Energy-Conserving Data Aggregation In Wsn Using Migration Aware Compaction And Dynamic Clustering

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Abstract
Wireless Sensor Networks is essential for enabling energy-efficient information transfer from several sensors to the washbasin. The Energy Conserving Data aggregation technique through Migration aware Compaction and Dynamic Clustering (MCDC), which combines a novel clustering mechanism with a data migration protocol, which included into a new WSN topology presented in this study. In order to extend the lifespan of the network by implementing a novel clustering mechanism robust to network dynamics, in which picking a CH depends on residual energy and a limited communication distance, the topology's main objectives are to initially pick an unpredictable arrangement of head clusters for each data transmission round. Second, to raise the ratio of packets delivered through employing a data encoding technique; and thirdly, to address the connection problem, which affects network longevity by leading sensor nodes adjacent to the base station to support heavier relay demands. Migration models offer a simple solution to this problem; in particular, the connection issue is mitigated by using a Random Positioning of Grid Mobility model. According to the simulation results, the network layout that uses the suggested MCDC algorithm efficiently increases PDR, optimises average energy usage, and lengthens network lifespan. The suggested technique shows improvements in PDR and energy efficiency with gains better results respectively, when compared to the Energy-Efficient Multiple Data Fusion.
Keywords: Multipath routing, Transform, cluster head selection,

1.INTRODUCTION

A network model known as wireless sensor networks, or WSNs uses networked sensors to work together to collect and distribute data via wireless communication channels. Sensors having sense, processing, and interaction abilities work together to jointly monitor environmental or physical conditions in these networks, which are distinguished by their distributed nature. Smart agriculture, industrial automation, surveillance, healthcare, and environmental monitoring are just a few of the fields in which WSNs are used. A router or sink node, a number of sensor nodes, and occasionally a central control unit make up the architecture of WSNs. Sensor nodes are used in many different fields, such as smart agriculture, industrial automation, surveillance, healthcare, and environmental monitoring. Energy efficiency is a major concern because these devices frequently serve in harsh and distant situations. WSNs use protocols and algorithms that are customised to each application domain in order to maximise usage of energy and network performance.

These networks deal with issues such fluctuating network topologies, communication limitations, and scarce energy supplies. While tackling these issues and meeting the many application requirements across various sectors and domains, researchers are always looking for novel ways to improve the effectiveness, dependability, and scalability of WSNs. A situation known as the "connection issue" occurs in WSNs when sensor nodes close to the base station (BS) are busier and transmit more packets than nodes farther away [9].

Reduced network endurance and early battery depletion can result from this uneven workload distribution. Supporting a variety of use cases within sensor networks requires merging data [12,13].

Network performance is capable of being considerably improved by getting rid of redundant data and using effective fusion algorithms. In a WSN, in-network data fusion is essential for enabling the energy-efficient transfer of information from several sensors towards a central sink.To increase the efficiency of the data transmission, adaptive cluster head selection is proposed. A diverse objective was introduced to find the nodes fitness value in order to determine.To improve packet delivery ratio migration aware data fusion is proposed.

The paper is organised as follows: An overview of relevant work is given in Section 2. The system model and the suggested algorithm are explained in Section 3. The suggested algorithm's performance is assessed in Section 4, and the paper is concluded with findings in Section 5.

2. RELATED WORK

Wang, M et al introduced a fully distributed iterative algorithm that gradually improves a network’s

lifetime vector, providing results at each step rather than after extensive computations.

Gupta, V.; Kailkhura, B et al proposed a mobility- and energy-aware clustering scheme for Mobile WSNs (MWSNs), where cluster head (CH) candidates are selected based on movement similarity, residual energy, and node density. This scheme also introduced a slot scheduling method to minimize idle time.

Zayyani, H.; Korki, M et al was among the first to offer a distributed, energy-efficient clustering mechanism, featuring periodic CH rotation to balance energy load. HEED, an improvement over LEACH presented in [19], incorporates communication costs and node density into CH selection but may result in an excessive number of CHs, causing unnecessary latency.

Heinzelman, et al proposed both centralized and distributed clustering approaches were evaluated based on residual energy and node density. These methods showed improved network lifetime but increased computational load in centralized scenarios. Overall, clustering strategies focused on energy-aware CH selection help distribute the load more evenly across nodes, reducing individual energy drain.

A correlation-based clustering method was proposed in [21], leveraging spatial and temporal data correlations to form a dominating set for fusion. Similarly, [22] introduced a tree-structured communication scheme for gathering correlated data, optimized to reduce transmission cost.

These studies highlight the need for a holistic solution that integrates adaptive clustering, mobility-awareness, and data compression to address the unique constraints of WSNs. The proposed algorithm fills this gap by offering a unified framework to improve energy efficiency, reliability, and network longevity.

3. PROPOSED METHODOLOGY

The proposed MCDC algorithm aims to optimize energy usage and data transmission efficiency in Wireless Sensor Networks (WSNs). It integrates three core components: adaptive clustering, in-network data fusion using compression techniques, and energy-efficient multi-path routing. Additionally, mobility models are incorporated to enhance performance and address the hot-spot issue near the base station (BS).

3.1 Network Model

The network consists of **N** uniformly capable sensor nodes randomly deployed in a two-dimensional area. Key assumptions in this model include:

1. All sensor nodes have identical hardware capabilities.
2. Each node communicates within a fixed radio range, independent of its sensing coverage.
3. Communication links are symmetric, and nodes can estimate distances using signal strength.
4. Nodes are not equipped with GPS or location-awareness mechanisms.

The MCDC algorithm operates in three main stages:

1. Cluster Head (CH) Selection
2. In-network Data Aggregation
3. Multi-path Routing to the Base Station

3.2 Cluster Head (CH) Selection

Clustering enhances scalability, enables efficient resource utilization, and minimizes energy consumption by reducing direct transmissions to the BS. In this method, nodes are grouped into clusters, each governed by a CH responsible for aggregating and forwarding data to the BS.

The clustering process includes two sub-phases: the setup phase (cluster formation and CH selection) and the steady-state phase (data transmission).

3.2.1 Clustering Mechanism

A distributed approach is used to form clusters. Each node independently decides whether to become a CH based on its residual energy and a probabilistic threshold. CHs manage the cluster communication schedule using Time Division Multiple Access (TDMA), while member nodes communicate with their CHs via single-hop transmission.

To avoid early energy depletion, CH roles are rotated periodically. This dynamic reassignment ensures even energy distribution and extends overall network lifetime.

3.2.2 CH Selection Process

In the first round, a node becomes a CH if a random number it generates falls below a threshold After the first round, nodes announce their residual energy, and those with the highest values are selected as CHs. CHs broadcast their status, and non-CH nodes respond with join requests. Once clusters are formed, each CH assigns a TDMA schedule for efficient communication.

3.2.3 Cluster Joining for Non-CH Nodes

Non-CH nodes listen for CH announcements for a time duration t1t_1t1, and then choose the best CH based on signal strength and proximity. After sending join requests, they receive their time slots within the TDMA schedule. This ensures synchronized, energy-efficient data transmission.

3.3 Data Aggregation

Each CH performs data aggregation to compress and consolidate information from its cluster members. This is achieved in three steps (Figure 3):

1. **Wavelet Transform :** Separates signal components to increase data correlation.
2. **Amplitude quantization.:** Reduces redundancy by discarding insignificant high-frequency data.
3. **Slepian-Wolf coding :** Compresses correlated data streams for transmission.

3.3.1 Wavelet Transform(WT)

WT is well-suited for WSNs due to its efficiency and support for integer-to-integer reversible transforms. Its key advantages include:

- In-place computation
- Compatibility with irregular data sampling
- Simplified implementation without Fourier transforms

LWT consists of:

- **Split Phase:** Divides data into even and odd sets
- **Prediction Phase:** Predicts odd values based on even values (for high-pass filtering)
- **Update Phase:** Adjusts even values using predicted values (for low-pass filtering)

This process can be repeated for multi-level transformation (Figure 5).

3.3.2 Amplitude quantization

After WT, scalar quantization nullifies minor high-frequency components

3.3.3 Slepian-Wolf coding (SWC)

SWC allows independent compression of correlated sensor data without node-to-node communication. It reduces bandwidth, energy usage, and transmission collisions by offloading decoding complexity to the BS. SWC assumes:

- Strong correlation among sensor data
- Availability of statistical correlation models
- Synchronized data capture and transmission

Based on the Slepian–Wolf theorem, correlated sources can be separately encoded but jointly decoded with no performance loss.

3.4 Multi-Path Routing

After fusion, CHs forward compressed data to the BS using multi-path routing to avoid bottlenecks and improve reliability.

Routing Phases:

1. **Initialization:** CHs send HELLO messages to build neighbor tables and estimate hop distances.
2. **Primary Path Discovery:** The BS sends route requests (RREQs) through optimal paths based on a cost function (e.g., hop count).
3. **Alternative Path Discovery:** Backup routes are established to ensure data delivery if the primary path fails.-

The path with the least number of hops is selected as the primary route, with others as failover options (Figure 8).

3.5 Mobility Models

Mobility models are integrated to evaluate the algorithm's robustness and to balance load distribution, addressing the hot-spot issue.

3.5.1 Random Waypoint Model (RW)

Each node randomly selects a destination and moves toward it at a random speed between 0 and VmaxV_{max}Vmax. Upon arrival, it pauses for a set duration before selecting a new destination. This continues throughout the simulation.

3.5.2 Reference Point Group Mobility Model (RPGM)

In this model, nodes move in groups. Each node's speed and direction deviate slightly from a group leader's path, controlled by:

- **Speed Deviation Ratio (SDR)**
- **Angle Deviation Ratio (ADR)**

4.SIMULATION RESULTS AND DISCUSSION

To evaluate the performance of the proposed MCDC algorithm, simulations were conducted using the NS2 network simulator. A range of metrics—such as packet delivery ratio (PDR), network lifetime, average energy consumption, and average delay—were measured and compared against existing algorithms. Two mobility models, Random Waypoint (RW) and Reference Point Group Mobility (RPGM), were used to assess the impact of mobility on performance

4.1 Packet Delivery Ratio(PDR)

It states a proportion of delivered packets to the number of packets transmitted over the wireless network.

$$\text{Packet Delivery ratio} = \frac{Total\ number\ of\ Packets\ received}{otal\ number\ of\ Packets\ Sent} * 100 \quad (3.1)$$

The aggregate amount of packets transmitted and obtained by a network is displayed by the packet delivery rate. Table 4.1 shows the comparative analysis of the Packet Delivery ratio of proposed MCDC with existing method LEACH and EMDF.

Table 4.1 Comparison of Packet Delivery Ratio

Methods	Number of Nodes				
	100	200	300	400	500
MCDC	93	90	88	85	81
EMDF	85	80	76	74	71
LEACH	80	76	73	70	67

Table 4.1 exhibits the packet delivery ratios of Proposed MCDC and existing methods obtained by varying the range of nodes from 100 to 500.As demonstrated in the Table 4.1 the PDR of MCDC is 93%, which is higher than the PDR of EMDF and LEACH, which are 85% and 80%,

correspondingly when the number of node are 100 in network. From the analysis the Proposed MCDC attain maximum packet delivery ratio than the Existing methods.

METHODS	Number of Nodes				
	00	00	00	00	00
MCDC	.5	.5	.2	0.2	1.0
EMDF	.2	.7	0.1	0.8	1.8
LEACH	.9	.3	0.5	1.5	2.5

4.2 Energy Consumption

It is the total energy that is used on average by the entirety of its nodes during the duration of different transmission levels.

Energy Consumption=$\{\sum_{m=1} CH_i(m) + \sum_{m=1} CM_i(m)\}$ (3.2)

A key indicator that may increase the functionality of the network is energy consumption. Table 4.2 shows the comparative analysis of the Energy consumption of proposed PCHS-EAR with existing method LEACH and DEE.

Table 4.2 Comparison of Energy Consumption

METHODS	NUMBER OF NODES				
	00	00	00	00	00
MCDC	.35	.42	.49	.55	.70
MDF	.63	.72	.78	.81	.85
LEACH	.75	.79	.83	.88	.0

Table 4.2 reveals the energy consumption analysis of the proposed MCDC with existing method LEACH and EMDF.As demonstrated in the Table 4.2, the Energy consumption of MCDC is 0.35 joule which is lower than the Energy consumption for EMDF and LEACH, which are 0.63 joule and 0.75 joule respectively when the number of node are 100 in network. By using efficient head node selection in data accumulation, the proposed MCDC lessens energy consumption. The energy consumption of the network is substantially reduced by the proposed methods. From the Table 4.2 unveils, the Proposed MCDC obtain minimum energy consumption compared to the Existing method.

4.3 Network Lifetime

It is used for calculating the duration a packet ought to take to move through sender to recipient in the WSN.

Network Lifetime=$min_{ij} \frac{(\sum_{i=1} CO_{ij} * L_i)}{N_m}$ (3.3)

Network lifetime persists as an essential concern that utilizes to improve network processing. Table 4.3 illustrates the comparative analysis of the Network Lifetime of proposed MCDC with existing method LEACH and EMDF.

Table 4.3 Comparison of Network Lifetime

METHODS	NUMBER OF NODES				
	00	00	00	00	00
MCDC	170	109	010	50	27
MDF	103	093	84	35	47
LEACH	085	032	52	96	34

Figure 4.8 portrays the result analysis of Network Lifetime of MCDC,EMDF and LEACH with respect to the varying range of nodes. As illustrated in Figure 4.8 clearly shows that network Lifetime of the Proposed MCDC is 1170 seconds which is sophisticated the than the lifetime of the existing EMDF and LEACH which are 1103 seconds 1085 seconds respectively when the number of node are 100 in network.. Hence, it is evidenced that the Proposed MCDC has the maximum network lifetime then the existing methods EMDF and LEACH.

4.4 End to End delay

The amount of time needed for data sensed to travel from the data node's source to the node of destination is known as the delay.

End to End Delay= $\frac{\sum_{i=1}^{n} t_{ri} - t_{si}}{n}$ (3.5)

Delay is the period of time a data packet takes for it to proceed from its source node to its destination node, with regard to terms of sending and receiving. Table 4.5 reveals the comparative analysis of the End to End delay Performance.

Table 4.4 Comparison of End to End Delay

Table 4.5 Portrays the comparative results of Proposed MCDC and Existing EMDF and LEACH method obtained by varying range of nodes 100 to 500.Figure 4.10 clearly depicts that the End

to End delay of MCDC rarer than the existing EMDF and LEACH. As illustrated in figure 4.7 End to End Delay of MCDC is 7.5 seconds which is lesser than EMDF and LEACH whose End to End Delay values are 8.2 seconds and 8.9 seconds appropriately when a total of 100 nodes in the network. Hence, it is evidenced that the MCDC has the minimal delay than the Existing methods EMDF and LEACH.

5. Conclusion

This paper presented the MCDC algorithm, a comprehensive solution designed to enhance energy efficiency, improve packet delivery ratio (PDR), and extend network lifetime in Wireless Sensor Networks (WSNs). The Proposed approach integrates three key components: novel clustering based on residual energy, mobility-aware connection mitigation using the Random Positioning Grid Mobility model, and a three-stage data aggregation mechanism employing the Wavelet Transform, Amplitude quantization, and Slepian-Wolf coding Additionally, comparative analysis against EMDF and LEACH protocols highlighted MCDC superior residual energy management, confirming its scalability and adaptability across diverse WSN applications.Overall, the proposed MCDC algorithm offers a promising framework for achieving energy-aware, mobility-resilient data fusion in future WSN deployments.

6. Future Work

Building on the findings and results of this study, several avenues for future research are suggested:

1. **Dynamic Parameter Optimization:** Future work could explore real-time adaptation of MCDC parameters, such as CH election thresholds and mobility model settings, using machine learning techniques to further optimize energy use under changing network conditions.
2. **Heterogeneous WSNs:** This work assumed homogeneous node capabilities. Expanding MCDC to accommodate heterogeneous nodes (different energy levels, transmission ranges, or processing capabilities) could improve its practical applicability.
3. **Security Enhancements:** Data aggregation and multi-path routing are susceptible to security threats such as node compromise and data tampering. Future versions of MCDC could incorporate lightweight security measures like encryption or authentication protocols.

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