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Synergistic Intelligence: FCM-MGWO Fusion for Cluster-Based Heterogeneous Sensor Networks

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ABSTRACT: Heterogeneous Sensor Networks (HSNs) have emerged as a prominent and versatile paradigm for various real-world applications, encompassing diverse sensor nodes with varying capabilities and characteristics. The integration of heterogeneous devices with distinct energy levels, computing power, and communication ranges poses unique challenges and opportunities in the design and operation of such networks. This paper presents a novel approach that leverages the Fuzzy C-means (FCM) clustering algorithm for cluster formation and the Modified Grey Wolf Optimization (MGWO) algorithm for Cluster Head (CH) selection in heterogeneous sensor networks. The primary goal of this approach is to optimize node energy consumption and extend the overall network lifespan. The FCM algorithm accommodates the heterogeneity of sensor nodes by allowing data points to belong to multiple clusters with varying degrees of membership. Subsequently, the Modified GWO algorithm, an updated version of GWO, incorporates Levy flight and decay function to balance exploration and exploitation phases effectively. Additionally, we enhance the MGWO fitness function by incorporating four parameters: residual energy, communication distance, connection requests to the node, and maximum communication region. Results revealed that proposed model is outperforming traditional MOD- LEACH, M-GEAR and TEZEM models in terms of dead nodes, stability period, instability period and network lifetime to prove its supremacy.

KEYWORDS: WSN, Energy consumption, Network Lifespan, Optimization etc.

I. INTRODUCTION

Wireless Sensor Networks (WSNs) have revolutionized the world of technology, offering immense potential for various applications in numerous fields [1]. From environmental monitoring to surveillance, healthcare, industrial automation, and smart cities, WSNs have found their way into a myriad of domains, driving innovation and enabling smarter and more efficient systems. At the heart of these networks are multiple small, low-power sensor nodes that are strategically deployed across a designated geographical area [2]. These sensor nodes are equipped with sensing capabilities, enabling them to perceive and collect data from their immediate surroundings. The collected data, ranging from temperature, humidity, light intensity, to various other environmental parameters, holds valuable information that can be used for real-time monitoring and decision-making. With WSNs in place, industries, research institutions, and public services gain the ability to access timely and accurate data, empowering them to respond swiftly to changing conditions, detect anomalies, and optimize their operations. As WSNs continue to evolve, their impact on various domains continues to expand, offering new possibilities for improving efficiency, enhancing safety, and enabling sustainable development. However, the efficient and reliable functioning of WSNs faces numerous challenges [3,4]. One of the key challenges is the limited energy and resources available to individual sensor nodes. As these nodes are often powered by small batteries, energy conservation becomes crucial to prolonging the network's lifetime and ensuring its continuous operation. Moreover, direct communication between all sensor nodes and a central sink node can lead to high energy consumption and excessive network congestion.

In the quest to overcome the challenges faced by Wireless Sensor Networks (WSNs) and enhance their performance, two critical techniques have garnered widespread recognition: clustering and Cluster Head (CH) selection [5. 6]. Clustering

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is a fundamental approach that involves organizing sensor nodes into smaller, more manageable clusters, with each cluster being under the guidance of a designated CH. This hierarchical arrangement ensures efficient data management and communication within the network. The CH assumes the crucial role of an intermediary between the individual sensor nodes and the central sink node, responsible for aggregating and relaying data from all the members within its cluster. By efficiently bundling data at the CH level, the network experiences a significant reduction in data transmission and communication overhead, alleviating the burden on individual nodes and conserving their precious energy resources.

Moreover, clustering contributes to enhanced energy efficiency, as the data aggregation and relay process significantly reduces redundant transmissions and optimizes energy utilization [7, 8]. The clustering technique also facilitates more robust and scalable networks, capable of handling a large number of sensor nodes without compromising performance. Additionally, the CH selection process is of utmost importance in maximizing the network's efficiency and lifespan [9]. The CHs are carefully chosen based on specific criteria, such as their residual energy levels, communication range, and connectivity to neighbouring nodes. Selecting the most capable and energy-efficient nodes as CHs ensures effective leadership within the clusters, as these nodes can efficiently manage data aggregation and communication tasks. This intelligent distribution of responsibilities among the CHs leads to an overall balanced network, where energy consumption is optimized, and the network's lifespan is significantly prolonged. With the continuous development in technology, researchers are finding new and effective ways for making clusters and selecting CH in the wireless network. In this realm, nature inspired based optimization algorithms play a pivotal role in CH selection [10, 11]. These algorithms optimize the CH selection process by efficiently exploring the search space and finding optimal solutions that lead to minimized energy consumption, reduced data transmission overhead, and enhanced network scalability.

The remaining section of the paper are categorized as; Section 2 represents the literature review of existing wireless techniques along with the problem statement. Section 3 discusses the proposed work and its working methodology. Section 4 represents the results obtained for proposed model and finally, a conclusion of paper is given in section 6.

II. RELATED WORK

Over the last few decades, a number of techniques have been proposed by various researchers for enhancing the lifespan of wireless networks. This section of paper gives a brief overview of some of the latest techniques employed for clustering and CH selection processes to increase network lifespan. Some of them are; Jaffri, Zain ul Abidin, et al. [12], proposed TEZEM protocol specifically for homogenous sensor networks for optimizing energy usage of nodes and increasing network lifespan. Results revealed that proposed model outperforms traditional models in terms of stability, lifetime and throughput. Tyagi, Lalit Kumar, et al. [13], proposed an EE-CHRP model wherein the network is divided into two levels. The selection of CH in the network was done by analysing few parameters like initial node energy, BS distance and the highest neighbour node locations. M. Faheem et al. [14], a new technique named as, FFRP was proposed that was based on Firefly mating optimization algorithm. Results revealed that their protocol achieved high PDR, throughput with less latency and energy usage. Tripti Sharma et al. [15], proposed a Reinforcement learning based clustering approach for ensuing the network longevity. By utilizing the given approach, researchers aimed to increase network lifespan and reduce energy losses. Results showed that the proposed protocol successfully lowered the energy usage of sensor nodes and assured a longer lifespan for the network of sensors. P. Goswami et al. [16], suggested DAI and Self Organizing Map (SOM) based hybrid method for energy-efficient routing as well as an immediate reaction for node intra-cluster communication to get around ITS's problems. Similarly, R K Varun et al. [17], proposed an Energy efficient routing methods based on fuzzy system i.e., ERFN for reducing the energy usage among nodes by equalizing it properly among all nodes and increasing network lifespan. Proposed methodology was proven out to be effective in terms of alive nodes, dead nodes, and energy usage. Furthermore, Lin Li, et al. [18], proposed a EBRP techniques in which K-means ++ was utilized for dividing the network into various clusters and Fuzzy system was used for selecting CH in the network. Moreover, they also utilized GA for acquiring fuzzy rules. Results showed that proposed model enhanced network lifespan by 57%, 63% and 63% than LEACH, LEACH-C and SEP protocols. Abdul Zahra et al. [19], proposed an effective energy efficient routing protocol in which Bacterial foraging optimization (BFO) was used for increasing network lifespan. Outcomes revealed that proposed model not only reduced energy consumption but it also decreased end to end delay which improved network's performance. Also, Abdulai, JD et al. [20], modified distance-based energy-aware (mDBEA) routing protocol, was proposed for improving network lifespan by reducing energy consumption of nodes. They calculated the Euclidean distance between nodes for finding the shortest distance with least amount of energy consumption. Results showcases that proposed model was able to achieve a PDR value of 82% and 95% for direct to sink technique and greedy technique respectively.

After analysing the literature survey, it is observed that number of techniques have been proposed for enhancing the lifespan of wireless networks. However, there are some difficulties that needs special attention for further enhancing the efficacy of these systems. One of the significant challenges faced in such systems is optimizing energy of nodes because batteries of network components cannot be recharged or replaced. Moreover, the existence of heterogeneous devices presents another difficulty that makes communications in sensor networks more difficult. Moreover, we observed that not much research has been done for heterogenous networks which demand advanced algorithms and powerful components for creating efficient routing algorithms. In addition to this, present methods are not able to form effective clusters and select effective CH which decreases their overall lifespan. Keeping this in mind, an effective WSN approach must be developed in this work.

III. PRESENT WORK

In order to overcome the limitations of current wireless systems, a unique and effective approach is proposed in this work that is based on Fuzzy C-Means and Modified Grey Wolf Optimization (MGWO) algorithm. The main objective of proposed work is to efficiently utilize or optimize the energy consumption of nodes which in turn will increase its overall network lifespan. As we know, that clustering and CH selection are two important phases in WSN that significantly contribute to the network performance. In light of this, we decided to improve the performance of proposed WSN approach by working on these two phases (clustering and CH selection). In the first phase of our work, a Fuzzy C-Means clustering technique is applied in order to make optimum number of clusters in the network. The main reason for using FCM over other clustering approach is that it has the ability to handle overlapping fuzzy clusters, making it a good fit for heterogenous sensor networks. By employing FCM, the data of N points can be categorized into c clusters by using the following equation.

$$jm = \sum_{j=1}^{c} \sum_{i=1}^{n} \mu^m_{ij} \|x_i - c_j\|^2 \quad 0 < m < \infty \quad (1)$$

Wherein, c_j and x_i represents the centre of jth cluster and ith point of data respectively. $\|x_i - c_j\|^2 = d_{ij} = d_{xi,j}$ represents the total distance among cluster centre and sensor node. Moreover, μ_{ij} depicts the membership degree of ith node to jth cluster

Furthermore, as we know that nodes in heterogenous systems have different processing power, energy capacity, communication range, and sensing capabilities, therefore, selecting an appropriate CH is extremely important for managing and optimizing networks performance. To accomplish this task, a Modified GWO algorithm is proposed in the second phase of proposed work for selecting the effective CHs in each cluster formed by FCM. MGWO is basically an extension of standard GWO with two important modifications i.e., Levy Flight and Decay function. By including these two parameters in the proposed work, we aim to improve the exploration and exploitation capabilities of GWO, thereby making it more suitable for solving complex optimization problems. Another reason for using MGWO in proposed work is that it possesses high convergence rate and doesn't get trapped in local minima. Furthermore, we have enhanced the fitness value calculation in MGWO by incorporating multiple factors. These factors encompass residual energy, communication distance, connection requests to the node, and maximum communication region. In contrast to conventional CH selection techniques that solely consider distance and energy consumption, our method surpasses them by considering a broader range of critical parameters. This comprehensive approach enables more informed and strategic CH selection, leading to improved network performance and prolonged network lifetime in Wireless Sensor Networks. Therefore, by integrating FCM and MGWO for clustering and CH selection process, we aim to optimize the energy consumption of sensor nodes and increase network lifespan. The next section of this paper discusses the working flow of proposed model.

METHODOLOGY

In order to achieve the given objective of optimizing energy consumption of nodes sand increased network lifespan, the proposed model undergoes through a series of steps that are discussed in this section of paper.

- **Network Initialization:** This is the first step of proposed model wherein we need to define the parameters of the network. During this process, the network size, number of nodes, simulation rounds, initial energy and other parameters aredefined. The specific value of all the parameters used in proposed model are given in Table 1.
- **Deploy Nodes:** After the network is initialized, nodes are deployed in the sensing region so that entire area is covered. In the proposed model, a total of 100 nodes are deployed randomly in the sensing area of 100m2. The location of sink node in the deployment phase is kept (50, 50)., i.e., centre of the region.
- **Formation of Clusters:** Once the nodes are deployed, it is time to form clusters in the network. To accomplish this task, we have utilized Fuzzy C-Means clustering technique in the proposed work which forms optimum number of clusters by using equation 1.
- **CH Selection:** After this, CH is selected in each cluster which is mainly responsible for collecting the information from sensors and transferring it to sink node. To select the CH in proposed wireless network, MGWO algorithm is used whose initialization parameters are defined in Table 2. The proposed Modified Grey Wolf Optimization (MGWO) method selects Cluster Heads (CHs) within each cluster by evaluating the fitness function of every node in the cluster. This fitness function is determined based on four key parameters of the nodes: residual energy, communication distance, connection requests to the node, and maximum communication region. By considering these multiple parameters, the algorithm identifies the node with the most optimal fitness function and designates it as the CH for that specific cluster in the current iteration.

Table 1. Network Initialization Parameters

Parameters	**Value**
Number of nodes	100
Node Distribution	Randomly
Simulation rounds	3000
Network Size	100m2
Number of zones	9
BS Location	(50,50)
Initial node energy	0.5j
Energy dissipation during reception (erx - elec)	50nj/bit
Energy dissipation during transmission (erx - elec)	50nj/bit
Data Packet	4000 bits
Transmit Amplifier	100pj/bit/m2

- **Start Communication:** After selecting the CH in the network, it is time to start communication in the network. During this phase, the CH node senses the data from remaining nodes present in the cluster and pass this information to the sink node.
- **Performance Evaluation**: Finally, the performance of proposed WSN approach is tested and validated by comparing it with traditional model in terms of various performance dependency factors. The detailed description of results are given in next section of this paper.

Table 2. MGWO Initialization Factors

Parameters	**Value**
No of Population	5
Iterations	10
a	2 to 0
beta	0.2

IV. RESULTS AND DISCUSSIONS

The efficacy of the proposed approach is examined and validated by using MATLAB simulation tool. The simulating outcomes were obtained and compared with conventional MOD-LEACH, M-GEAR and TEZEM models in terms of dead nodes, stability period, instability period and network lifetime. This section of paper presents a detailed overview of results obtained for proposed approach.

PERFORMANCE ANALYSIS

The effectiveness of the proposed approach is firstly validated by putting it in comparison with traditional models in terms of dead nodes. Figure 1 shows the comparative graph obtained for the same, with x and y-axis depicting the number of rounds and dead nodes respectively. Upon analysing the provided graph, distinct patterns emerge in the traditional M-GEAR, MOD-LEACH, and TEZEM models, where nodes start dying relatively early, completing only 900, 1000, and 1150 rounds, respectively. This trend continues until all nodes become inoperative in these models. Notably, the lifespan of these traditional models is notably low, as all nodes perish after 1100, 1500, and 3100 rounds in M-GEAR, MOD-LEACH, and TEZEM, respectively. However, in proposed model, all nodes remain functional until the 2500th round, indicating superior longevity compared to traditional models. Subsequently, a gradual depletion of nodes is observed, but the proposed model continues to maintain effective communication until the completion of 4000 rounds, thereby increasing its lifespan.

Furthermore, we conducted a comprehensive evaluation and comparison of the proposed approach with other similar models, focusing on their stability periods. The comparative graph obtained for the same is shown in figure 2. The stability period is defined as the duration from the start of the network until the first node in the model dies. Our analysis of the graph reveals that the traditional MOD-LEACH model exhibits the lowest stability period of 1000 rounds. In comparison, the M-GEAR model and TEZEM model show slightly higher stability periods at around 1050 and 1250 rounds, respectively. Remarkably, the proposed approach stands out with an exceptional stability period of 2500 rounds, which is approximately 1250 rounds more than the TEZEM model. This significant improvement in stability period demonstrates the superior energy optimization capabilities of the proposed approach, ensuring prolonged network stability and enhanced performance.

Similarly, we conducted a thorough analysis to validate the performance of our proposed approach by comparing it with traditional models in terms of their instability periods. The comparative graph for instability period is shown in Figure 3. The instability period is defined as the duration between the death of the first node and the last node in the model. Upon examining the graph, we observe that the instability period in traditional MOD-LEACH and M-GEAR models is almost the same, both occurring at 1500 rounds. In contrast, the traditional TEZEM model exhibits a better instability period of around 3000 rounds, outperforming the other two models. Nevertheless, our proposed approach excels with the highest instability period, reaching approximately 4000 rounds, which is around 1000 rounds more than the TEZEM model. This significant improvement in instability period highlights the enhanced resilience and robustness of the proposed model. In addition to this, we have also evaluated the performance of proposed approach with few standard models in terms of stability period and network lifetime (as shown in figure 4). Upon analyzing the graphs, we observed that the stability period (FND) values were 1000, 1050, and 1250 in MOD-LEACH, M-GEAR,

and TEZEM models, respectively, whereas the proposed approach achieved a stability period of 2501 rounds. Similarly, the network lifespan (LND) values were 1500, 1540, and 3000 in MOD- LEACH, M-GEAR, and TEZEM models, respectively, while the proposed model remarkably extended the network lifespan to 3937 rounds. These results clearly demonstrate that the proposed model significantly improves the wireless network's lifespan and exhibits a higher stability period compared to the other three models. The specific value of these parameters is recorded in tabular format also and is given in Table 3.

Based on the presented graphs and tables, the proposed model demonstrates superior performance compared to MOD-LEACH, M-GEAR, and TEZEM models. The results clearly indicate that the proposed approach outperforms these models in terms of dead nodes, stability, instability, and network lifetime parameters, showcasing its effectiveness and supremacy. The proposed model exhibits better outcomes across these critical metrics, highlighting its potential as an advanced and efficient solution in Wireless Sensor Networks.

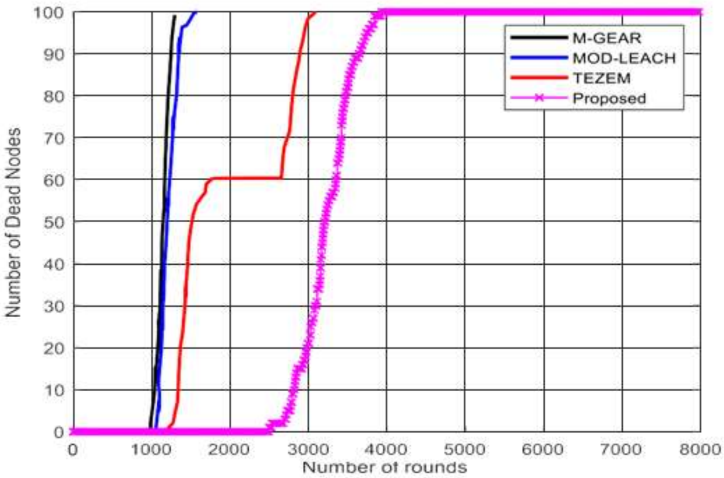

Figure 1. Comparative graph for Dead nodes

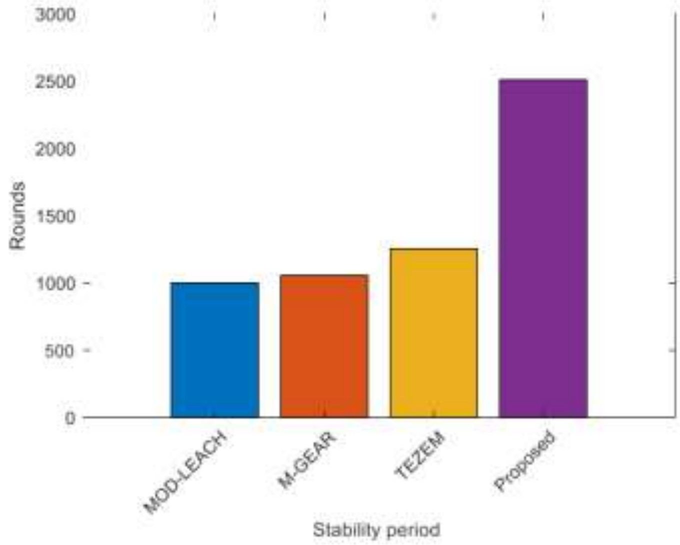

Figure 2. Comparative graph for Stability Period

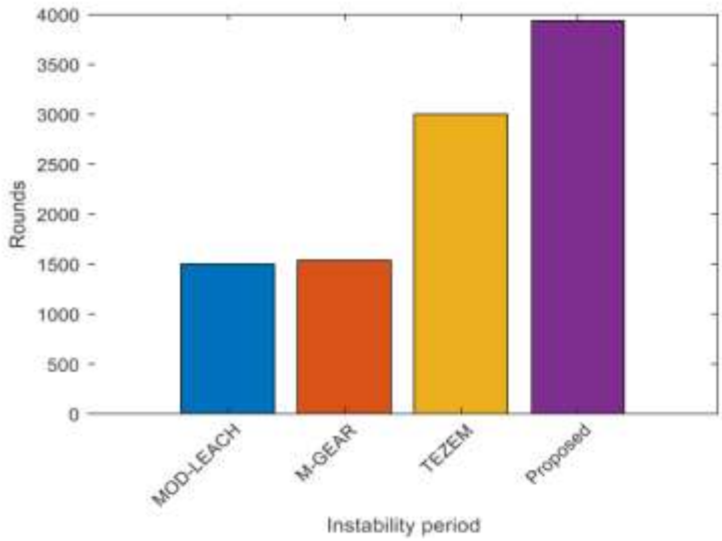

Figure 3. Comparative graph for Instability period

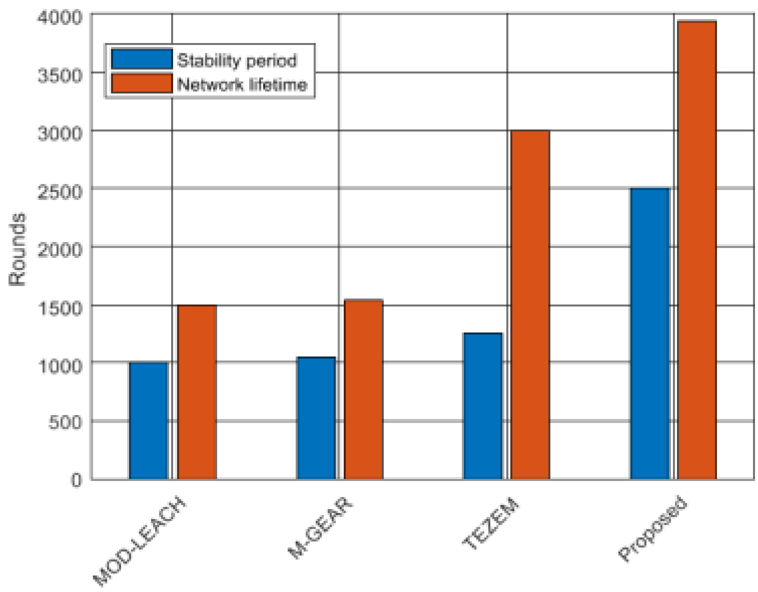

Figure 4. Comparative graph for stability and network lifetime Table 3. Specific Values of FND and LND

Algorithm	FND	LND
MOD-LEACH	1000	1500
M-GEAR	1050	1540
TEZEM	1250	3000
Proposed	2503	3937

V. CONCLUSION

This research paper presents an effective and efficient approach for enhancing the lifespan of wireless networks in which FCM is used for clustering and MGWO is used for CH selection. The efficiency and productivity of the proposed approach is analyzed in MATLAB software. Simulating outcomes were obtained and compared with traditional MOD-LEACH, M-GEAR and TEZEM models in terms of dead nodes, stability period, instability period, FND and LND respectively. Results showcased that nodes were dying at early stages of 1000, 1050 and 1250 in traditional MOD-LEACH, M-GEAR and TEZEM models respectively, while as, in proposed model nodes start dying after completing 2500 rounds. Moreover, we also observed that proposed model is outperforming all the three traditional models in terms of stability and instability period also. The values of FND were 1000 for MOD-LEACH, 1050 for M-Gear and 1250 for TEZEM while as, value of FND in proposed model came out to be 2503 rounds. Likewise, the LND determines the network lifespan of models which was 1500 in MOD-LEACH and 1540 and 3000 in M-GEAR and TEZEM models. However, the value of LND in proposed model came out to be highest at 3937 rounds, which demonstrates its supremacy over other approaches.

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