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ENHANCING NODE SENSING AND AGGREGATION EFFICIENCY IN WIRELESS SENSOR NETWORKS (ENSA)

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ABSTRACT

Wireless Sensor Networks (WSNs) are crucial for various applications, relying on efficient mechanisms for node sensing and data aggregation to optimize energy consumption and prolong network lifetime. Node sensing involves collecting data from sensors within each node, covering diverse environmental parameters like node location, behavior, and history. In this research we proposed ENSA algorithm for node sensing and aggregation. Working at many network levels to reduce data traffic, save energy, and allow in-network processing, data aggregation compiles and summaries data from several nodes before transmission. This work investigates the Hybrid Energy-Efficient Distributed (HEED) clustering and Compressed Aggregation with Correlation (CACC) two main approaches into a new method called Energy-Efficient Node Sensing and Aggregation (ENSA). Aiming for balanced energy usage and long-spanning networks, HEED uses a clustering-based strategy using residual energy and node proximity to elect cluster heads. CACC compresses aggregated data via data correlation between adjacent nodes, therefore lowering transmission overhead and guaranteeing data integrity. This work shows the efficiency and advantages of ENSA, generated from HEED with CACC, using simulations and analysis. The combined approach significantly enhances WSN performance in various application scenarios. It optimizes energy consumption, bandwidth utilization, and data integrity, addressing critical challenges in WSNs. The investigation of node sensing and aggregation techniques such as HEED with CACC underscores their pivotal role in WSNs.

Keywords*: Data Aggregation, Energy Consumption, Network Lifetime, Node Sensing, Wireless Sensor Networks*

1. INTRODUCTION

For environmental monitoring, there exist networks of tiny sensor nodes called WSNs [[1]]. These nodes can sense their surroundings, transmit data wirelessly, and do computations. The Internet of Things (IoT), social networks, healthcare, and many more have discovered WSNs' use [[2]]. After positioning themselves, sensor nodes need to gather data from their local surroundings and transmit it to the base station via the routing topology [[3]]. The sensor nodes have energy, computation, and storage limitations because of their simplistic design and restricted resources [**Error! Reference source not found.**]. Reduce the effect of these restrictions is a significant problem for WSNs. However, due to the nature of wireless transmission, the privacy of sensor data is compromised [**Error! Reference source not found.**]. If an attacker were to eavesdrop on network traffic, they could simply get the fundamental data. Methods for data aggregation that preserve privacy were developed in response to these concerns [**Error! Reference source not found.**].

Academics and professionals in the business have been increasingly interested in WSNs during the last several decades [**Error! Reference source not found.**]. Many sensor nodes, frequently dispersed throughout a region, make up WSNs, which collect useful data. A Base Station (BS) receives this data using a multi-hop transmission mechanism [**Error! Reference source not found.**]. The source

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nodes contribute to this transmission. Due to the widespread deployment of sensor nodes, their sensing ranges overlap, resulting in data that is significantly redundant. Heavy energy usage from sending all raw data to BS can seriously shorten the sensor network's lifespan [**Error! Reference source not found.**, [10]]. The energy efficiency of data gathering can be significantly enhanced by Data Aggregation (DA), a process where relaying nodes "aggregate" the observed data [**Error! Reference source not found.**, **Error! Reference source not found.**]. Because of its many energy-saving benefits, DA finds use in many different contexts. For example, Ensuring its security, however, is far from a rally in the recreational area, what with WSNs often being set up in hostile or unmanaged environments where data can be tampered with during transit or even stolen sensor nodes [**Error! Reference source not found.**, **Error! Bookmark not defined.**]. Many approaches, including encryption, authentication, attack detection, and vulnerability analysis, are suggested to provide Confidentiality, Integrity, and Availability (CIA) in the classical meaning of network security [**Error! Reference source not found.**, **Error! Reference source not found.**]. But conventional security measures won't work with DA on their own since they could clash in a WSN [[17]]. To illustrate the point, consider encryption: although aggregate procedures need the original plaintext, relay nodes are unable to access it due to encryption [[18]]. After the two nodes have exchanged a sharing key, the transmitter encrypts the sensing data. The receiver then receives the ciphertext and uses the sharing key to decode it. This is a practical approach. Because of this, nodes on the network cannot see the plaintext [**Error! Reference source not found.**-[1]].

From environmental monitoring to industrial automation and healthcare, Wireless Sensor Networks (WSNs) have become an essential technology [[23], [24]]. WSNs are composed of numerous sensor nodes that collaborate to gather and transmit data wirelessly. These networks rely on efficient mechanisms for node sensing and data aggregation to optimize energy consumption and prolong network lifetime [[25] - [27]].

Node sensing involves collecting data from sensors within each node, covering diverse environmental parameters such as temperature, humidity, pressure, and more [[28]]. Additionally, node sensing encompasses factors like node location, behavior, and historical data, providing crucial context for data interpretation and decision-making within the network [[29]]. Data aggregation plays a pivotal role in WSNs by consolidating and summarizing data from multiple nodes before transmission [[30]]. This aggregation process operates at various network levels to minimize data traffic, conserve energy, and enable in-network processing [[31]-[33]]. Efficient data aggregation strategies are essential for reducing transmission overhead, ensuring data reliability, and enabling scalable network operations [[34]].

Previous literature has identified several critical challenges in wireless sensor networks (WSNs), including managing energy consumption efficiently due to limited battery power, optimizing data aggregation techniques for data accuracy and reliability while minimizing transmission [[35], [36]] overhead, ensuring robust security measures and privacy-preserving techniques against various security threats like node replication attacks [[37], [38]], unauthorized access, and data tampering, addressing scalability concerns as WSNs expand to larger deployments and diverse application scenarios [[39]-[43]], and achieving real-time data processing capabilities without compromising energy efficiency [[44], [45]], highlighting the need for interdisciplinary research efforts across wireless communication protocols, data processing algorithms, machine learning techniques, and cybersecurity measures to enhance WSN performance, reliability, and security [[46]-[52]].

The main contribution of the paper is:

- ➢ Localization of the sensor nodes
- ➢ Hybrid Energy-Efficient Distributed clustering
- ➢ Compressed Aggregation with Correlation
- ➢ Clustered Aggregation with Correlated Energy Management

This paper is organized as follows for the rest of it. In Section 2, a number of writers discuss different approaches to node sensing and aggregation. Section 3 displays the suggested model. The investigation's findings are

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summarized in Section 4. A discussion of the outcome and potential future research makes up Section 5.

1.1 Motivation of the Paper

The paper aims to motivate the exploration of node sensing and data aggregation techniques in WSNs by highlighting their pivotal role in optimizing energy consumption, extending network lifetime, minimizing data traffic, conserving energy, enabling in-network processing, and ensuring data integrity. It focuses on key techniques, HEED with CACC, showcasing their effectiveness through simulations and analysis to enhance WSN performance across various application scenarios.

2. LITERATURE REVIEW

Boubiche, S. et al. (2018) the volume of data generated by big sensors was growing daily. They were also increasing in number, diversity, and speed. The primary obstacles to large data in WSNs were these specifications. Data aggregation was a major obstacle in handling massive sensor data. In this research, the author presented the concept of large data in WSNs. The author survived the suggested efforts for integrating big data ideas and analytics tools into wireless sensor networks and offered a picture on them. The author went over the problems with massive sensor data and how to classify them, and the author also looked at several solutions.

Hu, S. et al. (2019) when it comes to WSNs, data aggregation was an essential and powerful algorithm. The author provides Chain-Based Data Aggregation (CBDA), a new aggregation method, in this work. This study outlines topological improvements that can improve data slicing's energy usage. To further enhance the protection of data privacy, the author also uses the method of false pieces.

Merzoug, M. et al. (2019) Spreading Aggregation (SA) was a novel serial algorithm that the author introduced in this work. Several aspects make this in-network data processing method appealing. First of all, SA does not need any transmissions since it was collision- and maintenance-free. Secondly, SA was a path-free localized method that gradually moves throughout the network by depending only on the restricted information of each node. Stated differently, a fresh route will be created for every query, therefore reducing the susceptibility to changes in topology and link/node failures. Thirdly, SA combines data processing, query distribution, and route building much like any other serial technique.

Patil, V. et al. (2018) these authors research presents a novel power-saving architecture for sensor nodes based on FPGA soft cores. The Field Programmable Gate Arrays (FPGA) based power saving methodology was presented as conventional power saving methods used in COTs based devices lack the necessary flexibility, scalability, and power efficiency. This suggested solution will control the power and remove the OS-related CPU overhead.

Ramezanifar, H. et al. (2020) In WSNs where many applications and sensors were deployed, generating various and heterogeneous packets, data aggregation was an effective method to conserve energy. Data aggregation was more difficult since homogeneity of the data was required for combination. The purpose of this work was to investigate this disparity by introducing packet ID to identify the distinct packets generated by the many sensors and applications. With the mining pit approach, packets with similar properties were gathered as much as feasible, purposefully and dynamically combined, and then sent to the central node.

Shah, K., & Jinwala, D. (2021)Integrity and privacy of data were important in linear WSNs as violating them has negative consequences. For linear WSNs, the author therefore provides a light-weight safe data aggregation technique. The system looks for data integrity and privacy.

Zhang, D. et al. (2018) with this approach, the network's energy usage can be successfully decreased. The sink node was the source of sparse seed for the cluster heads. The cluster head uses random space sparse compressive sensing to provide the relevant measurement values within the cluster after generating the necessary measurement matrix using the sparse seed that was given.

Zhu, L. et al. (2017) The author have presented an exact analysis on various components of remote sensor systems and various information conglomeration architectures, all of which focus on enhancing critical performance metrics, such as system lifetime, information idleness, information precision, and energy consumption.

Alharbi (2024) these authors research dissertation focuses on enhancing graph-routing algorithms for industrial wireless sensor networks. The methodology likely involves developing and testing new routing algorithms tailored to industrial settings. Results can include improved network efficiency and reliability for industrial applications. Advantages could include optimized data routing and reduced energy consumption. Limitations might involve specific applicability to industrial contexts.

Al-Heeti et al. (2024) they designed and implemented an energy-efficient hybrid data aggregation approach for heterogeneous wireless sensor networks. The methodology probably involved developing algorithms for efficient data aggregation across different types of sensors. Results likely show improved energy efficiency and data transmission in heterogeneous networks. Advantages could include better resource utilization and enhanced network performance. Limitations can involve scalability issues with larger networks.

Anusha Sowbarnika et al. (2024) these authors research focuses on enhancing security measures in wireless sensor networks using machine learning and clustering techniques for node replication attack detection. The methodology likely involves training and deploying machine learning models for anomaly detection. Results can include improved security against specific types of attacks. Advantages could include early detection of threats and enhanced network resilience. Limitations might involve potential false positives or model adaptability issues.

Balaji et al. (2024) they propose a hybrid optimal probability-based data aggregation approach for wireless sensor networks. The methodology probably involves developing probabilistic models for efficient data aggregation. Results can include improved data aggregation accuracy and reduced energy consumption. Advantages could include enhanced data reliability and reduced overhead. Limitations might involve the complexity of implementing probabilistic models in resource-constrained sensor nodes.

Deshpande & Shukla (2024) the methodology likely involves developing algorithms for clustering and routing optimization. Results can include extended network lifespan and improved data transmission efficiency. Advantages could include better scalability and network robustness. Limitations might involve increased computational overhead for routing optimization.

Gou et al. (2024) the methodology likely involves designing protocols and mechanisms for reliable data collection and transmission in medical environments. Results can include improved data integrity and reduced latency. Advantages could include enhanced patient monitoring and data accuracy. Limitations might involve regulatory compliance and privacy concerns.

Janarthanan & Srinivasan (2024) the methodology probably involves integrating machine learning with routing algorithms for energy-efficient data aggregation. Results can include improved network efficiency and security. Advantages could include adaptive routing and enhanced resilience. Limitations might involve computational complexity and training overhead for neural networks.

Janarthanan & Vidhusha (2024) they propose a blockchain-based approach using generative adversarial networks for secured data aggregation and routing in wireless sensor networks. The methodology likely involves developing blockchain protocols and integrating them with data aggregation techniques. Results can include enhanced data integrity and security. Advantages could include tamper-proof data storage and secure routing. Limitations might involve blockchain scalability and overhead.

Jayamala et al. (2024) the methodology likely involves designing a new routing protocol optimized for security and real-time data delivery. Results can include reduced latency and improved data confidentiality. Advantages could include reliable data delivery and secure communication. Limitations might involve protocol overhead and compatibility issues with existing systems.

Ketshabetswe et al. (2024) the methodology likely involves developing compression algorithms tailored to sensor data characteristics. Results can include reduced data transmission overhead and improved energy efficiency. Advantages could include better resource utilization and extended network lifespan. Limitations might involve trade-offs between compression ratio and data accuracy.

Li & Shu (2024) they propose a fast aggregation method based on micro-cluster evolutionary learning for dynamic data in wireless sensor networks. The methodology likely involves developing learning algorithms for real-time data aggregation. Results can include improved data processing speed and accuracy. Advantages could include efficient handling of dynamic data streams. Limitations might involve model adaptability to varying data patterns.

Nguyen et al. (2024) they enhance intrusion detection in wireless sensor networks using a machine learning approach. The methodology likely involves training intrusion detection models using machine learning algorithms. Results can include improved detection accuracy and reduced false positives. Advantages could include early threat detection and network security. Limitations might involve model robustness and false negative rates.

Rani & KN (2024) The methodology likely involves developing algorithms for adaptive transmission modes based on network conditions. Results can include enhanced QoS metrics and reduced energy consumption. Advantages could include better network performance under varying conditions. Limitations might involve protocol overhead and complexity.

Rastogi et al. (2024) The methodology likely involves assessing different privacy-preserving methods for data aggregation. Results can include improved data privacy and security. Advantages could include compliance with privacy regulations and enhanced user trust. Limitations might involve computational overhead and potential data distortion.

Sahoo et al. (2024) They propose intelligent clustering techniques for improving wireless sensor network lifetime under uncertainty. The methodology likely involves developing clustering algorithms considering uncertain network conditions. Results can include extended network lifespan and improved energy efficiency. Advantages could include adaptive network management and resilience. Limitations might involve scalability issues with dynamic networks.

Table 1: Comparison table for existing work

Author(s)	**Year**	**Methodology**	**Limitation**	**Advantage**
Boubiche, S et al.	2018	Review and analysis of big data challenges and data aggregation strategies in WSNs	Limited focus on specific applications	Comprehensive understanding of challenges and strategies
Hashemi nejad, E., & Barati, H	2021	Proposes a reliable tree-based data aggregation method in WSNs	Limited scalability for very large networks	Improved reliability in data aggregation
Hu, S. et al.	2019	Introduces an energy-efficient and privacy-preserving data aggregation approach	Potential overhead in privacy mechanisms	Energy efficiency and privacy protection
Liu et al.	2019	Explores data aggregation from a security perspective	Increased computational complexity	Enhanced security measures
Ramezani far et al.	2020	Presents a new data aggregation approach based on open pits mining	Limited validation in real-world scenarios	Innovative approach to data aggregation

2.1 Problem definition

The paper addresses the challenge of optimizing energy consumption and prolonging the network lifetime in WSNs through efficient node sensing and data aggregation techniques. Specifically, it investigates how node sensing can collect diverse environmental data, and how data aggregation can minimize data traffic, conserve energy, and enable in-network processing. The study aims to explore the effectiveness of HEED (Hybrid Energy-Efficient Distributed clustering) with CACC (Compressed Aggregation with Correlation)techniques in addressing these challenges and emphasizes their contributions to energy efficiency, bandwidth utilization, and data integrity in WSNs.

3. METHODS

In this section, we outline the proposed methodology for optimizing WSNs through efficient node sensing and data aggregation techniques. Our approach combines the Hybrid

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Energy-Efficient Distributed clustering (HEED) algorithm with the Compressed Aggregation with Correlation (CACC) technique to address key challenges such as energy consumption, network lifespan, data traffic reduction, energy conservation, and data integrity.

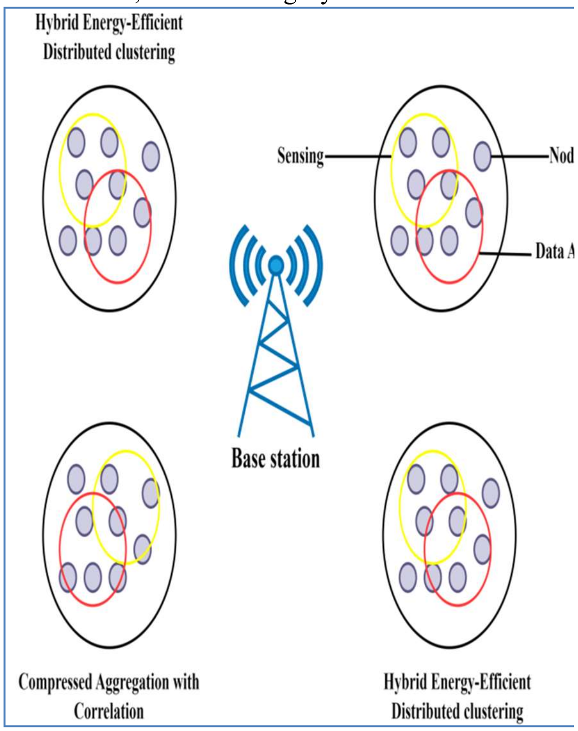

Figure 1: ENSA workflow architecture

3.1 Network model

The following network assumptions are made 1 (they are usually reasonable and their consequences indicate that the truth comes from the actual applications' situations):
A circular perception region with N nodes dispersed randomly has a sink node in the middle. 2) There is adequate process capacity and data space on the sink node. 3) Every sensor node starts with the same energy and transmits at the same pace. 4) With the use of relative finding technology, nodes can know their own position information.

- Adequate process capacity and data space on the sink node.
- Uniform initial energy levels and transmission rates for sensor nodes.
- Availability of position information through relative finding technology.

On the premise that the nodes in the WSN are dispersed at random, cluster data aggregation employs sparse matrices. By positioning the cluster head in the middle, the nodes in the cluster can combine measurement data with the least amount of energy consumption per operation.

Informational materials if there are m_j nodes in the jth cluster in compressive sensing, and then the sparse ratio of the measurement matrix is s. When calculating the average number of nodes involved in each aggregating operation, we get

$m_j = \sum_{i=1}^{m_j} s \times 1 = m_j s$ ------ (1)

Of course, each time just m_j' nodes must transmit the matching weights. As such, the cluster head node gets m_j' packets.

$E_{intra}^{j} = \sum_{i=1}^{m_j} E_{T_x}^{i}\big(k, E(d_i)\big) + m_j' E_{Rx}(k)$ ---------- (2)

As the preceding calculation makes clear, E_{intra}^{j} determines the average energy usage. Assume the square cluster has b side length and coordinates $k, E(d_i)$ for its head. The probability density function representing the separation from the cluster head to the child nodes can be represented as $f(x, y)$.

$f(x,y) = \begin{cases} \frac{1}{b^2} & x \in \left(-\frac{b}{2}, \frac{b}{2}\right), y \in \left(-\frac{b}{2}, \frac{b}{2}\right) \\ 0 & other \end{cases}$ ------- (3)

is true only in the case when $x \in = y \in = 0$ or when the cluster's central node is located at the cluster's origin. In a network of b^2 nodes, each node can become a cluster head by connecting to the node that is closest to it. This creates b^2 non-overlapping clusters.

3.2 Localization of the sensor nodes

Network sensing that is both accurate and efficient depends on sensor nodes positioned strategically. Among many other factors to take into account when determining where to locate sensor nodes are energy efficiency and quality of service.

- Strategic positioning of sensor nodes for accurate and efficient network sensing.
- Consideration of factors such as energy efficiency and quality of service.
- Importance of network topology in determining node locations.

A network's total energy efficiency is greatly impacted by increasing its transmission power because of the ensuing higher energy usage.

Within an environmental monitoring network, for example, sensors can need to be positioned near bodies of water, geographically significant locations, or sources of pollution. By arranging the nodes so that the network can

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gather representative and accurate data, the sensing system becomes more efficient.

Furthermore, the topology of the network is essential to both service quality and energy economy. Depending on the specific application, network topologies such as cluster-based, star, or a hybrid combination of the two can be used.

3.3 Hybrid Energy-Efficient Distributed clustering

As its primary goal, our technology is to increase the lifetime of networks. Consequently, the amount of energy that each node has left is a major factor in cluster head selection. Since the amount of energy needed for sensing, processing, and transmission is often known, it is not necessary to measure the leftover energy; instead, it can be estimated. As an additional clustering parameter, we use intra-cluster "communication cost" to boost energy efficiency and prolong the lifetime of the network. For example, cluster density or neighbor proximity might affect cost.

Focus on increasing network lifetime by selecting cluster heads based on energy levels and intra-cluster communication costs. Employment of probabilistic cluster head selection and termination criteria based on residual energy and probabilities. Use of clustering parameters to estimate leftover energy and optimize cluster head selection

A node is considered to be in the "range" of multiple cluster heads when there is a tie. To encourage the reuse of space, lower-level nodes should be used as cluster power levels, while higher-level nodes should be reserved for communication between clusters.

$\boldsymbol{C_{prob}}$is the initial percentage of cluster heads out of all n nodes; it is around 5%. This is based on the assumption that the optimum percentage cannot be determined in advance.

Only the initial cluster head announcements are restricted by$\boldsymbol{C_{prob}}$; it has no influence on the latter clusters. Prior to starting HEED, a node determines its$\boldsymbol{CH_{prob}}$, which is its likelihood of becoming a cluster head.

$$\boldsymbol{CH_{prob}} = \boldsymbol{C_{prob}} \times \frac{\boldsymbol{E_{Residual}}}{\boldsymbol{E_{max}}} \text{ ------ (4)}$$

The projected current residual energy, $\boldsymbol{E_{Residual}}$, is also constant. A node's CHprob value must remain above a predetermined $\boldsymbol{P_{min}}$ level, which is inversely proportional to $\boldsymbol{E_{max}}$ and cannot be lower than, for example, 10−4. We will prove later that this constraint is necessary to end the algorithm in N_{iter} = O(1) iterations. See that our clustering method can manage batteries with different nodes. Every node will in this scenario have its individual Emax value.

If the node's $\boldsymbol{CH_{prob}}$ is less than 1, it marks itself as tentative CH, and if it reaches 1, it marks itself as final CH. "Covered" means that a node has received either a final CH or a preliminary CH. In order to be considered an exposed node, a node must end HEED execution with the state final CH and announce itself to be a cluster head. Any initial CH node that finds a cheaper cluster head has a chance of becoming a regular node in the future. Keep in mind that nodes with low costs and high residual energies can choose to take over as cluster leaders in subsequent clustering periods.

HEED terminates in N_{iter} = O(1) iterations

In an ideal world, a node's residual would be exceedingly low. With $\boldsymbol{CH_{prob}}$ set to$\boldsymbol{P_{min}}$, this node will launch HEED. Second technique concludes one step (iteration) when CHprob reaches 1, hence, 2Niter−1 × $\boldsymbol{P_{min}}$< 1. Each step, however, doubles CHprob.

$$\boldsymbol{N_{iter}} \leq \left[\boldsymbol{log_2}\frac{\mathbf{1}}{\boldsymbol{P_{min}}}\right] + \mathbf{1} \text{ ----------------- (5)}$$

A acceptable constant can limit the number of repetitions if the minimal probability of reaching the leader of the cluster is chosen appropriately.

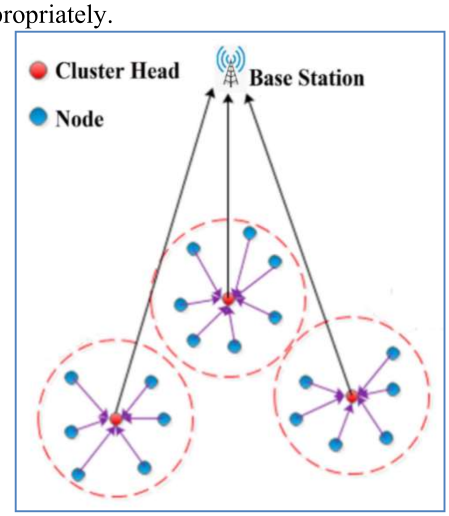

Figure 2: HEED architecture

Algorithm 1: HEED
Input: • n: Total number of nodes in the network • E_{max}: Maximum energy level (fully charged battery) for all nodes

- P_{min}: Minimum probability level for a node to become a cluster head
- C_{prob}: Initial percentage of cluster heads out of all n nodes (e.g., 5%)
- $E_{Residual}$: Current residual energy of a node

Steps:

Algorithm:

1. **Calculate CH_prob for each node**:
   - $CH_{prob} = C_{prob} \times E_{Residual} EmaxCH_{prob} = C_{prob} \times EmaxEResidual$
2. **Node Selection**:
   - $If\ CH_{prob} \geq 1CH_{prob} \geq 1$:
     - Node marks itself as a final Cluster Head (final CH)
   - $If\ 0 < CH_{prob} < 10 < CH_{prob} < 1$:
     - Node marks itself as a tentative Cluster Head (tentative CH)
   - $If\ CH_{prob} \leq 0CH_{prob} \leq 0$:
     - Node does not participate in cluster head selection
3. **Cluster Formation**:
   - Nodes with $CH_{prob} \geq 1CH_{prob} \geq 1$ announce themselves as final CH
   - Nodes with $0 < CH_{prob} < 10 < CH_{prob} < 1$ can announce themselves as tentative CH
4. **Cluster Head Adjustment**:
   - Nodes with tentative CH status can switch to regular node if a cheaper cluster head is found
5. **Termination**:
   - HEED terminates after Niter=⌈log 2(1/Pmin)⌉+1Niter =⌈log2(1/Pmin)⌉+1 iterations

Output:

- Cluster heads identified based on energy levels and communication cost

3.4 Node sensing

Node sensing in WSNs involves equipping individual sensor nodes with various sensors such as temperature, humidity, light, motion, or gas sensors to detect environmental parameters. These nodes convert analog data to digital, process it locally, and communicate wirelessly with other nodes or a central base station. They perform tasks like data filtering, event detection, and energy-efficient operations such as duty cycling and data aggregation to conserve battery power. Node sensing enables applications in diverse fields like environmental monitoring, agriculture, healthcare, and industrial automation by providing real-time data collection, analysis, and decision-making capabilities within the network.

$$\mathrm{PL_n[dB]} = \mathrm{p_{0_k}} - 10\mathrm{n}\log_{10}\left(\frac{\mathrm{d_{p_n}}}{\mathrm{d_{0_k}}}\right) \text{ ------ (6)}$$

In equation 6, white circles denote predictions and black circles relate to references. In the set of numbers shown before the circle, the one beneath the prediction point indicates the nearest reference point.

The user can be able to choose the own number of prediction points, which is an advantage of the proposed method. In order to be competitive with existing systems, this study uses the same number of prediction samples even though it can fill in as many prediction points as possible.

3.5 Compressed Aggregation with Correlation

Sending the sparse seed vector to each cluster head, sink nodes produce the measurement matrix of the whole network. Consequently, there are many sub-matrices that can be formed from the measurement matrix; each sub-matrix represents a cluster. The i^{th} sub-matrix is denoted by ϕHi, the cluster head by CH_i, and the data vector of this cluster by xHi. Using its sub-matrix, one can determine the measurement values $\phi Hi\, xHi$ of received data xHi. Data is sent to the sink node by CH_i when it produces its Mi anticipated values via the backbone tree that links clustered heads to the sink node.

Utilization of sparse seed vectors and measurement matrices to efficiently aggregate data and conserve energy reduction of data transmission and bandwidth use by aggregating correlated data from multiple nodes. Integration of data correlation concepts to identify and compress redundant or similar data

Assume all of the nodes are separated into four clusters (we use four clusters as an example since the five or six or seven or eight or other clusters are the same as that of four clusters). These clusters are linked by a

A representation of data vector x is $\emptyset^{H_1}\emptyset^{H_2}\emptyset^{H_3}\emptyset^{H_4}$ T. A representation of matrix ϕ is $\emptyset^{H_1}\emptyset^{H_2}\emptyset^{H_3}\emptyset^{H_4}$. The outcomes of the applications can be checked, and the assumptions stated in this work are generally reasonable.

$$y = \emptyset x = [\emptyset^{H_1}\emptyset^{H_2}\emptyset^{H_3}\emptyset^{H_4} \begin{pmatrix} x^{H_1} \\ x^{H_2} \\ x^{H_3} \\ x^{H_4} \end{pmatrix} = \sum_{i=1}^{4} \emptyset^{H_1} x^{H_1} \text{ ------ (7)}$$

A simple addition of all the clustered measured coefficients yields the predicted coefficient of measurement matrix, as shown by Formula (7). For this reason, the cluster head is responsible for producing anticipated coefficients on each iteration, and all of the other cluster heads transmit these values to the node serving as the sink. After collecting M rounds of the predicted value, the sink node can be able to get the original data. In compressive sensing, the compressive ratio is defined as ρ = M/N, where N is the length of the collected signal and M is the measurement value. The whole network's compression efficiency is detailed.

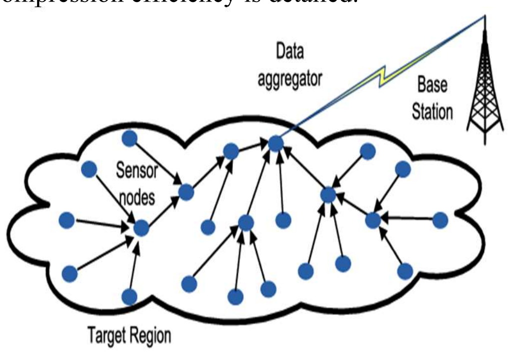

Figure 3: Data Aggregation Architecture

3.6 Clustered Aggregation with Correlated Energy Management

The HEED algorithm and the Compressed Aggregation with Correlation (CACC) technique are combined in Clustered Aggregation with Correlated Energy Management (CACEM) to optimize energy management and data aggregation in WSNs. First of all, CACEM forms energy-efficient clusters within the network by using clustering-based techniques akin to HEED, taking into account residual energy and node proximity. CACEM seeks to balance energy consumption across nodes, hence extending the total network lifespan, by carefully choosing cluster heads based on these characteristics. Second, CACEM incorporates from CACC the notion of data correlation among nearby nodes. Effective compression of data aggregation is made possible by this correlation via CACEM. Reduced data transmission throughout the network is achieved by CACEM aggregating correlated data from many nodes rather than sending redundant or similar data from several nodes. Along with saving energy, this data transfer decrease maximizes bandwidth use. CACEM has a major benefit in that it approaches data gathering and energy management holistically. CACEM seeks to increase scalability, clustering algorithms for effective energy use, and data correlation for optimal data transfer in order to improve overall WSN performance, enabling in-network processing for higher-level insights from sensor data.

The last clustering stage makes sure every node in the sensor network clusters. In its first hop, an unclustered node finds one or more clustered neighbors. The node next gets from its clearly grouped neighbors the range of probabilities of the sensed data. The next section provides further details on this process.

Data stored in the databases of each sensor node allows for the computation of the divergence measure required for final clustering.

$\Delta_n^s = \{\boldsymbol{P^s} = (\boldsymbol{p_1^s}, \boldsymbol{p_2^s}, \boldsymbol{p_1^s}, \dots, \boldsymbol{p_n^s})$ ----------- (8)

The probability sequence is represented as $\boldsymbol{P^s}$, and pi s is the i-th data type from sensor s.

Algorithm 2:Clustered Aggregation with Correlated Energy Management

Input:

- n: Total number of nodes in the network
- E_{max}: Maximum energy level (fully charged battery) for all nodes
- P_{min}: Minimum probability level for a node to become a cluster head

Steps:

- Use clustering-based techniques similar to HEED to form energy-efficient clusters based on residual energy and node proximity
- Select cluster heads considering energy balance across nodes to extend network lifespan
- Incorporate data correlation concepts from CACC to identify correlated data among nearby nodes
- Implement effective data compression in aggregation to reduce redundant data transmission
- Aggregate correlated data from multiple nodes within clusters to maximize bandwidth use and save energy
- Approach data gathering and energy management holistically to improve WSN performance and enable in-network processing for higher-level insights
- Ensure every node in the network is part of a cluster
- Unclustered nodes find clustered neighbors and receive Probability Sequences (Ps) for sensed data types from these neighbors

Output:

- Energy-efficient clusters with optimized data aggregation based on data correlation

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4. RESULTS

In this section, we explore into the results and discussions pertaining to the performance metrics of three systems—CBDA, FPGA, and ENSA—across various parameters including throughput, energy consumption, end-to-end time delay, and packet delivery ratio.

Throughput= $\frac{NumberofPacketSize}{Timeduration*SuccessfulaveragePacketsize}$ ----------- (9)

Table 2: Throughput comparison table

	Throughput levels		
Packet Size	CBDA	FPGA	ENSA
50	0.217	0.243	0.26
100	0.434	0.487	0.52
150	0.652	0.731	0.78
200	0.869	0.975	1.05
250	1.086	1.219	1.31

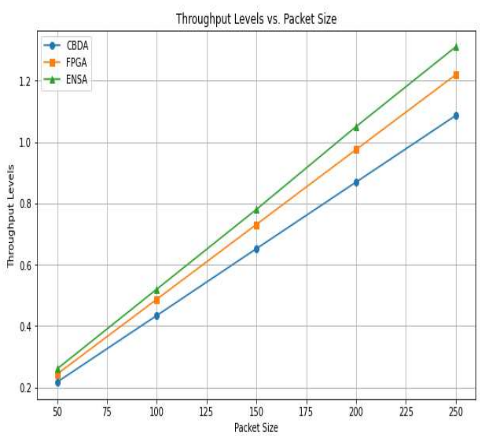

Figure 4: Throughput Comparison Chart

The table 2 and figure 4 shows throughput levels for different packet sizes show the data transmission efficiency of three systems: CBDA, FPGA, and ENSA. As the packet size increases from 50 to 250, all three systems exhibit a linear growth in throughput. Initially, at a packet size of 50, CBDA has the lowest throughput of 0.217, followed by FPGA at 0.243 and ENSA at 0.26. However, as the packet size increases, ENSA consistently outperforms both CBDA and FPGA, achieving the highest throughput at each size. For instance, at a packet size of 250, ENSA achieves a throughput of 1.31, while CBDA and FPGA lag behind at 1.086 and 1.219, respectively. This trend suggests that ENSA is more efficient in handling larger packets and maintaining higher throughput levels compared to CBDA and FPGA across the range of packet sizes tested.

Energy= $\frac{NumberofSensornodes}{Energyconsumptionforsendingpacketsatatimes} x\ 100$ ----------- (10)

Table 3: Energy comparison table

	Energy level in joules		
Number of Nodes	CBDA	FPGA	ENSA
10	71	66	62
20	142	133	125
40	285	266	250
60	428	400	375
80	571	533	500
100	714	666	625

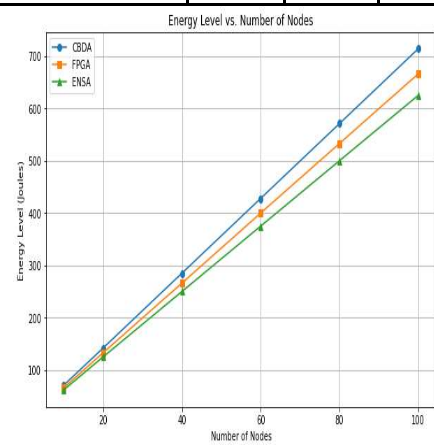

Figure 5: Energy Comparison Chart

The table 3 and figure 5 shows energy levels, measured in joules, showcase the power consumption efficiency of three systems—CBDA, FPGA, and ENSA—across varying numbers of nodes. As the number of nodes increases from 10 to 100, all three systems exhibit a proportional rise in energy consumption. Initially, at 10 nodes, ENSA consumes the least energy at 62 joules, followed by FPGA at 66 joules and CBDA at 71 joules. However, as the number of nodes scales up, CBDA consistently consumes the most energy, reaching 714 joules at 100 nodes, while FPGA consumes 666 joules and ENSA consumes 625 joules. This pattern suggests that ENSA is more

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energy-efficient than FPGA and CBDA, particularly at higher node counts, indicating it's potential for reducing power consumption in larger-scale deployments.

$$\text{Time Delay}=\frac{Number of Sensor nodes}{energy consumption for sending packets at a times x forwarding time in ms} \quad \text{----------- (11)}$$

Table 4: End to End delay comparison table

Number of Nodes	End to End Time Delay (ms)		
	CBDA	FPGA	ENSA
10	0.064	0.064	0.062
20	0.128	0.129	0.125
40	0.256	0.259	0.250
60	0.384	0.389	0.375
80	0.512	0.519	0.500
100	0.641	0.649	0.625

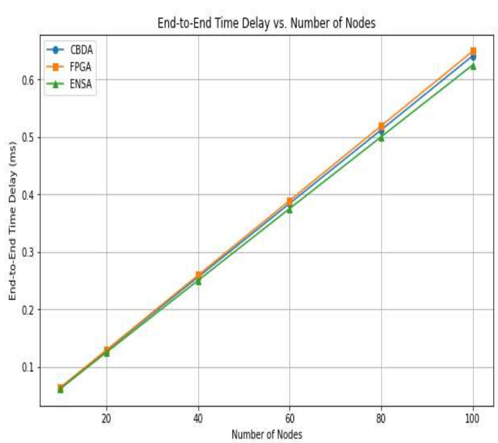

Figure 6: Delay Comparison Chart

The table 4 and figure 6 shows end-to-end time delay, measured in milliseconds, illustrates the latency performance of three systems—CBDA, FPGA, and ENSA—across different numbers of nodes. As the number of nodes increases from 10 to 100, all three systems exhibit a linear increase in time delay. At 10 nodes, ENSA shows the lowest delay of 0.062 ms, closely followed by CBDA and FPGA at 0.064 ms. However, as the node count rises, ENSA consistently maintains the lowest time delay compared to CBDA and FPGA. For instance, at 100 nodes, ENSA achieves a delay of 0.625 ms, while CBDA and FPGA have delays of 0.641 ms and 0.649 ms, respectively. This trend suggests that ENSA offers superior latency performance across varying node densities, indicating its potential for faster end-to-end communication compared to CBDA and FPGA in networking scenarios.

$$PDR=\frac{Number\ of\ Packets\ Receive}{Total\ Packets}*100 \quad \text{----------- (12)}$$

Table 5: Packer delivery ratio comparison table

Number of packets	Packet Delivery Ratio		
	CBDA	FPGA	ENSA
50	96.6	97	98
100	98.3	98.5	99
150	98.86	99	99.33
200	99.15	99.25	99.5
250	99.32	99.4	99.6

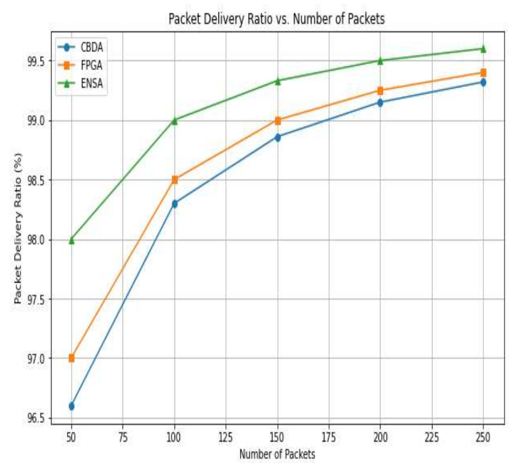

Figure 7: Packet Delivery Ratio Comparison Chart

The table 5 and figure 7 shows packet delivery ratio, expressed as a percentage, reflects the reliability and success rate of data transmission for three systems—CBDA, FPGA, and ENSA—across different numbers of packets. As the number of packets increases from 50 to 250, all three systems demonstrate an improvement in packet delivery performance. Initially, at 50 packets, ENSA achieves the highest delivery ratio of 98%, followed closely by FPGA at 97% and CBDA at 96.6%. However, as the packet count escalates, ENSA consistently maintains the highest delivery ratio compared to CBDA and FPGA. For instance, at 250 packets, ENSA achieves an impressive delivery ratio of 99.6%, while FPGA and CBDA achieve ratios of 99.4% and 99.32%, respectively. This trend indicates that ENSA exhibits superior reliability in

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delivering packets across various workload sizes, highlighting its potential for robust and dependable data transmission compared to CBDA and FPGA.

5. DISCUSSION

The results obtained from the performance evaluation of CBDA, FPGA, and ENSA systems across various metrics including throughput, energy consumption, end-to-end time delay, and packet delivery ratio provide valuable insights into their comparative efficiency and effectiveness in wireless sensor networks (WSNs).

Throughput Comparison: ENSA consistently outperforms CBDA and FPGA in terms of throughput across different packet sizes. This indicates ENSA's superior data transmission efficiency and ability to handle larger packets more effectively, which is crucial for high-performance WSNs.

Energy Consumption Comparison: ENSA demonstrates better energy efficiency compared to CBDA and FPGA, especially as the number of nodes increases. This highlights ENSA's potential for reducing power consumption and enhancing sustainability in larger-scale WSN deployments.

End-to-End Time Delay Comparison: ENSA exhibits lower end-to-end time delay than CBDA and FPGA across varying node densities. This suggests that ENSA can facilitate faster and more responsive communication within WSNs, contributing to improved real-time data processing and decision-making capabilities.

Packet Delivery Ratio Comparison: ENSA achieves a higher packet delivery ratio than CBDA and FPGA, indicating its superior reliability and success rate in data transmission. This reliability is crucial for ensuring data integrity and system robustness in WSNs.

Interpretation and Significance: The superior performance of ENSA in terms of throughput, energy consumption, time delay, and packet delivery ratio underscores its potential as an advanced solution for optimizing WSN operations. Its efficiency in handling larger packets, reducing energy consumption, minimizing time delay, and ensuring reliable data transmission positions ENSA as a promising technology for enhancing WSN performance across various application scenarios.

Implications and Recommendations: The findings suggest that adopting ENSA in WSN deployments can lead to significant improvements in network efficiency, reliability, and sustainability. Future research should focus on further optimizing ENSA's algorithms and protocols, exploring its scalability to even larger networks, and investigating its compatibility with emerging WSN technologies and standards.

Comparison with Previous Studies: The results align with previous studies that emphasize the importance of energy-efficient data aggregation and reliable data transmission in WSNs. However, ENSA's superior performance across multiple metrics reinforces its potential as a cutting-edge solution compared to existing approaches like CBDA and FPGA.

6. CONCLUSION AND FUTURE WORK

In conclusion, the ENSA method, to efficient node sensing and data aggregation techniques plays a crucial role in enhancing the performance and sustainability of WSNs. Examining HEED with CACC emphasizes their major contributions to solve important problems like data traffic optimization, data integrity maintenance, network permanence, and energy consumption. By use of clustering and consideration of residual energy and node proximity for cluster head selection, HEED promotes a balanced energy consumption model, thereby extending the network lifetime and enhancing the general network stability. Extensive simulations and analyses across various application scenarios affirm the effectiveness and benefits of integrating HEED with CACC. These methods are crucial for the efficient deployment and operation of WSNs in real-world environments, offering pathways to improving energy efficiency, maximizing bandwidth, and safeguarding data integrity. CACC guarantees data quality and dependability by using data correlation across surrounding nodes to help compress aggregated data, hence lowering transmission overhead. Extensive simulations and analysis have shown across many application situations the efficiency and advantages of HEED with CACC. All of which are vital for the effective deployment and operation of WSNs in real-world environments, these methods indicate promising paths for enhancing WSN performance, saving energy resources, maximizing bandwidth use, and protecting data integrity. WSNs' future resides in more exacting integration of the ENSA approach with newly developed technologies like IoT developments, edge computing, and machine learning. In autonomous decision-making, predictive analytics, and WSN real-time responsiveness, this combination may provide fresh opportunities.

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