The Nucleus **60**, No. 1 (2023) 35-44

https://doi.org/10.71330/thenucleus.2023.1279

www.thenucleuspak.org.pk

The Nucleus

ISSN 0029-5698 (Print)

ISSN 2306-6539 (Online)

Performance Evaluation of Various Algorithms for Cluster Head Selection in WSNs

Humaira Afzal[1], Saba Kanwal[1], Muhammad Zulfiqar[2], Humera Batool Gill[3], Muhammad Rafiq Mufti[4*]

[1]Department of Computer Science, Bahauddin Zakariya University, Multan, Pakistan

[2]Department of Telecom System, Bahauddin Zakariya University, Multan, Pakistan

[3]Department of CS&IT, The Women University Multan, Pakistan

[4]Department of Computer Science, COMSATS University Islamabad, Vehari Campus Vehari, Pakistan

ABSTRACT

With the huge growth of wireless sensor networks (WSNs) and massive rise in upcoming electronic devices, network management becomes difficult as it affects the overall performance of the wireless networks. Earlier, in WSN, simple clustering was employed to cover this limitation but over the time, it became evident that without an effective mechanism of the cluster formation and cluster head (CH) selection, effective WSN performance cannot be achieved. As CH selection is one of the important phases of wireless communication, that is why, it becomes essential to enhance this phase. This enhancement reflects the great improvement in the overall performance of WSNs. Different types of methodologies have been introduced in the last 10 years for cluster formation and especially for CH selection. In this article, we investigate some important methodologies such as A-LEACH, MWCSGA, DEEC-Gauss, and eeTMFO/GA of cluster formation and CH selection. From the analysis, significant results such as the energy consumption, reliability, number of alive nodes, the lifetime and throughput of network are computed that can be further utilized in selection of the best algorithm for CH selection.

Keywords: *Networks, Sensors, Algorithms, WSNs, Reliability, Nodes, Cluster head, Energy consumption*

1. Introduction

WSNs are a branch of the basic ad-hoc technology consisting of numerous sensor nodes distributed in a given area. In these types of networks, sensor nodes are interconnected and communicated wirelessly to gather data from the surrounding. These nodes are usually low-powered devices organized in an ad-hoc manner. Due to its huge rate of growth, WSNs have become a matter of concern for all researchers. Initially, these were used for monitoring different kinds of systems of military applications [1]. Now, these are being implemented in several types of scenarios like health monitoring, reducing pollution in the atmosphere, ecosystem observation, physical hazards inhibition, fire detection in forests and daily activity monitoring. With the immense growth and demand of these sensor nodes, it has become difficult to manage wireless environment. So, there is a need of controlling this situation by making the structures of WSNs flexible and adaptable to any environment.

The structure of WSN is illustrated in Fig. 1. The wireless devices also called sensors sense the environment to acquire useful information like state, values, etc. and transfer them to other sensors. In WSN, a sensor is termed as a node and the blue node indicates the member node, whereas, the red node indicates the head node also called cluster head (CH). Clustering is an important technique for increasing and extending the lifetime of WSNs because in general, WSNs have a limited lifetime.

If each node directly communicates with other nodes then the structure of WSN becomes easy but on the other hand, it will not be very efficient. The nodes which are far apart from each other cannot communicate because of signal loss. Due to this, a node that is selected or fixed as a CH of the cluster so that other nodes can communicate through it other than communicating directly with each other. Member nodes can send/receive data only through CHs. Being an integral part of all clusters, the base station (BS) controls the whole transmissions in the network. Since CHs act as a bridge between member nodes and BS, therefore, CH selection plays a vital role in WSN. In case, if this bridge is not efficient then the successful communication will not take place.

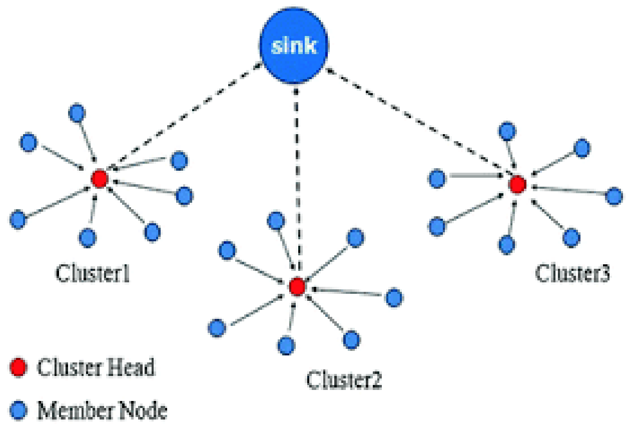

Fig.1: The general architecture of clustered WSN.

Due to the proliferation of nodes and to improve the data transmission in WSNs, the researchers are motivated towards the effective management methods of sensor nodes. The factors which are involved in the development and enhancement of WSNs depends upon the limitations on many issues particularly in the designing phase, energy consumption, reliability, network lifetime, scalability, cost, topology, etc. These limitations can be reduced by the use of clusters.

Different techniques have been reported in literature for the cluster formation. One is Low-energy adaptive clustering

*Corresponding author: rafiq_mufti@ciitvehari.edu.pk

hierarchy (LEACH) that is basically used to decrease the energy consumption. Further, many advanced versions of LEACH such as I-LEACH, T-LEACH, HLEACH and LEACH-II have been developed and the idea of CH selection is introduced. Particle swarm optimization (PSO) with bio- inspired aging model is developed for CH selection. Some other algorithms like gravitational search algorithm (GSA), genetic algorithm (GA) and multi-objective evolutionary algorithm (MOEA) have been designed for CH selection. These algorithms provide the optimal solutions [2]. Moreover, some hybrid techniques such as PSO with GSA, GA with MOEA, etc., are introduced for better optimal results.

In dynamic optimization of a sensor node, CHs selection is accomplished by GA. MOEA is multi-objective nature used GA and PSO for CHs selection. A fuzzy-based CH selection scheme is also described in [3, 4]. This scheme utilizes an eligibility index computed for each sensor node and then an optimal solution for CH selection is derived. In this paper, various algorithms and techniques for clustering and the CH selection are discussed comprehensively. Based on different parameters, the best algorithm is evaluated.

An algorithm using unique neighbor node approach was proposed in [5], where selection of CH took place based on connectivity to at least one neighbor node that is unique. In case if cluster had no unique neighbor node, then CH selection was carried out on the basis of maximum residual energy and the number of other neighbor nodes. This algorithm ensured the connectivity of the overall network. A mechanism for selecting dynamic CH was suggested in [6, 7] by introducing the first kind of CH, second kind of CH, and so on. The Voronoi diagram was incorporated for cluster formation in the monitoring area and due to redundant nodes death priority and network coverage performance, the first kind of CH was employed and when it became dead, then second kind of CH was selected on the basis of the average energy of the network nodes and the residual energy. In [3], a fuzzy-based balance cost CH selection technique (FBECS) was introduced by using an eligible index for each sensor node of each cluster, which was computed and the optimal value of the index was then chosen. A similar scheme for CH selection and clustering was also presented in [8] for enhancing the lifetime of the WSNs but these methodologies depending on one level head selection were not so efficient in the multi-hop systems. Therefore, there was a need for another algorithm that exploits two-level fuzzy CH selection. An energy-efficient dynamic scenario (EEDS) was reported in [9] which introduced a new mechanism of selection of CH based on network traffic and the node localization. The multi-hop decision-making technique named Fuzzy-Topsis for CH selection was also introduced in [10] using distances between neighbor nodes, the distance from the BS and the remaining energy of the nodes, as parameters. A high-quality and high-power clustering algorithm (HQCA) was incorporated in [11], where selection of CH was carried out based on energy that is remaining in the sensor nodes, the mean distance of sensors in the cluster and lowest distances of the sensors from the BS.

In [12], an energy-efficient CH selection technique was proposed describing the energy dissipation based on locations depending upon the residual energy. For this scheme, the radio energy model was employed for CH selection by measuring the distance from the sink, so increasing the lifetime of WSN. The rotating role is one of the approaches used for CH selection and the role of the head is rotated among all of the sensor nodes in a given cluster. In [13], the k-mean algorithm was suggested for finding the centroid node of the cluster and then adopted it initially as a head node. A Fault-tolerant head selection method was then proposed to compute the fitness function of the head node for initializing and updating CH, whenever the initial CH had a low fitness function and less residual energy. To improve this algorithm, another approach by combining the k-mean algorithm and Huffman coding algorithm was incorporated in [14]. Huffman's coding algorithm is efficient in terms of energy consumption but has a problem with respect to node residual energy and its communication distance. This problem can be resolved by using a gradient descent algorithm that reflects its effects in the form of an enhanced lifetime, latency, energy consumption and delivery rates.

The flower pollination algorithm (FPA) is one of the famous bio-inspired algorithms consisting of two components: 1) self-pollination and 2) cross-pollination, where self-pollination performs local pollination search and cross-pollination is for global pollination search exploring. In [15], FPA was proposed for CH selection by doing a local search and then global search exploring. In [16], an improved flower pollination algorithm (IFPA) was designed to enhance traditional FPA in terms of capacity, energy and lifetime. In this technique, groups of parallel operation-based pollination were developed to follow the strategy of enhanced communication depending upon the replacement of old pollen by new high-quality pollen. The functional fitness of each group was then evaluated. In [17], the chicken swarm optimization (CSO) technique was discussed for selecting CHs based on the fitness function of all the type (roosters, chicks and the hens) together. However, the fitness function calculation requires more space and cost.

2. Selected Algorithms for Performance Analysis

2.1 Multi Weight Chicken Swarm based Genetic Algorithm (MWCSGA)

Multi weight chicken swarm-based genetic algorithm (MWCSGA) expresses the reflective view of bio-inspired GA and uses the clustering CSO method for CH selection [18]. Clustering is performed through GA and the head is selected through swarm optimization technique. In this strategy, the multi-weight clustering method is first constructed for cluster formation and a head for communication is then selected. This strategy comprising of two levels derives the individual's best fitness functions whose values are used for CH selection. The process is performed for three groups (indicate as rooster, hens and chicks by employing fitness value, swarm updating frequency, Energy, CHs count, mutation and the crossover, as a parameter. Based on efficient fitness function values for individual chicks (nodes), CH is selected and transferred to consequent generation. The consumed energy (E) of CH in this strategy is given as:

$$E = \left[L\left(\frac{N}{A} - 1\right) \times E_d + \frac{N}{A} E_{com}\right] + \psi(E_R, E_T)$$

where

$$\psi(E_R, E_T) = E_R(L, d) + E_T(L, d_{BS}),$$

Where L is the amount of data transferred by the transmitting node to the CH; N is the number of alive nodes; A is the number of clusters in the network; E_d is dissipated energy; d_BS is the distance from BS to CH; E_T and E_R is energy consumption of transmitter and receiver respectively. Here, fitness function value calculation is carried out through a new mechanism because the old CSO is not so efficient in terms of cost and speed.

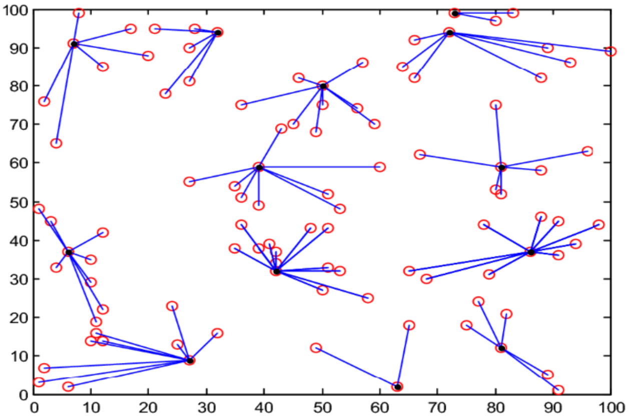

Fig. 2: Structure of cluster eeTMFO/GA.

2.2 *Energy-efficient Trusted Moth Flame Optimization and Genetic Algorithm-based Clustering Algorithm (eeTMFO/GA)*

The eeTMFO/GA introduced in [19] is an optimal selection algorithm for cluster formation to enhance network performance. Structure of a cluster eeTMFO/GA is shown in Fig. 2. Due to its GA feature, it has the ability for selecting the cluster head with minimum energy consumption. Fitness function is evaluated by using residual energy of elected node, connected node density, packet forwarding progress, the average delay of transmission and average cluster distance as parameters.

2.3 *Advanced LEACH (A-LEACH)*

LEACH was the first algorithm designed for WSN for the formation of clusters, CHs, measuring network lifetime, throughput and reliability. It uses simple and traditional parameters such as residual energy and distance from BS in the selection of CH. In [20], CH selection is carried out based on the distance between BS and the CH. The cluster is divided into semi-clusters and threshold is given as:

$$T_r = P_G + P_C$$

where

$$P_G = \frac{\kappa}{\eta - \kappa\left(\tau \, mod \frac{\eta}{\kappa}\right)}$$

$$P_C = \frac{E_{current}}{E_{initial}} \times \frac{\kappa}{\eta}$$

P_G denotes the general probability; P_C represents the current state probability; τ represents any round; κ shows the expected number of CHs in a round; η denotes the total number of sensor nodes in the network; $E_{current}$ is the current energy of the node relative to initial energy $E_{initial}$. A node having higher residual energy nearer to sink is to be selected as a CH. This technique is beneficial for energy-aware techniques and dissipates energy from clusters leading to improve overall network lifetime.

2.4 *Distributed Energy Efficient Clustering with Gaussian (DEEC-Gauss)*

Enhanced distributed energy-efficient clustering (E-DEEC) presented in [21] set a node as CH having higher remaining energy. DEEC used the probability of ratio of average energy and residual the energy. E-DEEC introduced the supernode to increase the heterogeneity and enhance the network lifetime. Using some additional parameters, an enhanced version of the E-DEEC algorithm was designed and combined with the Gaussian algorithm that filters out the best supernode (i.e. CH) of the cluster.

3. Comparative Studies

Tables of comparative studies are given in Appendix 1. The comparative analysis of existing techniques used in CH selection is discussed in Table 1. The methodologies along with its parameters such as fitness value, mutation, residual energy, sense power, node position, etc. are listed in the table. These parameters play an important role in performance evaluation. The research gaps are also identified in the given methodologies. From the parameters given in Table 1, five parameters are selected for Table 2 as a benchmark for performance evaluations. These parameters are the key points in our proposed work.

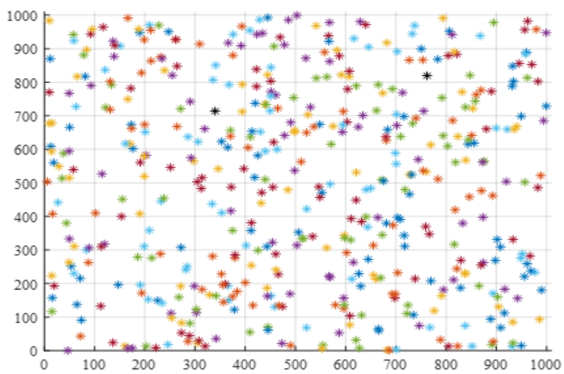

Fig. 3: Wireless sensor network.

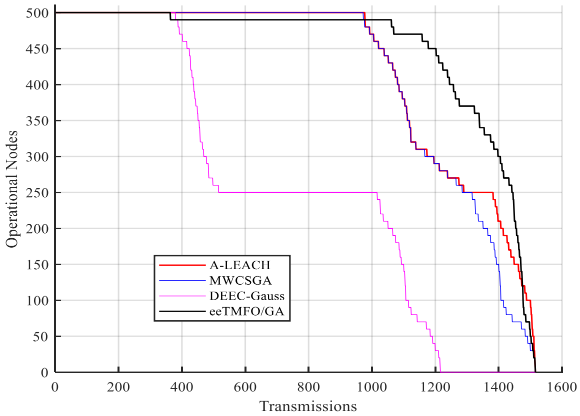

Fig. 4: Data transmissions.

4. Performance Evaluation

4.1 Simulation Procedure

The effectiveness of the algorithms discussed in Section 3 is evaluated based on alive node, energy consumption, time complexity and throughput. The simulation is done by using MATLAB/SIMULINK environment. The basic level parameters used for simulations are given in Table 3 (Appendix 1).

The experiments are performed with 500 operational nodes of WSN by setting the rounds as 50 and 100. Assume that, data length is 12000 bits and the transmission power is 0.0175 nJ/bit/m^2. The initial energy assigned to every node is 0.28 Joule. The model under consideration for WSN is illustrated in Fig. 3. The data transmission rates of A-LEACH, MWCSGA, DEEC-Gauss and eeTMFO/GA algorithms are represented in Fig. 4. The data transmission rates of MWCSGA and A-Leach are almost the same, whereas eeTMFO/GA has the highest data transmission rate for particular operational nodes.

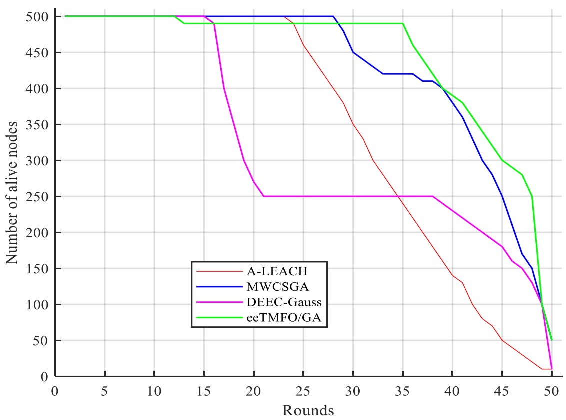

Fig. 5a: Number of alive nodes with 50 rounds.

4.2.1 Analysis of alive nodes

Alive nodes are used to send data to BS/sink immediately after successfully aggregated it. These nodes calculate the weights of randomly selected numbers dynamically. This concept of random number selection was first introduced in the LEACH protocol for CH selection. Fig. 5 depicts the number of alive nodes of each algorithm with 50 and 100 rounds. The increment of rounds affects the first node death (FND), half node death (HND) and last node death (LND) percentage of each algorithm.

In 50 rounds, the FND of MWCSGA is the highest and of eeTMFO/GA is the lowest but the HND and LND of eeTMFO/GA are larger that make the total percentage of alive nodes highest. On the other hand, in 100 rounds, the eeTMFO/GA has a high percentage in terms of FND, HND and LND. In general, the dimension of alive rate depends upon the number of nodes. As the number of nodes increases, the alive rate decreases, i.e., it almost goes to zero. It can be observed that the lowest possible alive rate of any node is approximately 0.00003s. From Fig. 5, it is clear that eeTMFO/GA algorithm has a large number of alive nodes as compared to other algorithms.

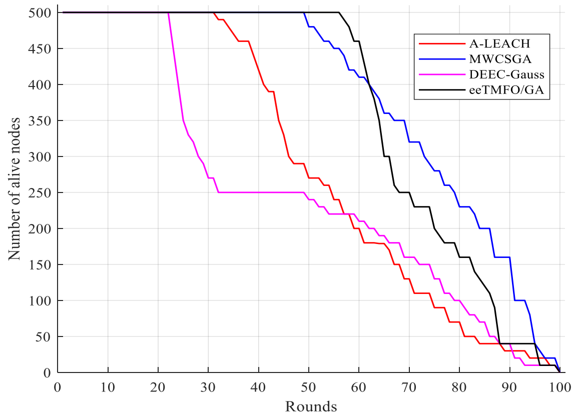

Fig. 5b: Number of alive nodes with 100 rounds.

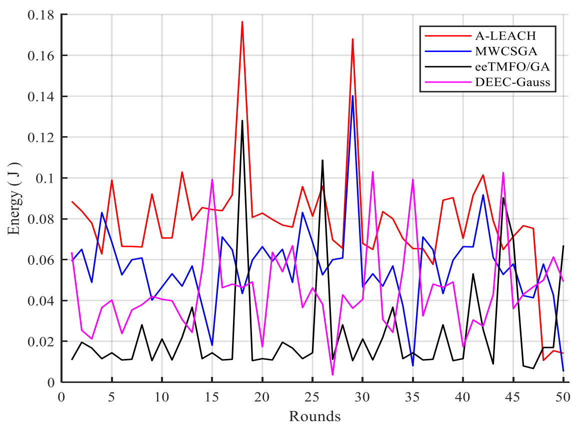

Fig. 6a: Energy with 50 rounds.

4.2.2 Analysis of Energy Consumption

Energy utilization is the main concern in WSNs, as it plays a vital role in the selection of CH. A node having minimum amount of energy consumption is to be selected as a CH in the cluster. Fig. 6 shows the flow of energy consumption in which the energy or power consumption of A-LEACH is high. This is due to its traditional structure and transmission. MWCSGA and DEEC-Gauss have an average energy consumption but eeTMFO/GA consumes less energy as compared to others. From this figure, it can be observed that energy consumption is directly proportional to the number of rounds. The number of rounds increases with the increase of consumption.

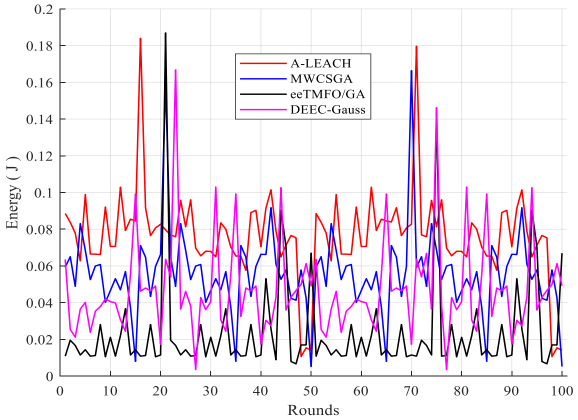

Fig. 6b: Energy with 100 rounds.

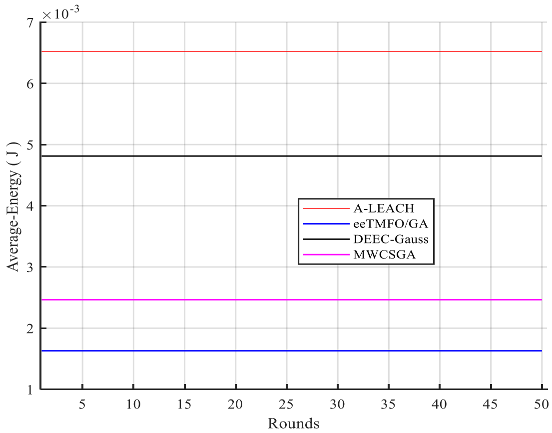

Fig. 7a: Average energy for 50 rounds.

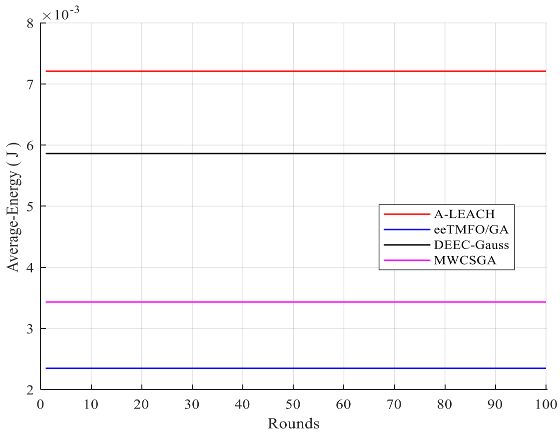

Fig. 7b: Average energy for 100 rounds.

Fig. 7 represents the average consumed energy at 50 and 100 rounds. MWCSGA and DEEC-Gauss have low average consumption whereas eeTMFO/GA has the lowest average energy consumption.

Similarly, Fig. 8 shows the overall energy consumption of head selection. eeTMFO/GA has the lowest energy consumption as compared to other algorithms regarding CH selection.

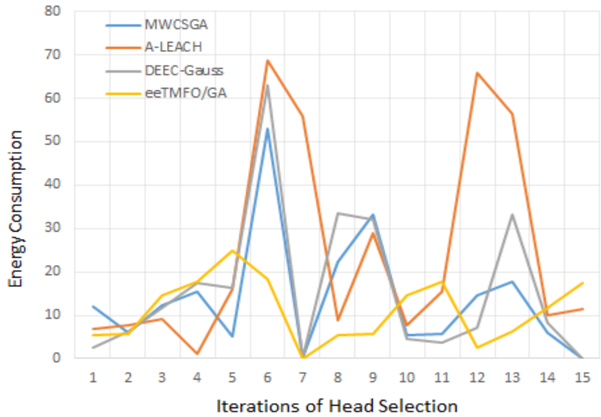

Fig. 8: Overall energy consumption.

4.2.3 *Cluster Head Selection Phases*

CH selection takes place in four phases. In the first phase, CH selection using residual energy and fitness factor provides the large number of nodes selected as CHs as shown in Fig. 9a. DEEC-Gauss provides the selection of CHs that is high at the beginning but low at the end, so this behavior is not acceptable. On the other hand, eeTMFO/GA and MWCSGA provide the average rate of CHs and the average ratio of eeTMFO/GA is higher than the average ratio of MWCSGA, so it implies that eeTMFO/GA provides the optimal and efficient CHs selection in the first phase.

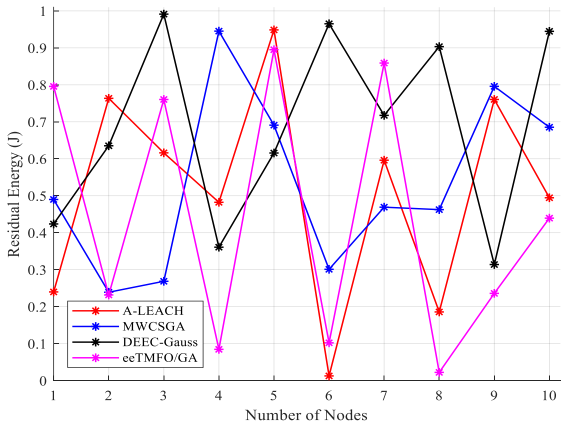

Fig. 9a: Head selection phase 1.

In the second phase as shown in Fig. 9b, CH selection takes place by using residual energy and node position for (x, y). MWCSGA provides the lowest selection rate and A-LEACH has either the same effect or higher selection rate. eeTMFO/GA and DEEC-Gauss have an average ratio of selection but the ratio of eeTMFO/GA remains higher than the ratio of DEEC-Gauss. In the third phase, A-LEACH and DEEC-Gauss have a larger selection ratio than MWCSGA.

eeTMFO/GA leads with their highest ratio in the average rate of selection and the same is the case in fourth phase.

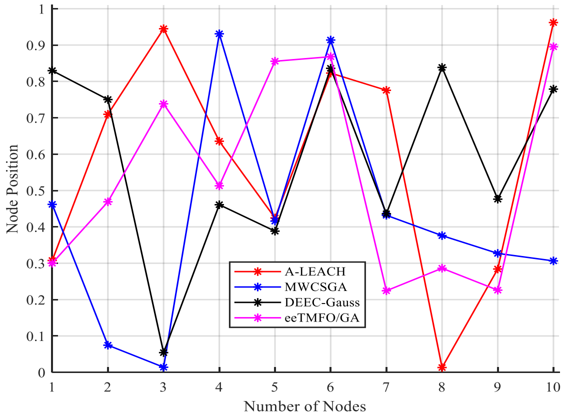

Figure 9b: Head selection phase 2.

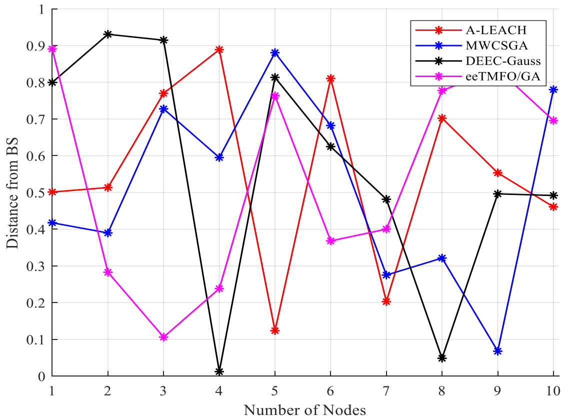

Fig. 9c: Head selection phase 3.

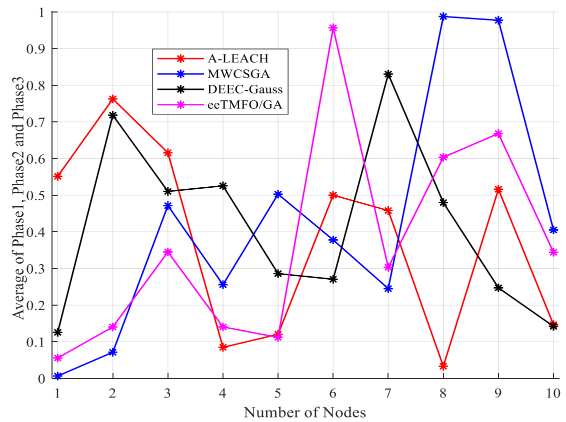

Fig. 9d: Head selection phase 4.

4.2.4 *Analysis of Throughput*

Throughput is mainly concerned with data transfer rate in unit time. The basic goal of WSN is to increase the network lifetime with enhanced reliability by improving the throughput. Residual energy is used as a primary aspect in the improvement of throughput. As energy resources increases and energy consumption decreases, then throughput increases. The performance analysis in terms of throughput is given in Table 4. It is obvious from Table 4a, eeTMFO/GA has the highest throughput as compared to other algorithms for all aspects. This enhancement is due to the involvement of certain factors such as death rate, transmission media, power consumption and scalability and their impacts are given in Table 4b.

Table 4a: Throughput performance of algorithms for various rounds.

Algorithm	With 50 Rounds	With 100 Rounds	Overall
MWCSGA	65%	56%	60%
eeTMFO/GA	68%	60%	64%
A-LEACH	55%	49%	52%
DEEC-Gauss	65%	53%	59%

Table 4b: Throughput enchantment factors.

Algorithm	Death Rate	Transmission media	Power consumption	Scalability
MWCSGA	Mediam	Stable	Low	High
eeTMFO/GA	High	Very Stable	Low	High
A-LEACH	Mediam	Not Stable	Large	Mediam
DEEC-Gauss	High	Sometime Stable	Mediam	Mediam
		Sometime not stable		

Table 5. Overall analysis

	MWCSGA	eeTMFO/GA	A-LEACH	DEEC-Gauss
Average Consumed energy With 50 Rounds	2.34J	1.98J	6.4J	4.5J
Average Consumed energy With 100 Rounds	3.5J	2.48J	7.2J	5.9J
The difference with an increment of Rounds 50-100	1.16J	0.5J	0.8J	1.4J
First Node Death Percentage with 500 Nodes	60%	25%	61%	27%
Half Node Death Percentage with 500 Nodes	80%	71%	86%	32%
Last Node Death Percentage with 500 Nodes	76%	94%	94%	76%
Throughput	60%	65%	51%	59%

4.2.6 *Time Complexity*

Big-O is one of the common factors used to evaluate the complexity of any algorithm. It is the worst-case analysis to determine the execution time of an algorithm. The Big-O of algorithms is described in Table 6 which shows that A-LEACH consumes a lot of costs as compared to others, whereas eeTMFO/GA exhibits the lowest cost. The cost consumed in A-LEACH is n5 which is large enough to affect the overall contributions of network reliability. DEEC-Gauss consumes the cost in factorial of iterations that reflect its drawback in terms of memory rudiments. Similarly, the cost utilized in MWCSGA is in binary form that gives a bit effect of high energy consumption in peak value. Overall, the efficiency of MWCSGA and eeTMFO/GA is significant in terms of throughput as compared to others.

Table 6: Big-O analysis.

Algorithm	Big-O
MWCSGA	$O(n(n-r)2^{n-1})$
eeTMFO/GA	$O\big(c(n^2+n)\big) = O(n^2)$
A-LEACH	$O\big(n^4(n-1)logn + n^2 + n^3(n-1)\big) = O(n^5)$
DEEC-Gauss	$O\big((n-1)n! + (n-1)(n+1)!\big) = O\big((n-1)(n+1)!\big)$

5. Conclusion

Cluster Head (CH) selection has become a matter of attention for researchers because of its contribution to the overall performance of WSNs. In this paper, the previous studies of CH selection have been discussed. The well-known techniques for CH selection such as A-LEACH, DEEC-Gauss, MWCSGA and eeTMFO/GA have been investigated and evaluated in terms of energy consumption, alive rate, lifetime and reliability. Based on performance, it can be concluded that eeTMFO/GA method perform better as compared to the traditional methods in terms of energy efficiency. Moreover, eeTMFO/GA has efficient energy consumption, a high network lifetime and a large rate of alive nodes. It provides 12%, 9% and 8% performance improvements in all aspects as compared to A-LEACH, DEEC-Gauss and MWCSGA respectively.

A low power and trust aware network has become one of the essential parameters of WSNs. Our future work is mainly focused on the design of an energy efficient algorithm which may be expected to have reliability and high network lifetime.

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Appendix

Table 1: Comparative studies of existing approaches.

References	Parameter	Methodology	Limitations
Nader Ajmi et al. (2021) [18]	Fitness value, mutation, swarm updating frequency, crossover Energy, and the cluster heads count	CSO and GA work together, Selects the CH based on efficient fitness function values for individual chicks(nodes) and transfers it to consequent generation.	Fitness function calculation needs more space and cost
D. Laxma Reddy et al. (2021) [24]	Residual Energy, Sense power, Node Position, Fitness of nodes	Combination of ACI and GSO, selection based on local searching and global searching. Rapid discovery of solution by ACO and GSO based non-centralized control	More Cost required
Oluwasegun Julius Aroban et al. (2021) [22]	Communication range, data packet size, residual energy, distance with sink	An enhanced version of the E-DEEC algorithm that uses Gaussian formula that shows the efficient performance	The complex structure of Gaussian make cost higher
Atefeh Rahiminasab et al. (2020) [25]	Energy, effeicent use of the size od data queues, distance to the center, and the mobility.	Multi-factor decision-making, a combination of AHP and CSP.	Dead rate not enhanced
Ramadhani Sinde et al. (2020) [2]	Node degree, residual energy, and distance	Combine PSO with AP for selection. Selection is done with local and then global best solutions	AP exemplar selections are not effective after a little enhancement
eeTMFO/GA (2020) [19]	Density, Energy, Distance with packet forwarding progress, Transmission delay,	Combination of GA and MFO, Selects the optimal solution	This procedure has network delay
Thi-Kien Dao et al. (2020) [16]	Data aggregation, network status, Classification Support Vector Machine(SVM)	Decision function classification deployed the data aggregation. Improved flower pollination algorithm (IFPA) solves this problem by dividing the parallel operation into groups and then calculate the fitness function of each group. Replace the optimal solution with the original one.	The complexity of the overall algorithm is increased that reflects the problematic outcomes in terms of cost function calculations.
Kashif Naseer Qureshi et al. (2020) [25]	Gateway Node weight, centroid position, energy consumption model,	Gateway Energy-Efficient Centroid (GCEEC) routing protocol nature-inspired algorithm for agriculture. Selects the CH by calculating the centroid position of node and gateway node for transmission of data with BS.	Inter-cluster Multi-Hop communication needs more energy, also has network delay
G Pius Agbulu et al. (2020) [14]	Aggregation-energy, Network Traffic	A combination of K-mean and Huffman algorithms. K-mean calculates the nearest node and the Huffman algorithm is used to organize the nodes.	Huffman algorithm complexity affects the overall cost or complexity of cluster formation.
Pawan Singh Mehra et al. (2020) [3]	Nodes States(Show the current state of the node), RegionvBased probability	Enhanced Version Of BCSA algorithm. The density and power level of nodes is used to calculate the energy expenditure of selected CH.	Requires More Cost for Node Status Calculation
Amir Abbas Baradarana et al. (2019) [11]	Based on residual energy of node, all node distance with BS, amount of energy per cluster, and cluster density	Uses Fuzzy Decision Block (FDB) and checks the parameters. A node that has less distance from BS, has higher in remaining energy, enhanced cluster quality, and less mean distance	Fuzzy logic in high vagueness

		is selected as CH.	
Amanjot Singh Toor et al. (2019) [34]	NetworkvStatus, Residual Energy, node location	Energy-Aware Cluster-Based Multi-hop (MEACBM), uses Subcluster formation and residual energy-based selection. Also Calculates efficient multi-hop routes for commination.	The structure becomes complex and has network overhead due to sub-cluster formation processes
Somaye Jafarali Jassbi et al. (2019) [26]	Communication range, data packet size, residual energy, distance with sink	Backup Cluster Head (BCH) is selected after HEED CH selection based on minimum distance and maximum residual energy.	Overhead of HEED is deployed but not fully removed
Jin-Gu Lee et al. (2019) [27]	Objective Function, Homogeneous Energy, aggregation rate, Location	SSMOECHS protocol for CH selection based on sampling-based SMO by using the received information	Delay increases
Krishnasamy Gomathi (2019) [34]	The trust factor, Energy	Secure CH selection, fuzzy logic is used for selection of CH	More memory is required as you consider
Liang Zhao et al. (2018) [28]	ResidualvEnergy, Network Address	LEACH-M is an improved version of LEACH, a distributed approach used to find Optimal Solution	Delay increases
Adem Fanos Jemal et al. (2018) [13]	Energy and power consumption, and the packet loss	Uses k-mean to select initial cluster header and use Euclidean distance for CH selection	Network delay increases
Bilal Muhammad Khan et al. (2018) [10]	Data aggregation, member Nodes,	Selection is done by multi-conditional decision. Network robustness and effective network expectancy	Fuzzy logic in highly vagueness and sink mobility prediction is complex
Taj Rahman et al. (2020) [29]	Quality of Service (QoS)	Merge two ideas in MANET, first is cross-layer design and second is self-organization	The pre-specified version needs more memory
Payal Khurana Batra et al. (2016) [30]	Stability Period, Energy Consumption	Randomness is used in LEACH	Needs more cost function for prediction
Sachin Gajjar et al. (2014) [31]	Data aggregation, energy, BS location, Energy Consumption, reachability from its neighborhood,	CH selection protocol by using Fuzzy Logic (CHUFL), the selection is based on residual energy based on neighbor nodes.	Energy consumption is not so effective when the number of nodes increased
M. Senthil et al. (2014) [12]	The energy dissipated and the distance between the base station and the CH	Distance based CH selection between sink and CH. In this paper, cluster divides into semi-cluster that have less distance from the sink.	Network robustness effects
Tapan Kumar Jain et al. (2014) [5]	Residual Energy of neighbor nodes, unique nodes that connected to each node of the cluster	In this strategy, the CH is selected based on neighbor unique node connectivity. The selected CH fitness function is calculated. Then less distance with BS reflects the validity of CH.	This procedure has network delay
Chakchai So-In et al. (2013) [32]	Energy consumption, optimal weight	Uses moving energy window energy computation on previous LEACH algorithms and enhanced probability of CH.	Network robustness effects
P. K. Dutta et al. (2013) [9]	Network traffic, residual energy, remaining energy of node, the cost function for each node	Uses three parameters and select CH, initially CH is selected randomly, and then its remaining energy and cost fitness for CH is calculated. After that performance is measured by electing CH among these randomly selected CHs.	More memory is required for two way selection
Parul Saini et al. (2010) [21]	ResidualvEnergy, Distance With BS, Network Area	E-DEEC Algorithm uses for CH selection that is energy efficient and enhances the clustering	The death rate is very large

Table 2: Comparative study of parameters.

Reference	Reliability	Energy Consumption	Network Lifetime	Alive Node Per Round	Throughput
Pawan Singh Mehra et al. (2020) [3]	Dense	5J	✓	30%	✓
M. Senthil et al. (2014) [12]	Nearest Neighbor	1.6bJ	✓	7%	-
P.K. Dutta et al(2013) [9]	In terms of Cost Function	7J	✓	_-	✓
Tapan Kumar Jain et al. (2014) [5]	Stability	-	✓	48%	-
Amir Abbas Baradarana et al. (2019) [11]	Complexity	1.5J	✓	82%	✓

G Pius Agbulu et al. (2020) [14]	Latency	0.9bJ	✓	50%	✓
Thi-Kien Dao et al. (2020) [16]	Accuracy	4.7J	-	-	✓
Kashif Naseer Qureshi et al. (2020) [25]	Error Free	8.5J	✓	40%	✓
Amanjot Singh Toor et al. (2019) [33]	-	10J	✓	45%	✓
eeTMFO/GA (2020) [19]	effective and Secure	2.2J	✓	75%	✓
Sachin Gajjar et al. (2015) [31]	Latency	5J	✓	10%	✓
Somaye Jafarali Jassbi et al. (2019) [26]	Effective And Secure	4J	✓	38%	✓
Nader Ajmi et al. (2021) [18]	Efficiency	3J	✓	65%	✓
Ramadhani Sinde et al. (2020) [2]	Efficiency, Accuracy	11J	✓	17.50%	✓
Jin-Gu Lee et al. (2019) [27]	Accuracy	3J	✓	54%	✓
Bilal Muhammad Khan et al. (2018) [10]	latency, Mobility	0.08bJ	✓	_-	✓
D. Laxma Reddy et al. (2021) [23]	Scalable	12J	✓	56%	✓
Adem Fanos Jemal et al. (2018) [13]	Nearest Neighbor	3J	✓	34%	✓
Atefeh Rahiminasab et al. (2020) [24]	Mobility	2J	✓	65%	-
Payal Khurana Batra et al. (2016) [30]	-	5J	✓	54%	✓
Taj Rahman et al. (2017) [29]	Robust, Adaptive & Scalable	9J	✓	-	-
Krishnasamy Gomathi (2019) [34]	Secured	-	-	-	✓
Xin-She Yang et al. (2012) [15]	-	7J	✓	45%	_
Chakchai So-In et al. (2013) [32]	Adaptive	0-5% improved	✓	_	✓
Parul Saini et al. (2010) [21]	Energy	2J	-	25%	✓
Oluwasegun Julius Aroban et al. (2021) [23]	Energy	1.0891bJ	✓	70%	✓

Table 3: Simulation parameters.

Sr. No.	Parameters	Value
1	Number of Nodes	500
2	Sensed Area	$500*500m^2$
3	BS Coordinate	(250,250)
4	Initial Energy	0.28J
5	Length of data Packet	12000 bit
6	Elec(Elected Energy)	$25nJ/bit/m^{-1}$
7	efs (Free Space energy)	$0.0013pJ/bit/m^4$
8	emp()	$20pJ/bit/m^{-2}$
9	Number of Rounds1	20
10	Number of Rounds2	50
11	Number of Rounds3	100
12	Sense power	$0.0175nJ/bit/m^2$
13	Transmission power	$0.744nJ/bit/m^2$
14	Receiving Power	$0.0648\ nJ/bit/m^2$