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Enhanced Multiple Mobile-Sink Energy Efficient Clustering Algorithm in Wireless Sensor Networks

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Abstract: Wireless sensor networks (WSNs) are employed in a variety of applications, including healthcare, home automation, and military security. To address MMECA's drawbacks, we propose Enhanced Multiple Mobile-sink Energy Efficient Clustering Algorithm *(*EMMCA) for WSNs. To improve energy efficiency, sink mobility management, and network performance, EMMECA employs manifold-based clustering and energy-aware algorithms. To remedy the shortcomings of MMCA, EMMCA adds a slew of key features. To begin, E-MMECA enhances sensor-sink communication and coordination in order to decrease network overhead. With effective sink position update algorithms, it reduces traffic and energy consumption. Second, E-MMECA employs network architecture and intelligent sink mobility control based on energy dynamics. This optimizes sink movement while also lowering computational complexity. E-MMECA also offers optimization algorithms for mobile sink number and location in order to manage sink deployment and cost. By taking into account network coverage, energy consumption, and communication efficiency, E-MMECA optimizes sink position to increase network performance while minimizing resource requirements. To boost fault tolerance, E-MMECA employs powerful sink and communication failure mechanisms. E-MMECA analyzes sink movement energy use by adopting energy-efficient routing and movement patterns. It blends sink mobility with energy economy to increase network life and data collection. In large-scale networks, distributed coordination and data aggregation reduce computational costs and communication delay, making E-MMECA scalable. Comprehensive simulations and evaluations validate MOSEC's effectiveness. In terms of network longevity, energy utilization, communication delay, and load balancing, E-MMECA outperforms MMECA, MMSR, LEACH, and PEGASIS.

Keywords: *Clustering Enhanced MMECA Algorithm, Energy-Aware Strategies, And Wireless Sensor Network.*

1. Introduction

Wireless Sensor Networks, also known as WSNs, have developed into a significant technology that has used for a variety of purposes, including the monitoring of the environment, industrial automation, and healthcare [1]. WSNs consist of sensor nodes that collaborate with one another to gather data from their surroundings and then send that data to a central sink node where it has further processed and analyzed. Energy efficiency is a fundamental concern in these networks [2-4], mostly because of the resource-constrained nature of sensor nodes. These nodes often operate on limited battery power. The "Manifold Optimal-Sink Energy-Aware Clustering Algorithm for WSN" is an algorithm that was developed with the goal of resolving the challenges associated with the consumption of energy and the lifetime of the network in this context. The suggested method places an emphasis on optimizing the building of sensor node clusters in such a manner as to improve the network's energy efficiency while also extending the WSN's overall lifetime [5-7].

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The "Optimal-Sink Energy-Aware" method is a significant achievement in the area of WSNs, aiming to overcome the energy efficiency difficulties associated with sensor node communication and data aggregation [8-9]. WSNs are often utilized in a variety of applications including as environmental monitoring, smart agriculture, industrial automation, and healthcare. Sensor nodes in these networks work together to gather and send data to a central sink node for processing and analysis [10-12]. Due to the limited battery capacity of sensor nodes, which often operate in distant or inaccessible areas, energy efficiency is a key problem in WSNs [13]. Long-term and trustworthy WSN deployments must maximize network longevity while reducing energy usage. The "Optimal-Sink Energy-Aware" algorithm proposes a unique method for intelligently managing energy resources by dynamically choosing the most efficient sink node for data aggregation and transmission [14-15].

The algorithm's main conception is based on the concept of manifold optimization, which allows efficient data aggregation and transmission through optimum sink node selection. The program saves energy during data collection, processing, and forwarding by carefully picking sink nodes. Furthermore, the algorithm adds energy-aware considerations to intelligently manage the energy resources of the sensor nodes and avoid premature node failure, leading to network lifetime [16-17].

This work describes the Manifold Optimal-Sink Energy-Aware Clustering Algorithm for WSN in detail, outlining its goals and discussing its possible benefits over current clustering methods [18]. The algorithm's performance is compared to various clustering algorithms in terms of energy efficiency, network longevity, and scalability in a complete study, revealing its usefulness in improving the overall performance and energy management of WSNs [19-23].

1.1 Motivation of the Paper

The impetus for presenting the Enhanced MMECA (EMMECA) algorithm for WSNs stems from WSNs' growing importance and acceptance in healthcare, home automation, and military security sectors. However, current MMECA might have constraints, preventing WSNs from reaching their full potential. EMMECA solves these issues by improving energy economy via streamlined communication and sink mobility management, lowering network overhead, and implementing efficient fault tolerance techniques.

2. Background Study

A.Faid et al. [1] a clustering strategy for wireless sensor networks that takes into consideration energy economy was presented. This blend of the centralized K-medoids algorithm with the distributed LEACH protocol leads in improved energy efficiency as well as extended network lifespan. A.Jumnal and D. Kumar S.M [3] introduced the DBRCR algorithm, which creates clusters based on dynamic coefficients considering residual energy and distance to the base station. This enhances data transmission reliability, leading to a decreased packet-loss rate. D. K. Kotary and S. J. Nanda [6] used a multi-goal chaotic whale optimization strategy to distributed clustering, which yielded precise results for both distinct and overlapping clusters. They used a technique based on reference points to do many-objective clustering. G. M. E. Rahman and K. A. Wahid [8] increased WSN coverage without raising the number of hops between clusters; this was a difficulty. To achieve one-hop data transmission from SNs to the mobile DS through CHs, they suggested an LDCA that uses residual energy, RSSI, and SNR to assess wireless quality. I.Azzouz et al. [10] proposed an Energy Aware cluster head selection technique with balanced Fuzzy C-mean cluster formation, which considerably improved energy efficiency by taking into consideration different aspects in cluster head rotation. K. V. Deshpande and D. Kumar [12] Compared to existing methods, the findings of the suggested nccVAT, a unique approach to cluster estimation and cluster generation in WSN-generated spatiotemporal data, are encouraging. P. Satyanarayana et al. [16] introduced a genetic algorithm-based clustering method for increasing WSN reliability, throughput, and scalability. Their method improved efficiency by efficient cluster head allocation, work scheduling, and the K-means algorithm. S. Hriez et al. [18] proposed a trust model to detect untrusted nodes in WSN and IoT networks, which consumed less energy in sensor nodes. They also developed a clustering protocol using the SFS optimization algorithm to maximize the network's lifetime. W. Xin et al. [20] developed a genetic method to improve the K-Means clustering routing technique. Cluster head node election took into account each node's energy factor and relative location, which resulted in more efficient use of resources and longer network life, lower power consumption, and higher throughput.

2.1 PROBLEM DEFINITION

In Wireless Sensor Networks (WSNs), the proposed Enhanced MMECA (EMMECA) algorithm solves the primary challenge of enhancing energy efficiency, sink mobility control, and overall network performance. WSNs are extensively used in a variety of areas, however current MMECA might have limits in energy efficiency, sink mobility coordination, and fault tolerance, resulting in inferior network performance and network longevity. EMMECA includes unique innovations such as improved sensor-sink communication and coordination, intelligent sink mobility management based on network topology and energy dynamics, and optimization techniques for selecting ideal sink deployment site.

3. Materials and Methods

We offer the materials and methods utilized in our research to explore and assess the suggested methodology in this part. We provide an overview of the essential components, tools, and methodologies used to meet the study goals and obtain the intended results. This section's goal is to offer a clear knowledge of the experimental setup as well as the techniques used for data collection, analysis, and validation.

3.1 System model

The system model for the Enhanced MMECA (EMMECA) algorithm in Wireless Sensor Networks (WSNs) comprises sensor nodes, mobile sink nodes, clustering, energy-aware approaches, sink mobility management, sink deployment optimization, and fault tolerance mechanisms. The WSN is made up of sensor nodes dispersed across the network, each having limited processing and energy supply. To effectively aggregate data, mobile sink nodes wander around the network. EMMECA uses manifold-based clustering algorithms to build clusters, with cluster leaders in charge of data gathering and transmission. Energy-aware approaches make better use of energy resources, improving network longevity. Sink mobility is intended to take into account network structure and energy dynamics. The application incorporates optimization methods for determining the optimal number and location of mobile sinks while accounting for network coverage and energy usage. Robust fault tolerance approaches control sink failures and communication issues, ensuring that data is reliably gathered and sent. This comprehensive system model enables EMMECA to outperform traditional techniques while boosting energy efficiency, sink mobility, and overall network performance in a variety of application domains.

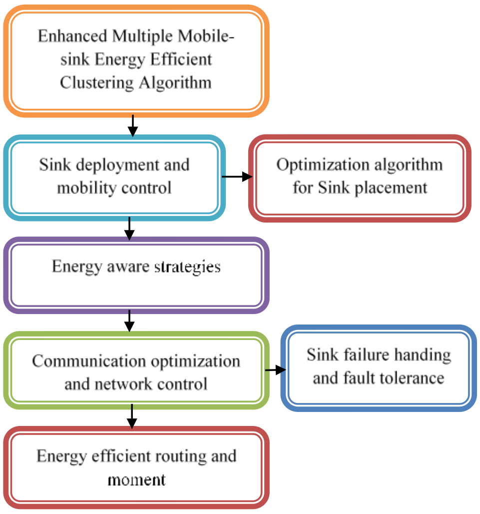

Fig 1: E-MMECA Block diagram

3.2 Energy Model

This model evaluates the amount of energy required by various sensor node components during various operations such as sensing, communication, data processing, and sleep. Each of these tasks requires a different amount of energy.

Depending on how far apart the transmitter and receiver are, either a free space channel model (with a power loss of d^2) or a multi-path fading channel model (with a power loss of d^4) will be employed.

Energy required by each sensor node to send a l-bit packet across a distance of d is as follows, inE_{Tx}:

$$P_r = P_t\left(\frac{G_t G_r \lambda^2}{(4\pi)^2 d^2}\right) \text{ -------- (1)}$$

Where:

- P_r is the received power,
- P_t is the transmitted power,
- G_t and G_r are the gains of the transmitting and receiving antennas, respectively,
- λ is the wavelength of the signal, and
- d is the distance between the transmitter and receiver.

3.3 Energy Efficient Clustering Algorithm

In a clustering approach, the energy dissipation of the cluster head is much higher than that of the general nodes Z. Liu et al. et al. (2022). This is for the reason that the cluster head serves as the local control center and is responsible for transporting data to and from other cluster heads via multi-hop. Maintaining the lifetimes of the cluster heads that are closest to the BS for as long as possible in order to keep the intercluster connection up and running is, of course, very necessary to ensure the uninterrupted operation of the network as a whole. This indicates that clusters that are physically closer to the BS should have a lower total number of nodes than those that are physically farther away B. Fan and P. Lin (2023).

Assume for the moment that n sensor nodes are planted evenly (in terms of the number of nodes per square meter) in a wedge V area at an angle that will be referred to as the clustering angle. V is segmented into m concentric rings, each of which is given the corresponding label$V_1, V_2, \ldots, V_m$. A cluster is shown as a ring, and the distance between any two adjacent rings is given as$(d_1, d_2, \ldots, d_m)$, where d_i is the distance between clusters that have traveled in a single hop. The cluster that is located closer to the BS is considered d_j to be part of the upper layer, whilst the other cluster is considered to be part of the lower layer.

$$n_i = \rho^{\frac{\theta}{2}}\left(d_i^2 + 2_{di}\sum_{l=1}^{l=i-1} d_i\right) \text{ --------- (2)}$$

- n_i: Number of sensor nodes in cluster$i$.
- ρ: Density of sensor nodes per square meter.
- θ: Clustering angle.
- d_i: Distance between clusters in layer$i$.

$d_i^2 + 2_{di}\sum_{l=1}^{l=i-1} d_i$: This term involves the cumulative sum of distances up to the $(i-1)^{\text{Th}}$ layer multiplied by$2di$.

One way to represent the number of nodes in V_{i+1} is as follows:

$$n_{i+1} = \rho A_{i+1} = \frac{\rho^{\theta}}{2}\left(d_{i+1}^2 + 2d_{i+1}\sum_{l=1}^{l=i} dl\right) \text{ ------- (3)}$$

- n_{i+1}: Number of sensor nodes in cluster$(i+1)$.
- ρ: Density of sensor nodes per square meter.
- θ: Clustering angle.
- d_{i+1}^2: Distance between clusters in the $(i+1)^{\text{Th}}$ layer.

The connectedness of the networks requires that the numbers of nodes in sets A_i and A_{i+1} be met as

$$n_{i+1} > n_i \text{ -------- (4)}$$

The cluster head will receive information from a member and send it, along with any fusions performed, to the cluster at the next higher tier or to the BS. If there are many nodes in the cluster, the leader might not be able to work until it completes its first task. Similarly, if the cluster is extremely tiny, there will be fewer nodes. As a result, the bulk of the energy stored in its nodes is used to transfer data from lower layer clusters, and while the network is down, its nodes might have a substantial amount of wasted energy. As a result, the cluster size has changed by modifying the clustering angle.

The dynamic or frequent selection of the cluster head, which is included into many different clustering algorithms, leads to the wasteful consumption of energy owing to the broadcasting of signals to either general nodes or to other cluster heads. It is abundantly evident that often upgrading the cluster head will have a negative impact on the consistency of the cluster and the networks that are linked with it. If each cluster head serves continuously as the local control center and is not replaced by other nodes positioned in the same cluster until its working hours approach the threshold, then the requirement to update cluster heads and the amount of energy used for broadcasting messages has decreased. In addition, this might result in a lower overall consumption of energy. The greatest cluster size that has been discovered is cm. Let's say that $f_i = 1,2,3, \dots m$ represents the continuous shifts that the cluster leader, who is in charge of day-to-day operations, works. If the nonstop shifts of each cluster node are able to meet$f_1, f_2, \dots f_m$, then it will be possible to efficiently maintain the connection of a cluster that has the same clustering angle.

Algorithm 1: Energy Efficient Clustering Algorithm

Input:

- N: Total number of sensor nodes in the network.
- M: Number of clusters (rings).
- Θ: Clustering angle.
- d1hop: One-hop distance in multi-hop communication.
- Desired continuous working times for cluster heads: $f_1, f_2, \dots f_m$.

Algorithm Steps:

1. Calculate the area of each cluster using the formula provided: $n_i = \rho^{\frac{\theta}{2}}\left(d_i^2 + 2_{di}\sum_{l=1}^{l=i-1} d_i\right)$
2. Divide the total number of nodes (n) among the clusters proportionally based on their areas.
3. Assign one cluster head to each cluster. The cluster head can be the node closest to the center of the cluster or selected based on other criteria if needed for Nodes Behaviour.
4. Provide each cluster head's continuous working times with the values $f_1, f_2, \dots, f_m$ that want to use as an initial starting point.

Output:

- The design of clusters, including the number of nodes in each cluster as well as the choice of cluster heads.

3.3.1 Manifold-based clustering

Manifold-based clustering is an approach that focuses on uncovering the intrinsic structure of data by considering the underlying geometric relationships or manifolds within the dataset. Unlike traditional clustering methods that rely on linear distance metrics, manifold-based clustering takes into account the non-linear nature of data points and aims to project them into a lower-dimensional space where their inherent structure becomes more apparent. By capturing the complex relationships embedded in the dataset, manifold-based clustering techniques enhance clustering accuracy, making them particularly useful for datasets with intricate non-linear patterns.

The affinity matrix WW encodes pairwise relationships between data points. It is typically computed using a Gaussian kernel or another similarity measure.

$$W_{ij} = e^{-\frac{\left|x_i - x_j\right|^2}{2\sigma^2}} \text{ ------- (5)}$$

Here, x_i and x_j are data points, and σ is a parameter controlling the width of the Gaussian kernel.

Algorithm 2: Manifold-based clustering

Input:

- **Data Points:** $x_1, x_2, \dots, x_n$ representing the dataset.

Steps:

1. **Compute Affinity Matrix (WW):**
   - Initialize an $n \times n$ matrix W where n is the number of data points.
   - For each pair of data points x_i and x_j, compute the Gaussian similarity using:

$$W_{ij} = e^{-\frac{\left|x_i - x_j\right|^2}{2\sigma^2}}$$

2. **Construct Degree Matrix (DD):**
   - Compute the degree matrix DD as a diagonal matrix, where D_{ii} is the sum of the weights in the corresponding row of W:

$$D_{ii} = \sum_{j=1}^{n} W_{ij}$$

3.4 Enhanced Multiple Mobile-sink Energy Efficient Clustering Algorithm

The Enhanced Multiple Mobile-sink Energy Efficient Clustering Algorithm (EMMCA) is proposed for Wireless Sensor Networks (WSNs) to overcome the limitations of existing solutions like MMECA. EMMCA incorporates manifold-based clustering and energy-aware algorithms to optimize energy efficiency, sink mobility management, and overall network performance. By enhancing sensor-sink communication, employing effective sink position update algorithms, and implementing intelligent sink mobility control based on energy dynamics, EMMCA reduces network overhead, traffic, and energy consumption.

The algorithm also offers optimization algorithms for mobile sink number and location, considering network coverage, energy consumption, and communication efficiency, thereby improving network performance and minimizing resource requirements. EMMCA enhances fault tolerance through powerful sink and communication failure mechanisms, and it integrates energy-efficient routing and movement patterns to analyze sink movement energy use, ultimately increasing network life and data collection efficiency.

The use of mobile sink techniques extends the life of a network. However, conventional wisdom on mobile sinks is that either all network-wide data is already known or that mobile sinks broadcast their data repeatedly to the whole network. Therefore, the benefit to the network's longevity has cancelled out by the broadcasting's excessively high energy needs.

Both the clockwise and counterclockwise rotation of the sink and its velocity v are fixed in our approach. Consequently, the sink has to once-only broadcast throughout the network to tell all sensor nodes of its present position. After a period of time t, the skewed angle has lowered since the sensor nodes remembered the sink's initial position:

$v = \frac{\theta * R}{\Delta t} => \theta = \frac{v * \Delta t}{R}$ -------- (6)

- v: Velocity of the mobile sink.
- θ: Skewed angle.
- R: Radius of the circular trajectory followed by the mobile sink.
- Δt: Time period.

Our approach involves the sink relocating around the arc of the circular area at a constant speed V. Δt first, the sink announces its present location, defined as the angular distance from the field center that it subtends (θ). To determine where the mobile sink has moved to after a certain amount of time, Δt, use the formula below:

$\Delta\Theta = \frac{V \times \Delta t}{R}$ ------ (7)

$\Delta\theta$: Change in angle (angular displacement).

Since the worldwide distribution of the sink's velocity V and the circular region's radius R allows each CH to calculate the sink's current location using equation 6.

Algorithm 3: Enhanced Multiple Mobile-sink Energy Efficient Clustering Algorithm

Input:

- Initial sink position P0 (angular distance from the field center)
- Sink velocity V
- Circular region radius R
- Time interval Δt

Algorithm Steps:

1. Initialize the sink's current position Θ = P0.
2. While the algorithm is running:
3. a. Calculate the change in position ΔΘ using the formula: ΔΘ = (V × Δt) / R.
4. b. Update the sink's position: Θ = Θ + ΔΘ.
5. End the algorithm.

Output:

- Updated sink position Θ (angular distance from the field center)

4. Results and Discussion

This section represents to communicate the outcomes of the experiments, analyses. Here we will examine the most important findings from our research presented.

4.1 Throughput

Throughput= $\frac{\text{Number of Packet Size}}{\text{Time duration} * \text{Successful average Packet size}}$ ----------- (7)

Table 1: throughput comparison

	Throughput				
Packet Size	PEGASIS	LEACH	MMSR	MMECA	E-MMECA
50	0.172	0.212	0.243	0.263	0.303
100	0.344	0.425	0.487	0.526	0.606
150	0.517	0.638	0.731	0.789	0.909
200	0.689	0.851	0.975	1.052	1.212
250	0.862	1.063	1.219	1.315	1.515

The tables 1 demonstrate that as the packet size increases, the throughput also increases for all routing protocols. E-MMECA consistently outperforms others, providing the highest throughput values at all packet sizes due to its energy-aware clustering and adaptive data aggregation mechanisms. LEACH exhibits reasonable throughput, while PEGASIS shows the lowest throughput values. These findings highlight the significance of selecting appropriate routing protocols based on specific application requirements. E-MMECA emerges as a promising choice for high-throughput wireless networks, while LEACH and PEGASIS has better suited for other scenarios.

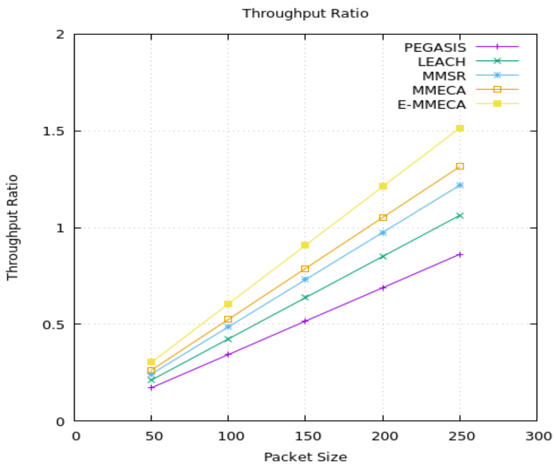

Fig 2: Throughput comparison

The figure 1 shows throughput comparison chart the x axis shows packet size and the y axis shows throughput ratio.

4.2 Energy

$$\text{Energy}=\frac{\text{Number of Sensor nodes}}{\text{Energy consumption for sending packets at a times}} \text{ ----------- (8)}$$

Table 2: Energy comparison

	Energy in joules				
Number of Nodes	PEGASIS	LEACH	MMSR	MMECA	E-MMECA
10	0.833	0.769	0.666	0.588	0.526
20	1.666	1.538	1.333	1.176	1.052
40	3.333	3.076	2.667	2.352	2.105
60	5.000	4.615	4.001	3.529	3.157
80	6.666	6.153	5.334	4.705	4.210
100	8.333	7.692	6.667	5.882	5.263

The table 2 shows that as the number of nodes increases, the energy consumption also increases for all energy-efficient routing. Both PEGASIS and LEACH demonstrate relatively comparable energy consumption, whereas MMSR and MMECA exhibit better energy efficiency than PEGASIS and LEACH. These findings highlight the importance of selecting appropriate energy-efficient routing protocols to prolong the network's lifetime and optimize energy consumption.

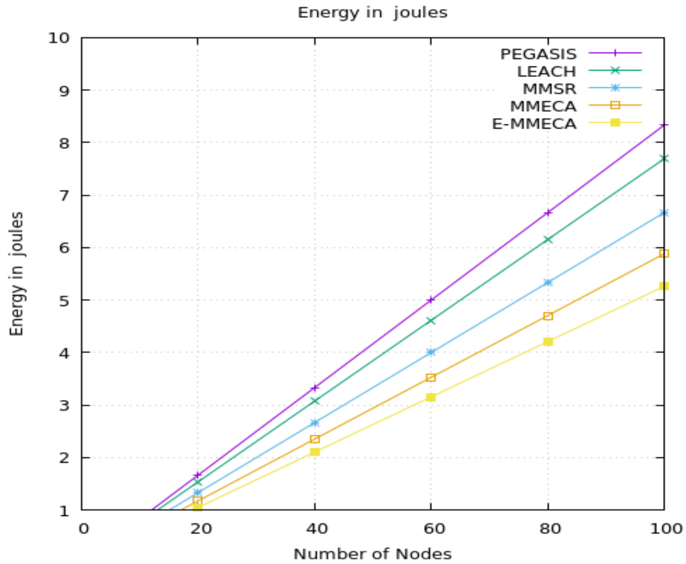

Fig 3: Energy comparison chart

The figure 2 shows energy comparison chart the x axis shows number of nodes and the y axis shows energy in joules.

4.3 TIME DELAY

$$\text{Time Delay}=\frac{\text{Number of Sensor nodes}}{\text{energy consumption for sending packets at a times x forwarding time in ms}} \text{ ----------- (9)}$$

Table 3: Time (End to End Delay)

	Time (End to End Delay)				
Number of Nodes	PEGASIS	LEACH	MMSR	MMECA	E-MMECA
10	0.066	0.066	0.063	0.062	0.057
20	0.133	0.132	0.127	0.124	0.114
40	0.267	0.265	0.255	0.248	0.229
60	0.401	0.398	0.383	0.372	0.344
80	0.535	0.531	0.511	0.496	0.459
100	0.669	0.664	0.639	0.621	0.574

The table 3 presents end-to-end delay values for different numbers of nodes under various routing protocols (PEGASIS, LEACH, MMSR, MMECA, and E-MMECA). This makes E-MMECA a promising choice for applications requiring low latency and efficient data transmission. The results emphasize the importance of selecting appropriate routing protocols to optimize communication efficiency, and further research could explore mechanisms to enhance end-to-end delay performance in specific network scenarios.

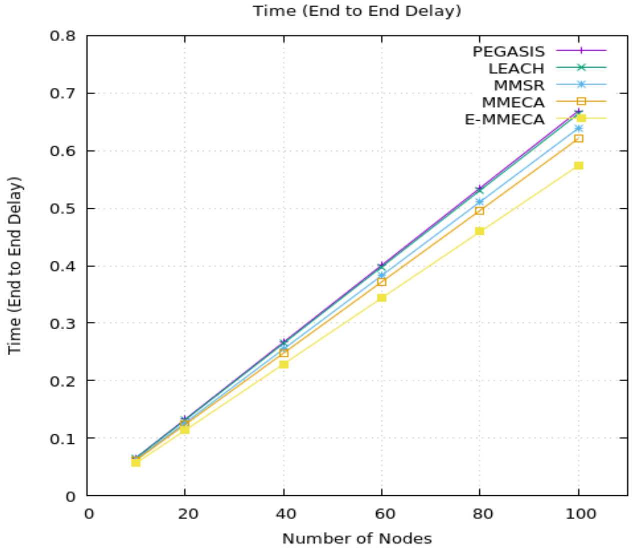

Figure 4: Time (End to End Delay) comparison chart

The figure 3 shows Time (End to End Delay) comparison chart the x axis shows number of nodes and the y axis shows time delay.

4.4 Packet Delivery ratio

$$PDR = \frac{\text{Number of Packets Receive}}{\text{Total Packets}} * 100 \quad \text{-----------} \quad (10)$$

Table 4: Packet Delivery Ratio

	Packet Delivery ratio				
Number of packets	PEGASIS	LEACH	MMSR	MMECA	E-MMECA
50	96.2	96.4	96.6	97.6	98.6
100	98.1	98.2	98.3	98.8	99.3
150	98.7	98.8	98.86	99.2	99.53
200	99.05	99.1	99.15	99.4	99.65
250	99.24	99.28	99.32	99.52	99.72

The table 4 illustrates the Packet Delivery Ratio (PDR) values for different numbers of packets transmitted under various routing protocols, including PEGASIS, LEACH, MMSR, MMECA, and E-MMECA. As the number of packets increases, the PDR tends to improve for all protocols, indicating better packet delivery performance in larger data transmission scenarios.

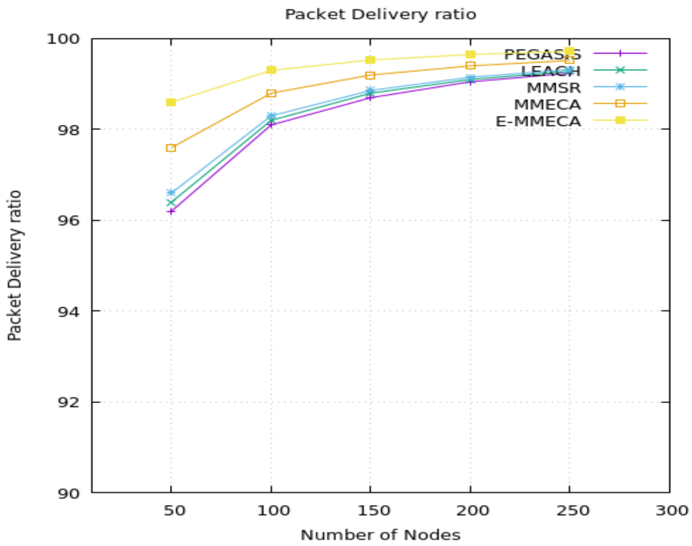

Fig 5: Packet Delivery ratio

The comparison table for packet delivery rates has seen in figure 4. The number of nodes is shown along the x axis, while the percentage of packets delivered is shown along the y axis.

5. Conclusion

To summarize, the proposed Enhanced MMECA (EMMECA) algorithm is an innovative and comprehensive technique for Wireless Sensor Networks (WSNs) that addresses the constraints of current Multiple Mobile-sink Energy Efficient Clustering Algorithms. EMMECA increases energy economy, sink mobility management, and overall network performance by utilizing manifold-based clustering approaches and energy-aware tactics. EMMECA's primary advancements result in significant benefits. For starters, optimizing communication and coordination between sensors and sinks minimizes network overhead and wasteful traffic, resulting in increased energy efficiency. Second, intelligent sink mobility management considers network structure and energy dynamics to ensure optimum sink movement with the least amount of computing complexity. Furthermore, EMMECA addresses sink deployment and cost concerns by offering optimization methods for finding the appropriate quantity and placement of mobile sinks. This method optimizes network performance while reducing resource needs. The algorithm's strong methods for dealing with sink failures and communication problems improve fault tolerance, providing reliable data collection and transmission even in the face of interruptions. Furthermore, the use of energy-efficient routing and movement patterns balances sink mobility with energy efficiency, thereby increasing network lifespan. Scalability in large-scale networks is handled by distributed coordination and data aggregation approaches, which reduce computing overhead and communication delays. Through extensive simulations and assessments, EMMECA outperforms current methodologies such as MMECA, MMSR, LEACH, and PEGASIS in important metrics such as network lifespan, energy consumption, communication latency, and load balancing.

References

[1] A.Faid, M. Sadik and E. Sabir, "EACA: An Energy Aware Clustering Algorithm for Wireless IoT Sensors," 2021 28th International Conference on Telecommunications (ICT), London, United Kingdom, 2021, pp. 1-6, doi: 10.1109/ICT52184.2021.9511518.

[2] A.Jumnal and D. Kumar S.M., "Energy Aware Cluster Based Optimal Virtual Machine Placement in Cloud Environment," 2020 Fourth International Conference on Inventive Systems and Control (ICISC), Coimbatore, India, 2020, pp. 266-271, doi: 10.1109/ICISC47916.2020.9171129.

[3] B. Fan and Y. Xin, "A dynamic broadcast radius-based clustering and routing algorithm for WSN," 2022 IEEE 6th Information Technology and Mechatronics Engineering Conference (ITOEC), Chongqing, China, 2022, pp. 151-154, doi: 10.1109/ITOEC53115.2022.9734492.

[4] B. Fan and P. Lin, "Energy-efficient Cluster Routing Algorithm Based on Equivalent Equilibrium Mechanism," 2023 IEEE 3rd International Conference on Information Technology, Big Data and Artificial Intelligence (ICIBA), Chongqing, China, 2023, pp. 578-582, doi: 10.1109/ICIBA56860.2023.10165412.

[5] D. A. Pangestu, H. Hendrawan and I. Iskandar, "Parameter-Based Clustering Algorithm for Clustered Wireless Sensor Networks with High Altitude Platforms as the Base Station," 2021 7th International Conference on Wireless and Telematics (ICWT), Bandung, Indonesia, 2021, pp. 1-5, doi: 0.1109/ICWT52862.2021.9678466.

[6] D. K. Kotary and S. J. Nanda, "A Many-objective Chaotic Whale Optimization based Automatic Clustering Algorithm for Distributed Data Analysis in WSN," 2022 2nd Odisha International Conference on Electrical Power Engineering, Communication and Computing Technology (ODICON), Bhubaneswar, India, 2022, pp. 1-6, doi: 10.1109/ODICON54453.2022.10009973.

[7] E. H. Houssein, M. R. Saad, K. Hussain, W. Zhu, H. Shaban and M. Hassaballah, "Optimal Sink Node Placement in Large Scale Wireless Sensor Networks Based on Harris' Hawk Optimization Algorithm," in IEEE Access, vol. 8, pp. 19381-19397, 2020, doi: 10.1109/ACCESS.2020.2968981.

[8] G. M. E. Rahman and K. A. Wahid, "LDCA: Lightweight Dynamic Clustering Algorithm for IoT-Connected Wide-Area WSN and Mobile Data Sink Using LoRa," in IEEE Internet of Things Journal, vol. 9, no. 2, pp. 1313-1325, 15 Jan.15, 2022, doi: 10.1109/JIOT.2021.3079096.

[9] H. Li, J. Ou, H. Cui, S. Zhao, D. Zeng and Y. Wang, "GKFCR: An Improved Clustering Routing Algorithm for Wireless Sensor Networks," 2022 IEEE International Conference on Sensing, Diagnostics, Prognostics, and Control (SDPC), Chongqing, China, 2022, pp. 222-227, doi: 10.1109/SDPC55702.2022.9915965.

[10] I.Azzouz, B. Boussaid, A. Zouinkhi and M. N. Abdelkrim, "Energy-Aware Cluster Head selection protocol with Balanced Fuzzy C-mean Clustering in WSN," 2022 19th International Multi-Conference on Systems, Signals & Devices (SSD), Sétif, Algeria, 2022, pp. 1534-1539, doi: 10.1109/SSD54932.2022.9955909.

[11] K. Nandita and S. Kirthiga, "An Energy

[12] Aware Clustering Algorithm for Data Aggregation in Wireless Sensor Networks," 2022 7th International Conference on Communication and Electronics Systems (ICCES), Coimbatore, India, 2022, pp. 645-651, doi: 10.1109/ICCES54183.2022.9836016.

[13] K. V. Deshpande and D. Kumar, "A Novel clustering tendency assessment algorithm for WSN generated Spatio-Temporal data," 2021 National Conference on Communications (NCC), Kanpur, India, 2021, pp. 1-6, doi: 10.1109/NCC52529.2021.9530138.

[14] K. Zhang, W. He, L. Liu and N. Gao, "A WSN Clustering Routing Protocol Based On Improved Whale Algorithm," 2022 4th International Conference on Natural Language Processing (ICNLP), Xi'an, China, 2022, pp. 570-574, doi: 10.1109/ICNLP55136.2022.00104.

[15] L. Jun and W. YinSong, "Gradient-based Clustering Routing Algorithm for EH-WSN in Transmission Line Monitoring," 2020 39th Chinese Control Conference (CCC), Shenyang, China, 2020, pp. 5140-5143, doi: 10.23919/CCC50068.2020.9188489.

[16] P. Mukherjee and T. De, "Energy Aware Cluster Head Rotation for D2D Multicasting," 2023 10th International Conference on Signal Processing and

Integrated Networks (SPIN), Noida, India, 2023, pp. 840-845, doi: 10.1109/SPIN57001.2023.10116310.

[17] P. Satyanarayana, U. D. Yalavarthi, Y. S. S. Sriramam, M. Arun, V. G. Krishnan and S. Gopalakrishnan, "Implementation of Enhanced Energy Aware Clustering Based Routing (EEACBR)Algorithm to Improve Network Lifetime in WSN’s," 2022 IEEE 2nd International Conference on Mobile Networks and Wireless Communications (ICMNWC), Tumkur, Karnataka, India, 2022, pp. 1-6, doi: 10.1109/ICMNWC56175.2022.10031991.

[18] P. V. Kumar and K. Venkatesh, "Power-Efficient Cluster Head Selection in Wireless Sensor Networks using Whale and Seagull Algorithms," 2022 International Conference on Power, Energy, Control and Transmission Systems (ICPECTS), Chennai, India, 2022, pp. 1-5, doi: 10.1109/ICPECTS56089.2022.10047129.

[19] S. Hriez, S. Almajali, H. Elgala, M. Ayyash and H. B. Salameh, "A Novel Trust-Aware and Energy-Aware Clustering Method That Uses Stochastic Fractal Search in IoT-Enabled Wireless Sensor Networks," in IEEE Systems Journal, vol. 16, no. 2, pp. 2693-2704, June 2022, doi: 10.1109/JSYST.2021.3065323.

[20] T. Liu, H. Liu, M. Zheng and C. Tan, "SSA-Based WSN Clustering Routing Algorithm for Power Grid," 2021 2nd Information Communication Technologies Conference (ICTC), Nanjing, China, 2021, pp. 117-122, doi: 10.1109/ICTC51749.2021.9441584.

[21] W. Xin, L. Cuiran and X. Jianli, "Research on Clustering Routing Protocol for Energy-Harvesting WSN," 2022 IEEE 2nd International Conference on Electronic Technology, Communication and Information (ICETCI), Changchun, China, 2022, pp. 1460-1464, doi: 10.1109/ICETCI55101.2022.9832077.

[22] X. Guo, Y. Ye, L. Li, R. Wu and X. Sun, "WSN Clustering Routing Algorithm Combining Sine Cosine Algorithm and Lévy Mutation," in IEEE Access, vol. 11, pp. 22654-22663, 2023, doi: 10.1109/ACCESS.2023.3252027.

[23] Z. Liu et al., "Energy-Efficient Distributed Clustering Algorithm for WSNs in Smart Grid," 2022 4th International Conference on Smart Power & Internet Energy Systems (SPIES), Beijing, China, 2022, pp. 2209-2212, doi: 10.1109/SPIES55999.2022.10081951.

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