

Improving the performance of wireless sensor network using multi-hopping clustering partition

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ABSTRACT

Wireless sensor networks (WSNs) enable large-scale event monitoring; however, their performance is often constrained by low throughput. This study aims to develop a cluster-based routing protocol by implementing the multi-hopping clustering partition (MHCP) method. The MHCP process consists of three main stages: (i) cluster head (CH) selection, (ii) evaluation of node proximity to their respective CHs, and (iii) cluster partitioning to reduce intra-cluster variation. Four clusters were formed and interconnected through multi-hop communication, achieving throughput values of 142.0033, 244.1318, 119.0804, and 305.6159, respectively. In addition to the development of MHCP, the scientific contribution of this study is strengthened through the integration of the LEACH protocol and the K-means algorithm as a complementary methodological approach. LEACH improves energy efficiency through adaptive CH rotation, while K-means optimizes spatial node grouping. The combination of these methods ensures a balance between energy consumption and spatial proximity, resulting in improved throughput and extended network lifetime. Experimental results demonstrate that the proposed MHCP protocol achieves higher throughput than the conventional LEACH protocol across all clusters while maintaining acceptable delay and packet loss. These findings confirm that the integration of multi-hop communication and cluster partitioning effectively enhances data transmission efficiency and overall network performance in WSNs.

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1. INTRODUCTION

The main challenge in wireless sensor networks (WSNs) lies in low throughput caused by unbalanced cluster formation and inefficient data communication paths. Cluster-based routing mechanisms, exemplified by LEACH, often result in considerable internal cluster dispersion between cluster heads (CHs) and cluster members (CMs), thereby increasing communication latency and amplifying the likelihood of information degradation or packet loss. On the other hand, existing multi-hop and multi-channel approaches primarily focus on energy efficiency and channel utilization, without explicitly minimizing data variation and intra-cluster distance. As a result, WSN performance remains suboptimal, particularly in supporting high-speed and reliable data transmission requirements. The organization of this article is outlined in the sections that follow. Section 2 presents the proposed multi-hopping clustering partition (MHCP) method, including CH formation, distance calculation, and partitioning process. Section 3 describes the simulation setup and

evaluation metrics. Section 4 discusses the experimental results and compares the proposed MHCP protocol with existing routing schemes. Section 5 provides the closing synthesis of the work and identifies directions for forthcoming scholarly inquiry. The advancement of information technology (IT), particularly in the field of microprocessors, has enabled the support of a broad range of human activities, including healthcare, environmental monitoring, and military operations [1]. Ongoing technological advancements have led to the creation of highly efficient and compact microprocessors, facilitating the development of small computer devices with diverse functions [2]. Among the emerging technologies, WSN has gained significant attention [3]. WSN facilitates the observation of events and phenomena across vast areas through compact sensor node computer devices and wireless communication methods [4]. The development of data transmission media yearly has led to improvements in various functions, including transmission speed and performance on WSN [5]. WSN is one of the recent data transmission technology that allows for the transmission of sensor data with minimal power consumption [6]. Multiple nodes utilize WSN to collect information on various phenomena, such as changes in temperature, light intensity, and heat. The data collected by sensor nodes is transmitted to sinks through query responses using specific routing protocols [7]. Once the data arrives at the sink, it can be processed or stored in the data center [8]. Within a WSN, sensor nodes communicate with nearby nodes for routing purposes and data transmission, employing short-range radio waves [9]. WSN technology is commonly used to monitor environmental conditions and other applications in the current era [10]. In addition to environmental monitoring, WSN technology is widely applied in the agricultural sector and smart cities [11]. Good WSN performance is essential to optimize performance in smart agriculture and cities and achieve desirable results [12]. The performance of a WSN depends on factors such as transaction speed between nodes [13]. One approach to enhancing WSN performance is through routing algorithms [14]. An example of such an algorithm is the low-energy adaptive clustering hierarchy (LEACH), which involves creating CH to collect data from CM and follows a well-defined protocol [15]. However, one limitation of LEACH is the potential formation of poorly structured clusters, where CH and CM positioned far apart can lead to suboptimal performance [16].

To address this limitation, previous studies have improved the LEACH method by incorporating a distance parameter, which allows for selecting the closest CH to the sink in its multiple scenarios. To address the stray node issue in this study, a multi-hopping communication model with the shortest path routing (SGR) was implemented [17]. However, energy efficiency was not a primary concern in addressing multiple CH or stray node problems [18]. Another method utilized to improve WSN performance is the multi-channel model, which aims to reduce traffic density by utilizing multiple protocol channels [19]. In this model, CH serves as a reference channel for CM [20]. Although widely employed, the Multi-Channel model faces challenges such as the formation of distant CH and CM, resulting in increased energy consumption for transactions [21]. The multi-channel model reduces energy consumption and server burden by sending data only to CH, which then forwards it to the sink. However, the model also faces challenges when forming CH and CM, especially when they are located far from each other, which can result in hampered data transactions requiring substantial energy consumption. Despite extensive studies on clustering-based routing protocols such as LEACH and its variants, several fundamental challenges remain unresolved, particularly related to low throughput, inefficient cluster formation, and suboptimal data forwarding paths. Existing approaches often suffer from large intra-cluster distance between CHs and CMs, which leads to increased transmission delay and data loss. Moreover, conventional multi-hop and multi-channel routing schemes tend to focus on energy efficiency or channel utilization independently, without explicitly minimizing data variation within clusters. This research addresses these limitations by proposing a MHCP protocol that systematically integrates cluster partitioning and multi-hop routing to enhance throughput performance in WSN.

2. LITERATURE REVIEW

Several studies have developed a multi-channel model by integrating the clustering process, referred to as multi-channel clustering hierarchy (MCCH). This model consists of four stages. Firstly, the data is determined in terms of temperature and humidity. Secondly, CH is formed, thirdly, the proximity between CH and CM is established, and finally, the clustering process is implemented using a single linkage [22]. MCCH model has shown the potential to improve the performance of WSN [23]. Another strategy to optimize WSN efficiency involves a multi-hop scheme, whereby individual sensor nodes operate as forwarding intermediaries, relaying data incrementally to the base station and subsequently to the sink [24], [25]. Unlike the multi-channel model that divides channels, this model involves each node communicating with one another to send data [26]. In this study, the model utilized to improve the performance of WSN is multi-hopping [27]. To develop this model, a clustering process that grouped WSN nodes by partitioning and connecting them to CH was incorporated. This study is a theoretical development in the field of WSN, and it is the first of its kind [28]. Its novelty contribution is in the form of minimizing data variations within a cluster.

Figure 1 shows the topological design where each blue sensor node can act as a relay station in the chain that forwards data packets to the base station [29]. The base station then collects and analyzes the activities that have been performed. After that, the control station reads and analyzes the data for specific purposes [30], [31].

Figure 2 illustrates the clustering partition process, which includes the initial clustering, iterative process, and final clustering stages [32]. Figure 2(a) shows the initial grouping of sensor nodes into preliminary clusters. Figure 2(b) presents the iterative process where CM and centroid positions are updated. Figure 2(c) shows the final clustering result after the clusters become stable. In the partitioning clustering technique, a cluster center point (centroid) is determined. In this study, the centroid is represented by the CH, which collects data from CM [33]-[34]. This study aims to develop a WSN protocol that improves network performance by integrating multi-hopping and clustering partition techniques.

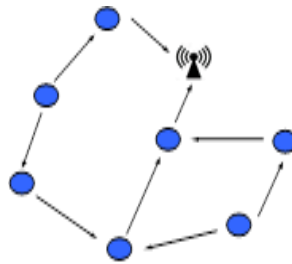


Figure 1. Multi-hopping routing network topology design

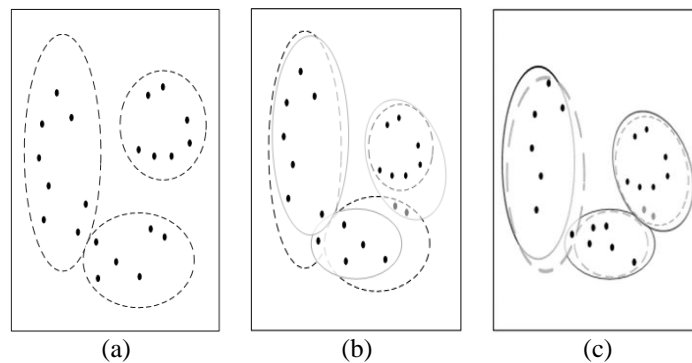


Figure 2. Partition clustering process; (a) first cluster, (b) iteration process, and (c) final cluster

The main contribution of this study lies in the development of an MHCP protocol that explicitly minimizes data variation within clusters while improving throughput performance in WSNs. Unlike conventional LEACH-based routing, which relies on probabilistic CH selection and may result in poorly structured clusters, the proposed MHCP integrates three key mechanisms: (i) adaptive CH formation inspired by LEACH, (ii) Euclidean distance-based proximity optimization between CH and CM, and (iii) clustering partition using a K-means-based approach to reduce intra-cluster variation. In contrast to existing MCCH and traditional multi-hop routing schemes, MHCP focuses on spatial optimization and cluster compactness rather than channel division alone. This integration provides a new routing perspective that balances data transmission efficiency and network performance, thereby offering a distinct methodological contribution to WSN routing protocol design.

3. METHOD

3.1. Multi-hopping clustering partition

The MHCP is a protocol developed for WSN that can address the low-performance issues regarding data loss and significant delays on WSN. The MHCP method improves WSN performance in three stages. These include forming CH as a reference for CM to send data, the determination of the proximity of nodes to CH, and grouping nodes using the partitioning technique.

3.2. Simulation environment and dataset description

The performance evaluation of the proposed MHCP protocol was conducted using a simulation environment developed in MATLAB. The simulated WSN consists of 100 sensor nodes randomly distributed within a two-dimensional area of 300×300 units. Each node is initialized with an energy level of 100 units, and the network operates with a predefined transmission velocity of 10,000 units. The dataset used in this study is synthetically generated through simulation and represents spatial node distribution and sensor data transmission behavior commonly adopted in WSN performance evaluation. This simulation-based dataset allows controlled analysis of throughput, delay, and packet loss under identical network conditions for fair comparison with LEACH and MCCH protocols.

To ensure a fair and controlled performance evaluation, the simulation environment and network configuration parameters are predefined and summarized in Table 1. These parameters describe the number of sensor nodes, initial energy, network area dimensions, and transmission velocity used throughout the experiments.

The MHCP method, as shown in Figure 3, consists of three stages. The first stage involves the formation of a CH ad that serves as a reference for CM. The second stage is the formation of proximity between CH and members. The third stage is the grouping process with the partitioning technique.

Table 1. Simulation parameters

Parameter	Value
Number of nodes	100
Energy	100
Xmax	300
Ymax	300
Velocity	10,000

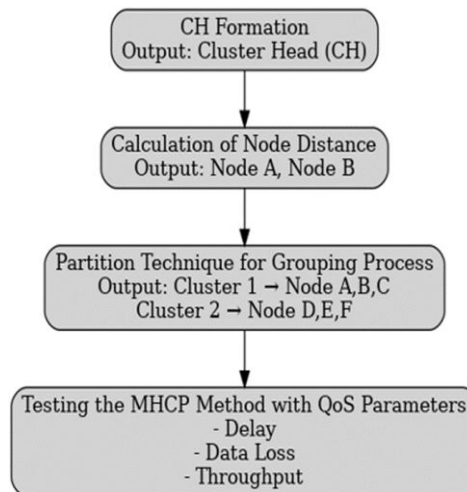


Figure 3. The MHCP method

3.3. Formation OF CH

In this stage, CH formation is performed using a random probability method that is divided into multiple sessions based on the desired number of CH and observation period. Each node is made CH for a session to ensure equal distribution. The position of CH is made unstable or alternating to create dynamic formation or changes in each session.

$$T(n) = \begin{cases} P \\ 0^{-P \times (r \bmod \frac{1}{P})} \end{cases} \quad (1)$$

$T(n)$, which is the Threshold per round node, becomes CH when $m > T(n)$. P , R , N , and G denote the applied CH probability, round, node in the form of a group, and nodes that have not yet become CH. For CH selection in Algorithm 1.

Algorithm 1. CH selection algorithm

```

Input  : N          total node
        CH         total CH
        X          the length of the map
        Y          the width of the map
        array [nodes] group of all node
Output : array [nodes] , a collection of filtered nodes
nodes ∈ N/CH
for i in CH:
    X0 = generate random value from 0 to X
    Y0 = generate random value from 0 to Y
    For j in range(len(nodes)):
        find min distance of node(x,y) to X0,Y0
        if found:
            Append to CH
            break
    
```

3.4. Distance calculation of each node and ch

The second stage involves finding the nodes closest to CH. The spatial gap between individual nodes and the CH is obtained through the Euclidean distance computation. This approach serves as a geometric measure to evaluate positional disparity or closeness between two coordinate points. During this phase, the primary output is the calculated Euclidean value linking each node to its adjacent nodes. In a two-dimensional coordinate system, the distance between two nodes defined by (x1, x2) and (y1, y2) follows the conventional Euclidean expression (Algorithm 2).

$$d(x_2, x_1) = \sqrt{\sum_{j=1}^d (x_2, x_1)^2} \tag{2}$$

D, X1, X2, Xij, and X2J denote the node point, X axis (CH), Y axis, X axis number (CH), and Y axis number.

Algorithm 2. Algorithm calculation of the distance of each node and CH

```

Input  : n1(x,y)      x dan y at node1
        n2(x,y)      x dan y at node 2
        X            the length of the map
        Y            the width of the map
Output : distance    distance from node1 and node2
    
```

3.5. The process of grouping with partition techniques

The third stage involves an iterative grouping process that partitions the dataset into K clusters predetermined from the start. Each node is assigned a cluster ID, and the dissimilarity between each centroid and data point is calculated. The cluster with the smallest dissimilarity is selected for data relocation in an iteration, and the relocation of data in the cluster is expressed by a membership value of 0 or 1, indicating the membership status of each observation within a given cluster. The clustering procedure defines K as the predefined cluster count and employs a selected distance metric to map observations to their nearest centroid. Afterward, centroid coordinates are recalculated based on the current cluster composition, and the iterative cycle continues until stability or convergence is achieved. The centroid is then recalculated based on the data that follows each cluster, and the process is repeated until convergent conditions are met. These include (a) a change in the objective function is below the desired threshold or (b) there are no data moving clusters, or (c) a change in centroid position is below the set threshold. Only one cluster has a membership value of 1, while the others have a value of 0 for each data point. This process is calculated using (3).

$$a_{ij} = \begin{cases} 1 & \text{arg min } \{d(x_i, c_j)\} \\ 0 & \text{others} \end{cases} \tag{3}$$

d(x_i,c_j) expresses the dissimilarity (distance) of the data i to cluster c_j

In determining the centroid, point C is obtained by calculating the average of each feature from all data belonging to each cluster. The average feature of all data in a cluster is expressed in (4).

$$c_j = \frac{1}{NK} \sum_{i=1}^{NK} x_{jl} \tag{4}$$

NK is the amount of data that is joined in a cluster. This process is carried out by choosing the closest cluster and minimizing the objective/non-negative cost function, as shown in (5).

$$J = \sum_{i=1}^N \sum_{j=1}^k a_{ij} d(X_i, C_j) \quad (5)$$

The process of minimizing the total squared distance between each point X_i and the nearest C_j cluster representation.

From a physical perspective, minimizing the Euclidean distance between CH and CM reduces transmission power requirements and propagation delay, which directly impacts throughput and packet delivery reliability. The clustering partition mechanism ensures that nodes within the same cluster exhibit lower spatial dispersion, thereby reducing data variation and congestion during multi-hop forwarding. Consequently, the MHCP protocol improves network performance by aligning routing decisions with physical distance constraints inherent in wireless communication.

4. RESULTS AND DISCUSSIONS

Figure 4 shows the MHCP protocol model that addresses the issue of low WSN performance through three stages. The first stage involves the formation of CH, where CH serves as a reference for CM. The second stage focuses on determining the proximity of nodes to their respective CH. Finally, the third stage partitions the nodes into K clusters and relocates them iteratively based on their dissimilarity and membership value. In the discussion of the first step, the number of K is determined as a constant variable, and the centroid of K is chosen randomly. The second step involves finding the closest centroid to each node in the cluster using distance calculations. The shortest distance to the centroid is calculated for each node, and the total distance from all nodes to the centroid is determined. This step is repeated iteratively, and the fitness value is calculated. The fitness value is defined as 1 divided by the mean distance from the node to the centroid plus 1. When the fitness value increases, the latest solution is accepted, and the newest centroid is used as a reference for the next random generation. The K-means clustering algorithm (Algorithm 3) is likely to stop when the value of d_n does not change for 5 iterations, thereby indicating the optimal point.

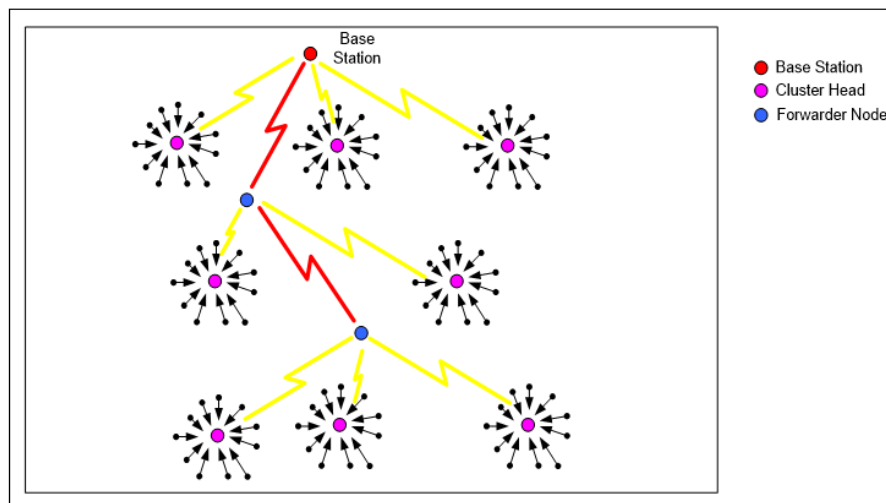


Figure 4. The MHCP protocol models

MATLAB was used to implement the MHCP protocol, as shown in Figure 5. In this protocol, each CM is linked to CH, and the clusters are interconnected using multi-hopping techniques. To highlight the contribution of the proposed MHCP protocol, a comparative analysis with existing routing protocols is presented in Table 2. The comparison focuses on clustering strategy, multi-hop capability, channel model, throughput performance, and inherent limitations of each method.

Algorithm 3. MHCP algorithm

```

Input : n (x, y)           the positions of the nodes in x and y form
       sensor_value      the value of the sensor reading carried by the node
       X                 the length of the map
       Y                 the width of the map
       F (x, y)          function of measuring the distance between nodes

```

```

Tot_node      total node
N             total CH
Output : clusted_head
Node_hop nodes that are connected between clusters
Generate random centroid C(x,y) = r[x1-x2]
nodes ∈ []
I = 0
While True:
    Find distance of all nodes
    Find minimum distance and node
    Append to array nodes
While true:
    Initiate x & y as max map
    Initiate random position of CH
    While true:
        Measure the minimum distance of the node and CH
        Generate new CH

I += 1
If I == tot_node:
    Break
    
```

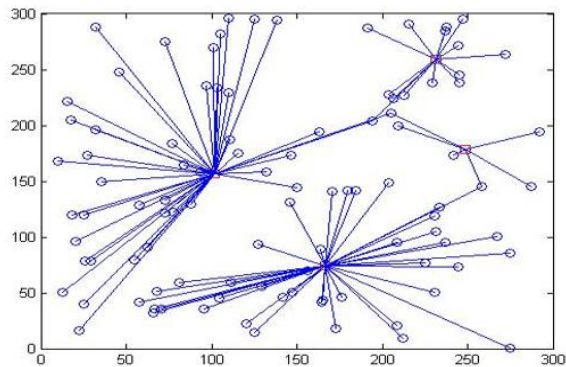


Figure 5. The MHCP protocol

Table 2. Comparison of MHCP with existing routing protocols

Method	Clustering	Multi-hop	Channel model	Throughput performance	Main limitation
LEACH	Yes	No	Single	Low-moderate	Poor cluster structure
MCCH	Yes	Yes	Multi-channel	High	High energy consumption
Multi-hop LEACH	Yes	Yes	Single	Moderate	No partition optimization
MHCP (Proposed)	Yes	Yes	Single	Improved	Simulation-based

4.1. Throughput

Throughput refers to the amount of data that a node can transmit or receive within a specified time interval. It provides insight into the data rate of a network and can be used as a performance metric for routing protocols. A higher throughput value typically indicates better protocol performance.

$$Throughput = \frac{\text{number of packets sent}}{\text{package delivery time}}$$

4.2. Packet loss

Packet loss is determined by comparing the number of unsuccessfully delivered packets to the overall quantity of packets transmitted from the source node to the destination within a network, usually expressed as a ratio or percentage. It occurs when one or more transmitted data packets do not successfully arrive at their designated destination.

$$Packet\ loss = \frac{\text{packets that experience loss}}{\text{package sent}}$$

4.3. Delay

Delay is the time required for data to travel from the source node to the destination node.

Delay = delivery time – reception time

Figure 6 illustrates the delay performance of the proposed MHCP protocol across different communication channels. The horizontal axis represents the channel index used in the multi-hop transmission process, while the vertical axis indicates the average delay measured in seconds. As shown in Figure 6, the delay performance varies across channels 1 to 4. Channel 2 exhibits the lowest delay value, indicating a more efficient data forwarding path, while Channel 3 shows the highest delay due to longer transmission paths or higher relay load. This variation confirms that channel selection and multi-hop routing structure significantly influence end-to-end delay in the MHCP protocol.

Figure 7 presents the packet loss performance of the proposed MHCP protocol across different communication channels. The horizontal axis represents the channel index, while the vertical axis indicates the packet loss rate observed during data transmission. As illustrated in Figure 7, Channel 2 experiences the highest packet loss rate, indicating a higher probability of packet drops due to congestion or longer multi-hop paths. In contrast, Channel 3 exhibits the lowest packet loss, suggesting a more stable communication path. These results indicate that the distribution of traffic across channels significantly affects packet delivery reliability in the MHCP protocol. Figure 8 illustrates the throughput performance of the conventional LEACH routing protocol across different communication channels. The horizontal axis represents the channel index, while the vertical axis indicates the achieved throughput measured in kilobits per second (kbps).

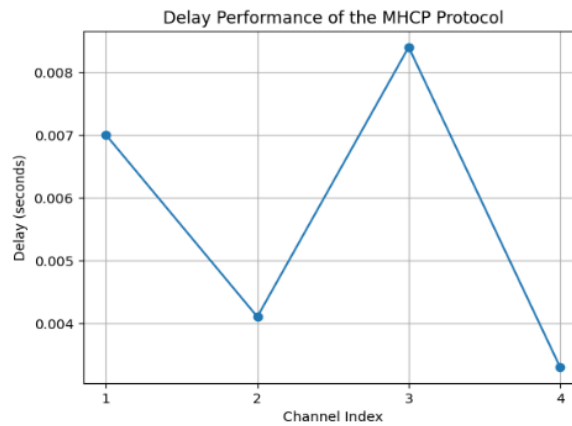


Figure 6. Delays

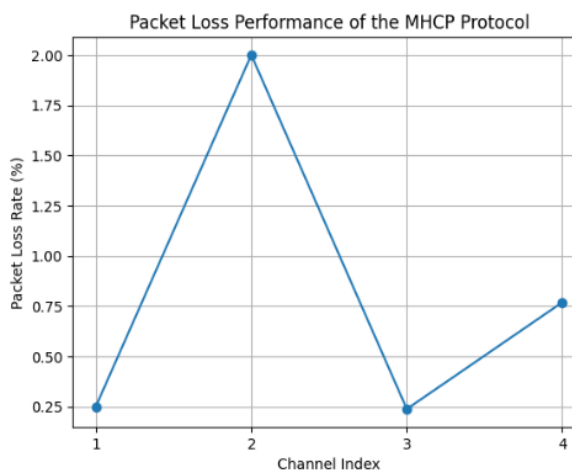


Figure 7. Data loss

As shown in Figure 8, the throughput achieved by the LEACH protocol varies significantly across channels. Channel 4 exhibits the highest throughput, while Channels 1 and 3 show relatively lower values.

This variation indicates that LEACH performance is highly dependent on cluster formation and transmission paths, which may result in unbalanced data forwarding and reduced throughput efficiency in certain channels. Figure 9 illustrates the throughput performance of the MCCH protocol across different communication channels. The horizontal axis represents the channel index, while the vertical axis indicates the achieved throughput measured in kbps.

As shown in Figure 9, the MCCH protocol achieves significantly higher throughput compared to the conventional LEACH protocol across all channels. Channel 4 records the highest throughput, while Channel 2 exhibits the lowest value. This improvement is mainly attributed to the utilization of multiple channels, which reduces traffic congestion and improves parallel data transmission. However, the high throughput in MCCH is achieved at the expense of increased energy consumption and channel management complexity. Figure 10 illustrates the throughput performance of the MHCP protocol across various communication channels. The horizontal axis represents the channel index, while the vertical axis indicates the achieved throughput measured in kbps.

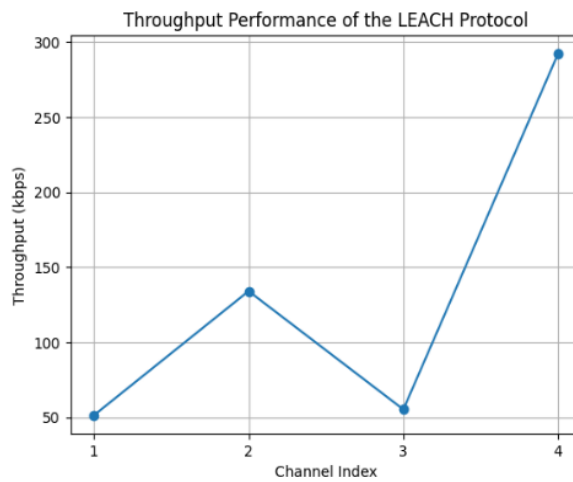


Figure 8. The LEACH throughput

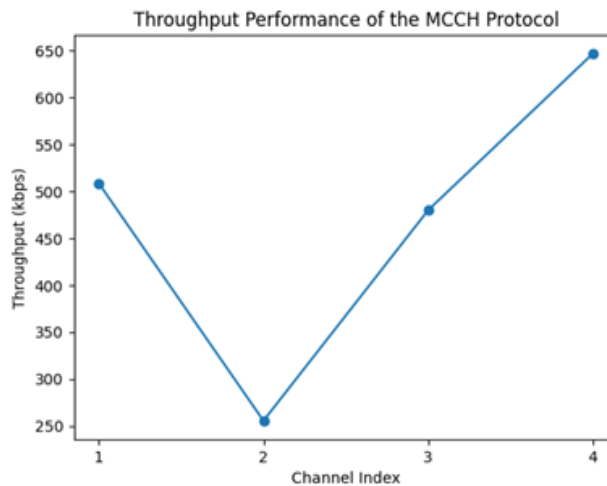


Figure 9. MCCH throughput

As shown in Figure 10, the proposed MHCP protocol achieves stable and improved throughput across all channels. Channel 4 records the highest throughput, while Channel 3 exhibits a relatively lower value due to longer multi-hop transmission paths. Compared to the conventional LEACH protocol, MHCP demonstrates a significant throughput improvement by optimizing cluster partitioning and reducing intra-cluster distance. Although MCCH achieves higher absolute throughput, MHCP offers a more balanced performance by avoiding excessive energy consumption and complex channel management, making it more suitable for energy-constrained WSN.

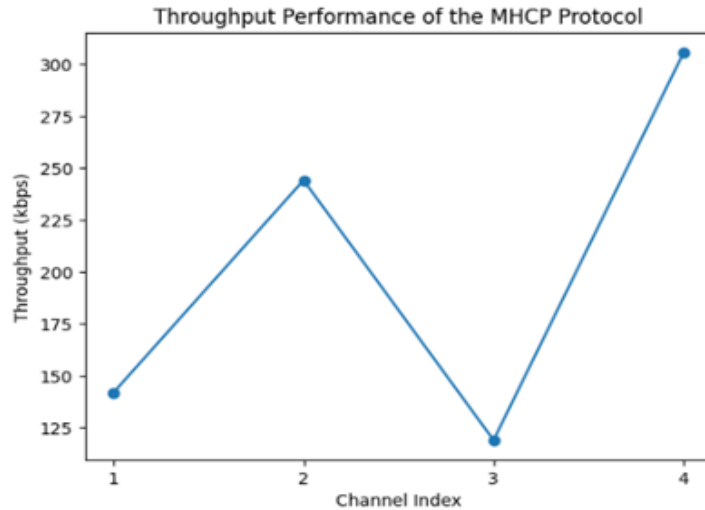


Figure 10. The MHCP throughput

5. DISCUSSION

This research seeks to enhance of WSNs by developing protocols using the MHCP method, a clustering technique designed to improve WSN performance for optimal results. The MHCP method comprises three stages: (i) forming CH as a reference for CM to transmit data, (ii) determining the proximity of nodes to the CH, and (iii) grouping nodes using a partitioning technique to mitigate transmission latency and packet loss. The primary contribution of this study lies in the development of a clustering method that brings CH and CM nodes closer together, optimizing the grouping process, and minimizing data variation within clusters.

To evaluate the performance of the MHCP method, The test data was simulated using MATLAB, with 100 nodes, energy of 100, Xmax of 300, Ymax of 300, and velocity of 10,000. The MHCP method was compared to the LEACH method, and the results showed that the MHCP method outperformed the LEACH method in terms of throughput values. The LEACH algorithm had throughput values of 51.2229, 134.0570, 55.1937, and 292.4273 for clusters 1, 2, 3, and 4, respectively. Meanwhile, the MHCP method had a throughput of 142.0033, 244.1318, 119.0804, and 305.6159 for clusters 1, 2, 3, and 4. These results demonstrate that the MHCP method has a higher throughput value compared to the LEACH algorithm, indicating better performance. The performance of the MHCP method was evaluated by comparing it with other similar studies that used the MCCH method to analyze performance. The simulations were performed using the same parameters, but the results differed. The throughput values for MCCH method were 508.5165, 255.5661, 479.8289, and 646.5618 for channels 1, 2, 3, and 4. On the other hand, the throughput values for the MHCP method in clusters 1, 2, 3, and 4 were 142.0033, 244.1318, 119.0804, and 305.6159. Based on this analysis, the MCCH method outperforms the MHCP.

6. CONCLUSIONS

In conclusion, the MHCP method was employed in the development of a WSN protocol, specifically by modifying the routing protocol to divide the network into clusters using a partitioning technique with CH as the reference channel. The selection of CH involved randomly choosing 100 nodes based on a probability formula and designing their distances from CM using the Euclidean approach. This design ensured efficient data transactions between CH and CM while conserving energy. The grouping process was carried out by selecting certain population components as initial cluster centers and classifying each component to the nearest cluster center based on the minimum distance. The position of the cluster center was recalculated iteratively until all data components were appropriately classified at each cluster center, resulting in the formation of new cluster center positions. This study combined three algorithms, namely the LEACH algorithm for CH formation, Euclidean distance calculation for positioning CH and CM closer together, and the K-means algorithm for the clustering process. The evaluation of the MHCP method yielded notable results. Cluster 1 achieved a throughput value of 142.0033, Cluster 2 had 244.1318, Cluster 3 showed 119.0804, and Cluster 4 exhibited the highest throughput value of 305.6159. These results demonstrate the effectiveness of the MHCP method in optimizing the throughput values within the formed clusters.

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REFERENCES

- [1] A. Dardar *et al.*, "Photovoltaic energy generation systems monitoring and performance optimization using wireless sensors network and metaheuristics," *Sustainable Computing: Informatics and Systems*, vol. 35, p. 100684, Sep. 2022, doi: 10.1016/j.suscom.2022.100684.
- [2] V. Rajpoot *et al.*, "Analysis of machine learning based LEACH robust routing in the Edge Computing systems," *Computers and Electrical Engineering*, vol. 96, p. 107574, Dec. 2021, doi: 10.1016/j.compeleceng.2021.107574.
- [3] Y. Mekonnen, S. Namuduri, L. Burton, A. Sarwat, and S. Bhansali, "Review-machine learning techniques in wireless sensor network based precision agriculture," *Journal of The Electrochemical Society*, vol. 167, no. 3, p. 037522, Jan. 2020, doi: 10.1149/2.0222003jes.
- [4] S. Jaiswal and M. S. Ballal, "Fuzzy inference based irrigation controller for agricultural demand side management," *Computers and Electronics in Agriculture*, vol. 175, p. 105537, Aug. 2020, doi: 10.1016/j.compag.2020.105537.
- [5] R. Ramya and D. T. Brindha, "A comprehensive review on optimal cluster head selection in WSN-IoT," *Advances in Engineering Software*, vol. 171, p. 103170, Sep. 2022, doi: 10.1016/j.advengsoft.2022.103170.
- [6] Y. Gong, J. Wang, and G. Lai, "Energy-efficient Query-driven clustering protocol for WSNs on 5G infrastructure," *Energy Reports*, vol. 8, pp. 11446–11455, Nov. 2022, doi: 10.1016/j.egyr.2022.08.279.
- [7] M. N and V. S., "Hierarchical autoregressive bidirectional least-mean-square algorithm for data aggregation in WSN based IoT network," *Advances in Engineering Software*, vol. 173, p. 103275, Nov. 2022, doi: 10.1016/j.advengsoft.2022.103275.
- [8] S. Ali and R. Kumar, "Hybrid energy efficient network using firefly algorithm, PR-PEGASIS and ADC-ANN in WSN," *Sensors International*, vol. 3, p. 100154, 2022, doi: 10.1016/j.sintl.2021.100154.
- [9] P. Maheshwari, A. K. Sharma, and K. Verma, "Energy efficient cluster based routing protocol for WSN using butterfly optimization algorithm and ant colony optimization," *Ad Hoc Networks*, vol. 110, p. 102317, Jan. 2021, doi: 10.1016/j.adhoc.2020.102317.
- [10] R. P. Mahapatra and R. K. Yadav, "Descendant of LEACH based routing protocols in wireless sensor networks," *Procedia Computer Science*, vol. 57, pp. 1005–1014, 2015, doi: 10.1016/j.procs.2015.07.505.
- [11] Moorthi and R. Thiagarajan, "Energy consumption and network connectivity based on Novel-LEACH-POS protocol networks," *Computer Communications*, vol. 149, pp. 90–98, Jan. 2020, doi: 10.1016/j.comcom.2019.10.006.
- [12] B. Cantoni, A. C. Riguzzi, A. Turolla, and M. Antonelli, "Bisphenol A leaching from epoxy resins in the drinking water distribution networks as human health risk determinant," *Science of the Total Environment*, vol. 783, p. 146908, Aug. 2021, doi: 10.1016/j.scitotenv.2021.146908.
- [13] A. Salim, W. Osamy, A. Aziz, and A. M. Khedr, "SEEDGT: secure and energy efficient data gathering technique for IoT applications based WSNs," *Journal of Network and Computer Applications*, vol. 202, p. 103353, Jun. 2022, doi: 10.1016/j.jnca.2022.103353.
- [14] N. Rouissi and H. Gharsellaoui, "Improved hybrid LEACH based approach for preserving secured integrity in wireless sensor networks," *Procedia Computer Science*, vol. 112, pp. 1429–1438, 2017, doi: 10.1016/j.procs.2017.08.103.
- [15] H. D. Hung, T. T. Duy, and M. Voznak, "Secrecy outage performance of multi-hop LEACH networks using power beacon aided cooperative jamming with jammer selection methods," *AEU - International Journal of Electronics and Communications*, vol. 124, p. 153357, Sep. 2020, doi: 10.1016/j.aeue.2020.153357.
- [16] F. Sulisty, F.; Mustika, "Load balancing protocol leach in wireless sensor network," in *Proceedings of the National Conference on Electrical Engineering, Informatics, Industrial Technology, and Creative Media*, 2019, pp. 25-31. [Online]. Available: <http://conferences.itelkom-pwt.ac.id/index.php/centive/article/view/83>
- [17] H. Yue, Q. Jiang, C. Yin, and J. Wilson, "Research on data aggregation and transmission planning with internet of things technology in WSN multi-channel aware network," *Journal of Supercomputing*, vol. 76, no. 5, pp. 3298–3307, May 2020, doi: 10.1007/s11227-018-2565-5.
- [18] K. Havashemi rezaeipour and H. Barati, "A hierarchical key management method for wireless sensor networks," *Microprocessors and Microsystems*, vol. 90, p. 104489, Apr. 2022, doi: 10.1016/j.micpro.2022.104489.
- [19] M. Rethfeldt, T. Brockmann, B. Beichler, C. Haubelt, and D. Timmermann, "Adaptive multi-channel clustering in IEEE 802.11s wireless mesh networks," *Sensors*, vol. 21, no. 21, p. 7215, Oct. 2021, doi: 10.3390/s21217215.
- [20] H. Cinar, M. Cibuk, and I. Erturk, "HMCA WSN: a hybrid multi-channel allocation method for erratic delay constraint WSN applications," *Computer Standards and Interfaces*, vol. 65, pp. 92–102, Jul. 2019, doi: 10.1016/j.csi.2019.02.004.
- [21] R. F. Fernandes, M. B. de Almeida, and D. Brandão, "Performance evaluation of asynchronous multi-channel MAC protocol for WSN," *Wireless Personal Communications*, vol. 113, no. 2, pp. 1115–1133, Jul. 2020, doi: 10.1007/s11277-020-07270-w.
- [22] L. R. Emmendorfer and A. M. de Paula Canuto, "A generalized average linkage criterion for Hierarchical Agglomerative Clustering," *Applied Soft Computing*, vol. 100, p. 106990, Mar. 2021, doi: 10.1016/j.asoc.2020.106990.
- [23] D. Delforge, A. Watlet, O. Kaufmann, M. Van Camp, and M. Vanclooster, "Time-series clustering approaches for subsurface zonation and hydrofacies detection using a real time-lapse electrical resistivity dataset," *Journal of Applied Geophysics*, vol. 184, p. 104203, Jan. 2021, doi: 10.1016/j.jappgeo.2020.104203.
- [24] S. Al-Sodairi and R. Ouni, "Reliable and energy-efficient multi-hop LEACH-based clustering protocol for wireless sensor networks," *Sustainable Computing: Informatics and Systems*, vol. 20, pp. 1–13, Dec. 2018, doi: 10.1016/j.suscom.2018.08.007.
- [25] Y. J. Wang, "A fuzzy multi-criteria decision-making model based on simple additive weighting method and relative preference relation," *Applied Soft Computing Journal*, vol. 30, pp. 412–420, May 2015, doi: 10.1016/j.asoc.2015.02.002.
- [26] C. W. Xiong, M. Tang, X. H. Wang, Y. Liu, and J. Shi, "Evolution model of high quality of service for spatial heterogeneous wireless sensor networks," *Physica A: Statistical Mechanics and its Applications*, vol. 596, p. 127182, Jun. 2022, doi: 10.1016/j.physa.2022.127182.
- [27] H. Jin and J. Zhao, "Real-time energy consumption detection simulation of network node in internet of things based on artificial intelligence," *Sustainable Energy Technologies and Assessments*, vol. 44, p. 101004, Apr. 2021, doi: 10.1016/j.seta.2021.101004.
- [28] V. Babu M, C. N. S. V. Kumar, S. Parthiban, U. Padmavathi, and M. Z. U. Rahman, "AE-LEACH: An Incremental Clustering Approach for Reducing the Energy Consumption in WSN," *Microprocessors and Microsystems*, vol. 93, p. 104602, Sep. 2022, doi: 10.1016/j.micpro.2022.104602.




- [29] H. Frey and I. Stojmenović, "Geographic and energy-aware routing in sensor networks," in *Handbook of Sensor Networks: Algorithms and Architectures*, Wiley, 2005, pp. 381–415. doi: 10.1002/047174414X.ch12.
- [30] V. Geetha, P. V. Kallapur, and S. Tellajeera, "Clustering in wireless sensor networks: performance comparison of LEACH & LEACH-C protocols using NS2," *Procedia Technology*, vol. 4, pp. 163–170, 2012, doi: 10.1016/j.protcy.2012.05.024.
- [31] M. Yiğit, Ö. D. Incel, and V. Ç. Güngör, "On the interdependency between multi-channel scheduling and tree-based routing for WSNs in smart grid environments," *Computer Networks*, vol. 65, pp. 1–20, Jun. 2014, doi: 10.1016/j.comnet.2014.02.025.
- [32] Y. He *et al.*, "The effects of Fe substrate orientations on Cu55 cluster deposition with different incident energies," *Nuclear Instruments and Methods in Physics Research, Section B: Beam Interactions with Materials and Atoms*, vol. 496, pp. 52–60, Jun. 2021, doi: 10.1016/j.nimb.2021.03.015.
- [33] J. I.-Z. Chen and H. P., "Enhanced dragonfly algorithm based K-Medoid clustering model for VANET," *Journal of ISMAC*, vol. 3, no. 1, pp. 50–59, Apr. 2021, doi: 10.36548/jismac.2021.1.005.
- [34] R. Rizky, Mustafid, and T. Mantoro, "Improved performance on wireless sensors network using multi-channel clustering hierarchy," *Journal of Sensor and Actuator Networks*, vol. 11, no. 4, p. 73, Nov. 2022, doi: 10.3390/jsan11040073.

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