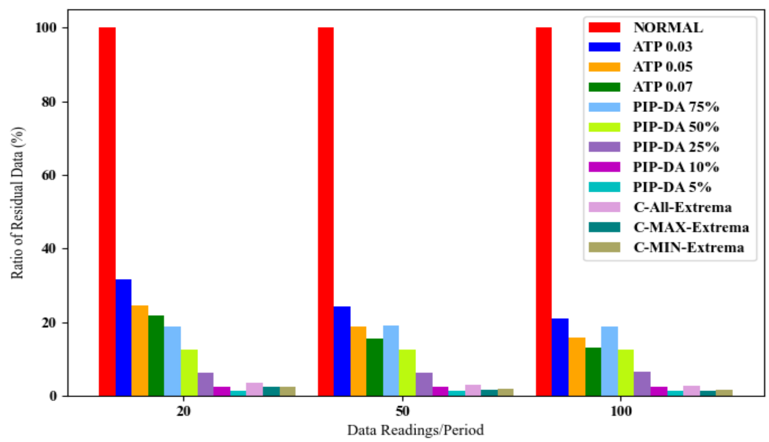

Fig. 6. The residual data after aggregation

4.3.2. Analysis of energy consumption

The objective of this study is to find out how often energy is consumed by a sensor node. The quantity of energy needed to transport data to the CH is equal to the amount of energy consumed at SN, the transmission requires more energy to amplify the signal due to its distance from the recipient. as shown in Fig. 7, The results show that our approach outperforms ATP and PIP-DA in terms of energy depilation, and when compared to PIP-DA and ATP, the proposed method reduces the amount of energy utilized by 90%

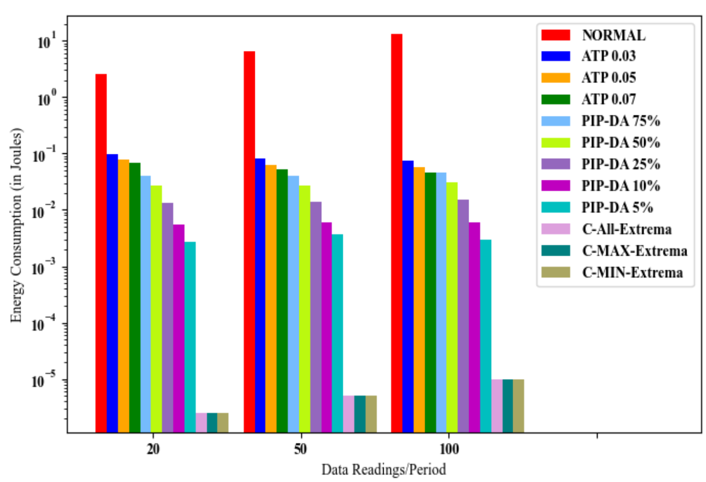

Fig. 7. Energy consumption

4.3.3. Accuracy

A crucial challenge for the WSN is the elimination of duplicate data without sacrificing accuracy. The accuracy of the data is affected by the "loss rate," which is the value that a sensor node obtains when the CH is not receiving it. Fig. 8 displays the accuracy percent that will not be provided to the CH following the aggregation of the data sets. To obtain higher accuracy, more data must be transferred, using more energy in the process. The results of all simulation tests with diverse settings reveal that the suggested methodology outperforms the ATP and PIP-DA methods in terms of data accuracy used in all scenarios. When compared to PIP-DA and ATP, the proposed method enhanced accuracy by 49–77% better than PIP-DA and enhanced the accuracy by up to 69.5% compared to ATP.

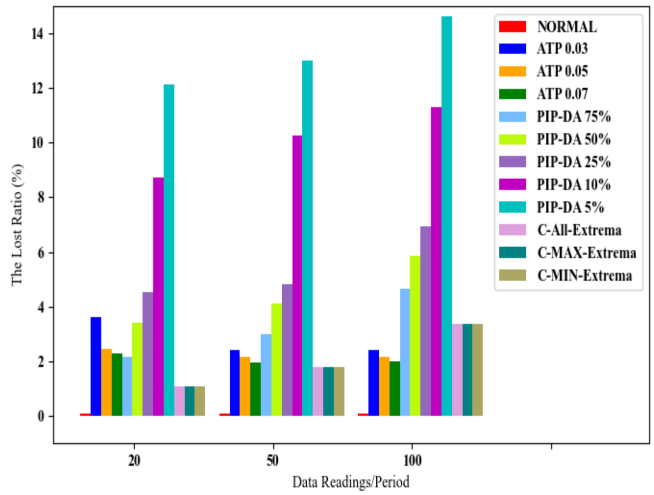

Fig. 8. Shows the percentage of accuracy

4.3.4. Number of data sets transmitted

The quantity of data sets delivered to each sensor's associated CH is reduced in this experiment by using DABOEP as described. A sensor node's data transmission ratio using the DABOEP, PIP-DA, and ATP protocols is shown in Fig. 9. In all simulation studies with varied parameters, the findings show that the suggested method outperforms the PIP-DA and ATP methods about the volume of data transmitted, and in comparison, to PIP-DA and ATP, the proposed technique reduces the quantity of data delivered by 44–76.6 with PIP, except 10% and 5%, and 79–84% with ATP, respectively.

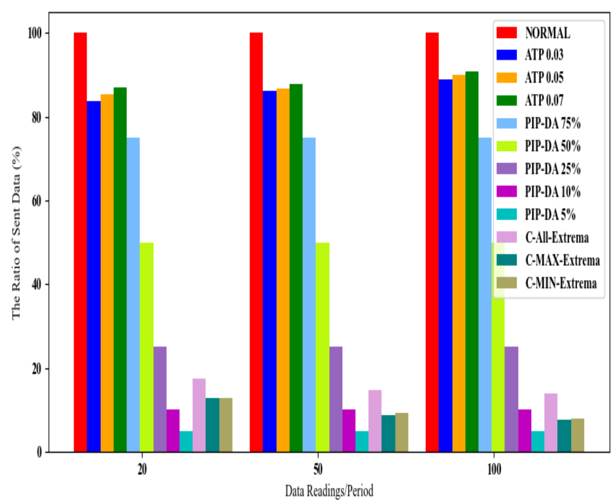

Fig. 9. Ratio of data sent

5. Conclusion

Energy consumption is still a hot topic in WSNs. Energy consumption reduction, or at least reduction, is a major topic for researchers. Through the elimination of duplicated data at regular intervals, data aggregation techniques will reduce the amount of detected data delivered to the CH. Energy can be saved, prolonging the lifetime of the network while decreasing transmission costs and maintaining base station data accuracy requirements. In comparison to the ATP and PIP-DA techniques, simulation findings show that our suggested solutions are more energy-efficient at increasing the lifespan of WSN by minimizing the quantity of data left by 56–81% with PIP except (10% and 5%), and 79–89%, the amount of energy utilized by 90%, enhancing accuracy by 49–77% better than PIP-DA, and enhancing the accuracy by up to 69.5% compared to ATP, reducing the quantity of data delivered by 44–76.6 with PIP, except 10% and 5%, and 79–84% with ATP, respectively.

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