Performance Analysis of Fractional Earthworm Optimization Algorithm for Optimal Routing in Wireless Sensor Networks

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Abstract

In Wireless Sensor Networks (WSNs), the data transmission from the sensing node to the sink node consumes a lot of energy as the number of communications increases, so the battery life of nodes is limited, and the network also has a limited lifetime. Recent studies show that the bio-inspired meta-heuristic algorithms for solving engineering problems such as energy reduction in autonomous networks in the multidisciplinary areas of WSN, Internet of Things (IoT) and Machine learning models. Hence to increase Network lifetime, optimized clustering and energy-efficient routing techniques are required. In all applications of WSN, not only energy-efficient but also delay and throughput of the network are important for efficient transmission of data to the destination. This paper analyses optimized clustering by selecting cluster heads based on fractional calculus earthworm optimization algorithm (FEWA). The route from cluster heads to sink node is selected based on the fit factor. This paper's main intention is to provide an extensive comparative study of the FEWA with all standard optimization-based clustering and routing techniques. This method's performance is compared with existing optimized clustering methods like GA, PSO, ACO, DE and EWO in terms of the number of energy, delay, and throughput. At the end of 1000 iterations, the analysis shows that the FEWA outperforms existing methods with maximum average remaining energy of the nodes as 0.216J, the minimum average delay of 0.208 sec and maximum average throughput of 88.57% for 100 nodes.

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1. Introduction

WSN finds various applications in gathering environmental data and solving real-world data gathering problems [1]. To boost the battery life of the network, efficient data aggregation procedures are required. Clustering is a data aggregation approach that enables a network's energy efficiency to achieve efficient transmission, load balance, and scalability. Many clustering algorithms exist in the literature, and very few concentrates on optimizing the necessary WSN constraints. Optimization algorithms are iterative-based approaches used to achieve the desired solution problem outcome. It gives an optimum solution because it is

minimized or maximized using one of the many optimization routines. Fractional calculus in engineering applications has been one of the most useful tools recently. It is an analysis of differential problems as fractional derivatives from mathematical calculus. The function of fractional calculation in different fields, such as mechanics, electricity, chemistry, biology, economy, notably control theory, and signal and image processing, has been very significant in recent years [2]. New trending approaches used to optimize engineering problems are bio-inspired methods of optimization. Clustering approaches on wireless sensor networks focused on optimization have brought promising advances over conventional clustering algorithms. This paper uses a newly developed bio-inspired optimization method for cluster head selection, called the FEWA algorithm [3].

Using the fractional calculus to solve the optimization problem increases algorithm efficiency by preserving the past background of solutions by choosing the solution equation's proper value for the fractional-order derivative. This paper mainly focuses on comparative analysis of the FEWA algorithm with traditional bio-inspired optimization-based clustering algorithms in WSNs.

The FEWA consists of incorporating a fractional definition into EWA to formulate the CH selection by the established algorithm. This algorithm records the best CH in the previous iterations and formulates the efficient CH of the current iteration with fitness based on energy, trust, and distance. The clustering methods used in WSN are focused mainly on saving and/or enhancing energy-related lifetimes. Data must also be transmitted via multi-hop communication to the sink node by selecting the most efficient cluster heads. Therefore, the task is to use data aggregation methods such as clustering in terms of energy, distance, and trust and collection of clusters head employing an effective algorithm for optimization. The selection of intermediate CHs based on necessary factors based on WSN restrictions must be made for multi-hop communication from the head to the cluster's sink node. This paper's main objective is to explore the performance analysis and comparative study of the FEWA algorithm with other optimization techniques in the literature regarding the delay, energy, and throughput.

2. Literature Review

This section provides an overview of WSN applications and several existing energy-efficient and optimized routing techniques to improve the network's lifetime. In [4], the authors provided an extensive review on network layer-based energy-efficient routing techniques related to both WSNs and the Internet of Things (IoT). Bio-inspired meta-heuristic solutions for engineering problems are dominant multidisciplinary research in recent years. Different categorization and detailed analysis of nature-inspired algorithms [5] have been explored in disease diagnosis with different data sets [28-34]. There are numerous applications of the nature-inspired optimization algorithms in different areas viz. disease diagnosis, query optimization, sentiment analysis, feature selection, routing, power management, load balancing etc. In cardiac arrhythmia disease analysis, swarm intelligence-based optimization methods [6] have been used to find the optimal values of the feature set for the diagnosis with standard benchmark UCI data set. Sharma, Manik, et al. [7] proposed an entropy-based genetic algorithm to optimize query execution plan in distributed database systems in terms of system size and query complexity. Prableen Kaur and Manik Sharma [8] have provided an extensive review of soft computing-based optimization algorithms for diabetes pre-processing and diagnosis [35-41]. Also, the rate of accuracy is analyzed in detail for data mining and hybrid optimization techniques [42-46].

In recent days, most researchers have focused their study on novel coronavirus (Covid-19). Nature-inspired optimization techniques are also used to detect Covid-19 cases and contact tracing [9]. Rachhpal Singh [10] proposed a hybrid MPG optimization algorithm with PSO and GA to feature gene expression. With this method, data dimension and duplication among the classified sets have been reduced significantly [47-51]. Nature-inspired optimization algorithm based on PSO is used for E-health services in Job scheduling on mobile competitive cloud distributed systems [11]. Samriti [12] provided a brief study of the Genetic Algorithm (GA) role in software engineering, distributed computing, and machine learning applications. Few existing CH collection and routing approaches in WSNs are provided below table and the merits and challenges. Data correspondence from CH to sink node is direct in many cluster-based literary algorithms [23-27]. The FEWA algorithm optimizes the selection of the route from CH to the sink node for multi-hop communication.

Table 1. Review of existing methods

Authors and References	Method	Implementation work	Advantages	Limitations
Wendi Rabiner Heinzelman, Anantha Chandrakasan, and Hari Balakrishnan[13]	LEACH	Random selection of cluster head based on threshold	Simple to implement	the CH selection is a randomized process, and the remaining energy of the nodes is not considered for the CH selection
Jitendra Singh, Rakesh Kumar, and Ajai Kumar Mishra[14]	Variants of LEACH	distributed and hybrid algorithms	Perform better compared to LEACH	didn't consider all the objectives to give the optimum result for CH selection.

Vipin pal et al.[15]	GA based CH selection	centralized clustering algorithms	improved the network lifetime compared to traditional LEACH protocols	the heterogeneity of nodes is not considered, and delay increases with the increase of population.
Tripti Sharma et al.[16]	PSO based	global optimum solution in a complex search	increases the CH energy and throughput	Data is directly transmitted to BS
Gai-Ge Wang et al. [22]	EWA	Optimization algorithm based on two reproduction types of earthworms	Performs well compared to GA, PSO, BBO, ACO to benchmark functions	Lack of the previous history of best solutions elected so far in the iterations

3. FEWA for clustering and data routing in WSN

This section extensively describes the implementation of the earthworm optimization and fractional calculus (FEWA) for CH selection and optimum route selection and data communication in the WSN. The rest of the chapter is as follows: chapter 2.1 reflects the method's network model and block diagram. Section 2.2 describes the energy model for WSN with energy consumption equations. Section 2.3 analyzes the CH selection of the WSN with the method based on the objective function and its algorithm. Section 2.4 represents the optimum route selection from CHs to the sink based on the fit factor.
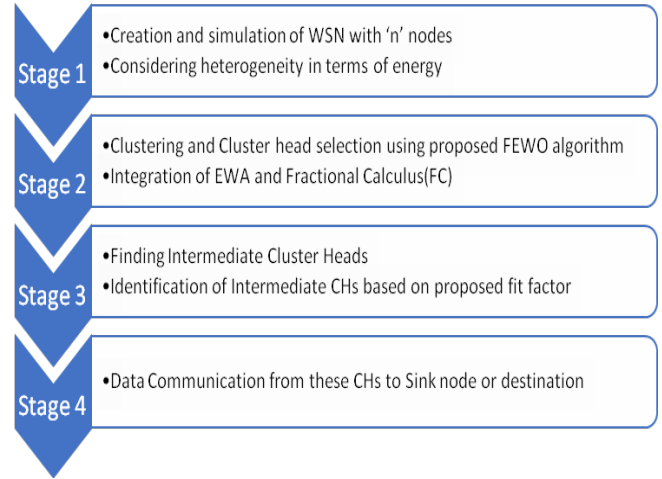

Figure 1. Block diagram of clustering and data communication in WSN

3.1. Network model of WSN with FEWA

In the method, it was assumed that in the 100x100 square sensor network area, there are 100 sensor nodes, and in the center of the region, there is a sink node or base station node. Based on the allocated CH probability, we assume 10 CH nodes out of 100 sensor nodes in this work. The optimum selection of CH for these 10 nodes is modeled with the suggested algorithm. The final data communication from the CHs to the base station through some intermediate nodes. According to The Fit Factor, these CH route nodes are chosen, which has the maximum value of the fit factor and is selected as the neighbouring node for the optimum route from CH nodes to the base station. Clustering and data communication using the FEWA algorithm is represented by the block diagram shown in Figure 1. All sensor nodes are supposed to be static at their predefined locations, and heterogeneity is included in the network by assigning some nodes as advanced nodes with original energy greater than ordinary nodes. All other nodes are assumed to have the same initial energy with a fixed communication range.

3.2. WSN Energy Model

This chapter discusses WSN's energy model. Energy dissipation is calculated based on free space and multipath propagation channels based on the source and destination node distance. When an ordinary sensor node sends the data packet, the energy dissipation model is based on the following model,

$$E_d(i) = E_{el} \times b + E_{pa} \times b \times d^4 ; \text{if } d \geq d_0 \quad (1)$$

$$E_d(i) = E_{el} \times b + E_{fs} \times b \times d^2 ; \text{if } d \leq d_0 \quad (2)$$

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{pa}}} \qquad (3)$$

$$E_{el} = E_t + E_{ag} \qquad (4)$$

Where $E_d(i)$ = energy dissipated at i^{th} the node for transmitting b data bits to the jth CH, which is at a distance d from node i.

E_{el} = energy dissipation due to electronics in the circuit

E_{pa} = energy dissipation by power amplifier at the transmitter side

E_{fs} = free space energy

d = distance between i^{th} node and j^{th} CH

E_{el} = transmitter energy

E_{ag} = energy for data aggregation

3.3. CH allocation with FEWA optimization method

Clustering is one of the most effective procedures to enhance the energy-constrained sensor networks' network lifetime. The FEWA the sensor node cluster optimization algorithm integrates EWA optimization and the fractional concept. EWA optimization is used to choose the optimal CHs according to the equation's highest fitness value (5). Adding the fractional concept in EWA's position calculation, the CHs are selected by interpreting the best CHs obtained so far in the previous iterations. So, the clustering accuracy is enhanced, and the optimal CH selection is assured, extending the network's lifetime.

The below equation represents the objective function for the FEWA algorithm in the WSN environment for optimum cluster head selection

$$F = \sum_{i=1}^{N} \left[E_{iNC} + (200 - D_{iNC}) + T_{iN} \right] \qquad (5)$$

where E_{iNC} = Energy required to transmit data from node to cluster head,

D_{iNC} = distance between a node to cluster head,

T_{iN} = trust of the node computed using satisfaction, similarity, and feedback

The CH is selected as the node with the highest function value, and the suggested FEWA optimization algorithm follows this evaluation protocol. The energy of the node is modified based on the energy equations.

3.4. Testing of FEWA algorithm

FEWA optimization algorithm is tested with some standard objective functions like Ackely, Schwefel,

Rastrigin and Rosenbrock. It was tested with minimization of the cost function simulated for 100 functional evolutions. The FEWA algorithm gives better depreciation compared to the existing EWA, PSO and GA.
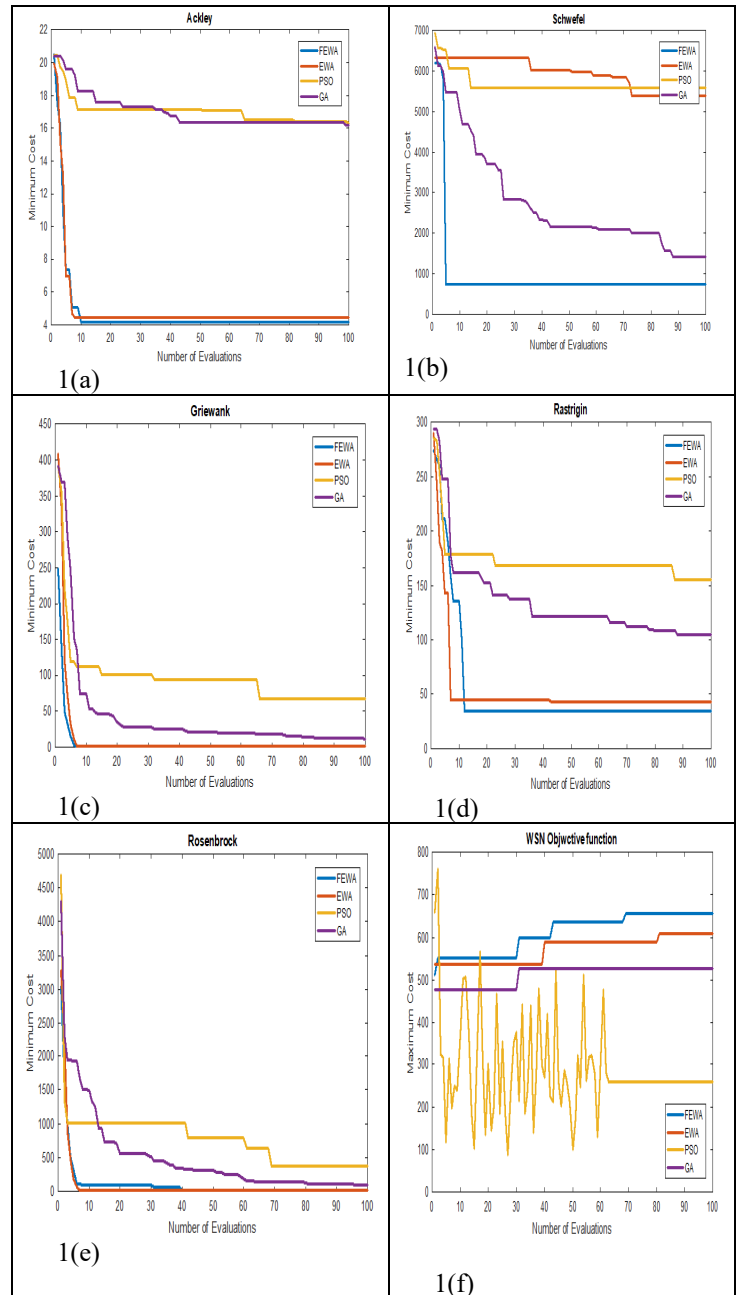

Figure 2. Convergence curves for different standard objective functions for all competing methods: 1a) Minimum Cost for Ackley, 1b) Minimum Cost for Schwefel, 1c) Minimum Cost for Griewank,1d) Minimum Cost for Rastrigin,1e) Minimum Cost for Rosenbrock, 1e) Maximum Cost for WSN objective function

FEWA also tested with the WSN objective function defined for our work and compared it with other optimization algorithms. From Figure 2, it was found that the FEWA algorithm gives better optimization results compared to other optimization algorithms. The objective function proposed in the WSN is a maximization function, and the optimization requirement is to maximize the cost function, as shown in table 2.

Table 2. Minimum Cost values for competing methods for different standard objective functions

Minimum Cost Values			
	FEWA	EWA	PSO	GA
Schwefel	737.7705	5395.614	5588.1	1422.894
Rosenbrock	15.68308	22.18178	378.3907	90.33895
Rastrigin	34.87853	43.14979	156.0612	104.7874
Griewank	1.879116	2.128162	67.24282	11.44927
Ackley	4.186098	4.45219	16.28359	16.1992

3.5. Optimum CH selection algorithm using FEWA algorithm

FEWA is the EWA modification by adding the fractional concept to the final optimization equation to enhance the optimum selection of CHs. Fraction theory is used in the algorithm to update the CH selection based on the history of CHs selected in the previous iterations. The accuracy in clustering and the lifetime of the network can be increased. EWA is developed based on the two types of earthworm breeding in nature. The offsprings generated from these two types are subjected to weighted summation to produce the final child earthworm. The Cauchy mutation operator is used to increase the search space and avoid local optimum. The two kinds of reproduction types are modelled as follows:

Reproduction 1:

Since earthworms are hermaphrodites, so the offspring are produced by a single earthworm. The following equitation models the offspring produced from the reproduction 1

$$x_{g1,i} = x_{\max,i} + x_{\min,i} - \alpha x_{g,i} \qquad (6)$$

where $x_{g,i}$ is the ith element of the earthworm x_g, which indicated the earthworm g and $x_{g1,i}$ represented the ith element of the newly generated offspring earthworm g1. $x_{\max}$ and $x_{\min}$ are the upper and lower limits of the earthworm position and α is a similarity variable between 0 and 1 that determines the distance between the earthworm and the freshly reproduced earthworm.

Reproduction 2:

More than one offspring is generated from certain earthworms modelled as reproduction system 2, a specific earthworm reproduction scheme. In this reproduction type, three different cases are considered by changing the number of parents (P) and the number of offsprings generated (G). These three cases are analyzed by

changing different improved cross over operations for better optimization processes such as single point crossover, uniform crossover, and multipoint crossover operations. Among all these improved operations, earthworm optimization gives better optimization for uniform crossover operation with case P=2 and G=2, which is considered in this algorithm.

For this uniform crossover operation, the two offsprings are generated by equation (7)

$$x_{12,i} = P_{1,i}; x_{22,i} = P_{2,i} \quad if \; rand > 0.5$$
$$x_{12,i} = P_{2,i}; x_{22,i} = P_{1,i} \quad elsewhere \qquad (7)$$

Where, $x_{12,i}$ and $x_{22,i}$ are the ith component of the two offsprings generated & $P_{1,i}$, $P_{2,i}$ are the two selected parents' ith elements for uniform crossover operation.

The earthworms generated for the reproduction 2 can be calculated by the equation (8)

$$x_{g2} = \begin{cases} x_{12} & rand < 0.5 \\ x_{22} & else \end{cases} \qquad (8)$$

The weighted summation of the two offsprings provided by equation (9) determines the newly produced earthworm from reproduction 2.

$$x_{g2} = w_1 x_{12} + w_2 x_{22} \qquad (9)$$

where w1 and w2 are the weight factors and can be obtained by the two offsprings' fitness values x_{22}.

Whenever the two reproduction types are implemented, the final position of the earthworm in the next generation is determined by the equation (10)

$$x_g^{t+1} = \beta x_{g1} + (1-\beta)x_{g2} \qquad (10)$$

The proportionality constant adjusts the proportional distance between two earthworms generated from two kinds of reproduction systems. This value is modified to the number of iterations to balance between local and global search. The above equation can be rewritten as

$$x_g^{t+1} - x_g^t = \beta x_{g1} + (1-\beta)x_{g2} - x_g^t \underset{=}{} D^\theta \left[x_g^{t+1} \right] \qquad (11)$$

From the fractional calculus[17], the differential term in a discrete-time implementation can be represented by fractional derivative given by

$$D^\theta[y(t)] = \frac{1}{T^\theta} \sum_{h=0}^{r} \frac{(-1)^k \Gamma(\theta+1) y(t-hT)}{\Gamma(h+1)\Gamma(\theta-h+1)} \qquad (12)$$

Equation (11) can be considered as the differential term, and this differential term can be represented by the fractional derivative mentioned in equation (12).

Applying the above fractional derivative term to the equation (11) and expanding it into r=4 terms and then formulated as

$$D^\theta \left[x_g^{t+1} \right] = x_g^{t+1} - \theta . x_g^t - \frac{1}{2}\theta . x_g^{t-1} - \frac{1}{6}(1-\theta).x_g^{t-2} - \frac{1}{24}\theta(1-\theta)(2-\theta).x_g^{t-3}$$

(13)

Substituting the equation(13) in equation (11), the final updated position of the earthworm using the FEWA algorithm is determined as

$$x_g^{t+1} = (\theta - 1).x_g^t + \frac{1}{2}\theta . x_g^{t-1} + \frac{1}{6}(1-\theta).x_g^{t-2} + \frac{1}{24}\theta(1-\theta)(2-\theta).x_g^{t-3} + \beta x_{g1} + (1-\beta)x_{g2}$$

(14)

Hence, from equation (14), the earthworm's position value is updated for every iteration. From the above equation, it is clear that the position's previous values can also be interpreted for deciding the best CH selection. Thus, from the FEWA optimization, n CHs are selected for the nodes selected for the optimum route selection from CHs to base station transmission.

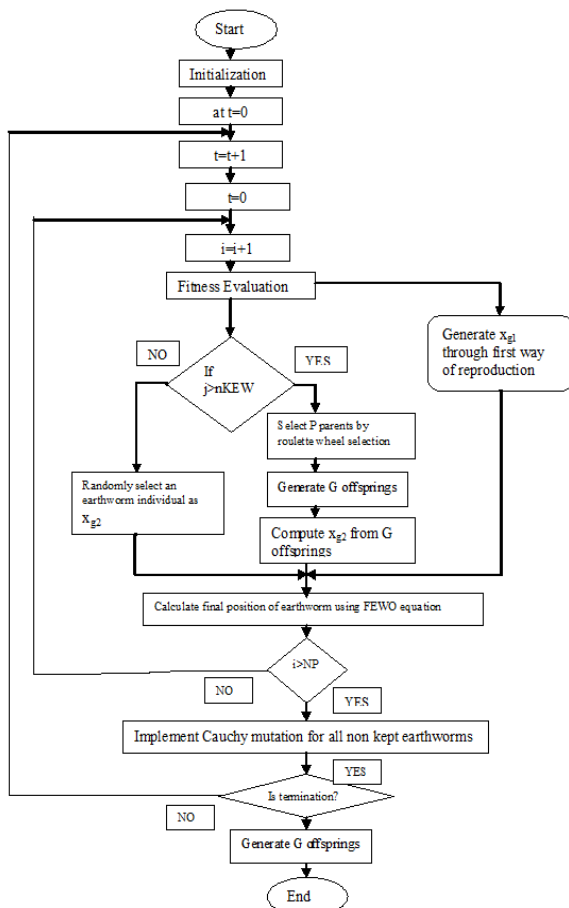The flow chart for the FEWA algorithm is shown in figure 3.

Figure 3. Flow chart for FEWA method's pseudo code

3.6. Optimal Route selection based on the Fit factor

Once the cluster head node is selected from the FEWA algorithm based on the objective function, then the cluster head's data must be communicated to the sink node in a multi-hop manner. So, the selection of the intermediate cluster heads is crucial for the routing path. Hence, to select the routes, route nodes are selected using the equation's fitness factor function (15). Therefore, the CH node with the highest fitness among the best cluster heads selected from FEWA is selected for the next routing path node.

The fitness factor function for choosing route cluster head node is designed based on energy, distance, and trust given as below

$$F\_factor = \left[E_{nc} + \left(\frac{1 - D_{nc}}{\sqrt{2 X_m Y_m}} \right) + T_{nc} \right]$$

(15)

Where, E_{nc}, D_{nc} and T_{nc} are the energy, distance, and trust of the present cluster head node from the previous node. All these values are summed uo together for all the cluster head nodes to get the fitness function value.

4. Results and Discussion

The simulation results of the FEWA algorithm and comparative analysis with other optimization methods are presented in this section. The simulation environment is set up using MATLAB.

The WSN created in 100m*100m area after the implementation FEWA algorithm is mentioned in Figure 4 at a random number of rounds:
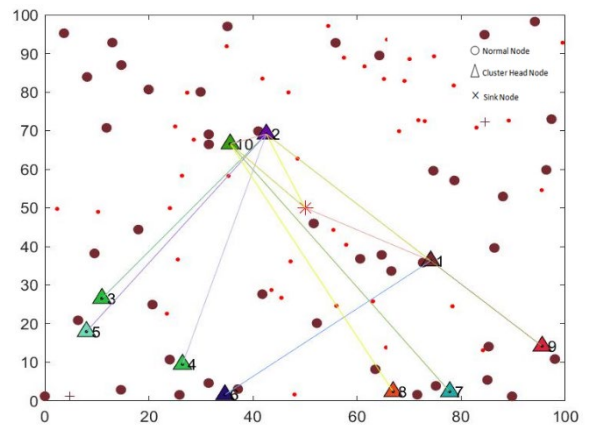

Figure 4. Simulation architecture of WSN created in 100m * 100m area using the method with 100 nodes in the simulation environment at round no.700

4.1. Performance parameters for comparison

The important constraints and performance parameters of wireless sensor network are residual energy remained in

sensor node after completing all the rounds, delay, number of alive nodes at the end of last round and throughput of the network. These performance parameters are calculated by using the following expressions.

$$Energy = \begin{cases} E_i - [(E_{tx} + E_{da}) \times 10^3 + E_{amp} \times 10^3 \times (d^4)]; & \text{if } d > d_0 \\ E_i - [(E_{tx} + E_{da}) \times 10^3 + E_{amp} \times 10^3 \times (d^2)]; & \text{if } d \le d_0 \end{cases}$$

$$\text{where } d_0 = \sqrt{\frac{E_{fs}}{E_{amp}}}$$

$$\text{Number of alive nodes} = \#\text{nodes with Energy} > 0$$
$$\text{for the current round}$$

$$\text{Overall Delay} = \frac{\text{time at which the packet is sent from node}}{\text{time it is reviewed by sink node}}$$

$$\% \text{ of Throughput} = \frac{\text{Number of packets recieved at base staion node}}{\text{Number of packets sent to base station node}} \times 100$$

All these performance parameters are compared for the proposed FEWO algorithm with other existing cluster-based optimization methods GA [18], PSO [19], DE [20], ACO [21], and EWO [22]. This method is simulated for different similarity factor values and different population sizes, and in comparative analysis, we choose $\alpha = 0.64$ and population size=30.

4.2. Comparative Discussion

4.2.1 Comparison in terms of number of alive nodes
Figure 5 provides a comparison of the number of live nodes for the strategy with the number of rounds dependent on PSO, EWA-based clustering and GA-based clustering. At the end of the 700 round, 91 for FEWA and 81 for PSO, 52 for EWA, and 86 for GA are provided for nodes still alive with some residual energy. The following figure shows clearly, as the number of dead nodes is smaller than other approaches, the algorithm will improve the network's existence.
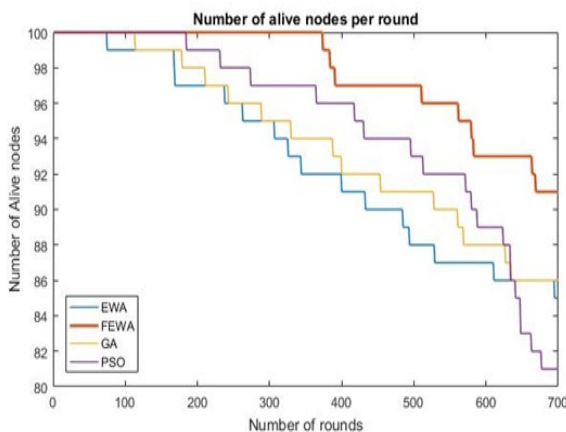

Figure 5. Comparative analysis of the number of nodes alive

4.2.2 Comparison in terms of delay

Figure 6 compares the delay value for the technique with the number of rounds with optimized clustering algorithms. At the end of the 1000 rounds, the delay evaluated by GA, PSO, DE, ACO, EWO, and proposed FEWA are 0.639sec, 0.583sec, 0.832sec, 0.604sec, 0.433sec, and 0.240sec. The contrast curve below shows that the algorithm can do better with less delay than others so that more transmissions can be done in a given time.
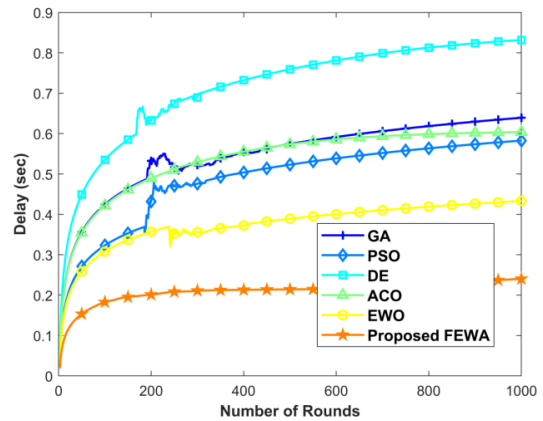

Figure 6. Comparative analysis of based on the overall delay

4.2.3 Comparison in terms of throughput
Figure 7 compares the throughput percentage value for the optimization-based clustering process to the number of rounds. At the conclusion of the 1000 rounds, the % of throughput values evaluated by GA, PSO, DE, ACO, EWO, and proposed FEWA are 0%, 0%, 0%, 0%, 0%, and 10% respectively. From the graph, it is clear that the throughput is improved for the proposed method.
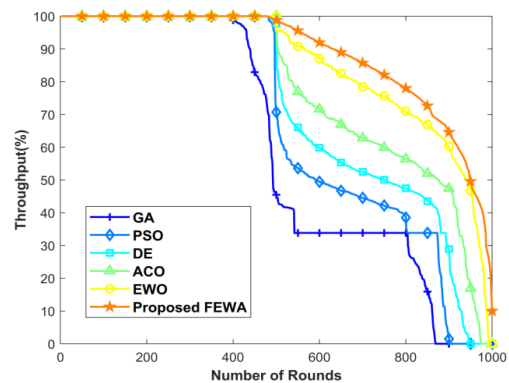

Figure 7. Comparative analysis based on throughput

4.2.4 Comparison in terms of energy
Figure 8 demonstrates the methodology's energy value relationships with other comparative methods in several rounds. At the end of the 1000 rounds, the energy evaluated by GA, PSO, DE, ACO, EWO, and proposed FEWA are 0J, 0J, 0J, 0J, 0J, and 0.019J. From the curve

below, while the system's energy is smaller initially, but as the number of rounds increases, the residual energy at the end of the 1000 round is high relative to the other methods.
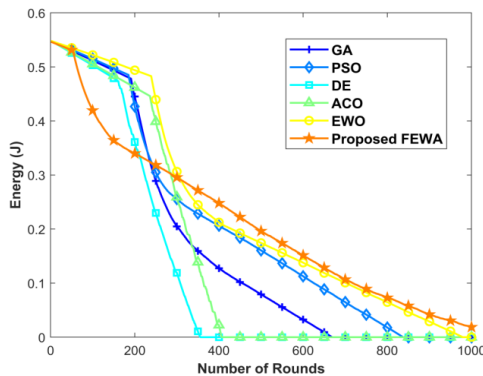

Figure 8. Comparative analysis of based on the overall delay

4.2.5 Comparative discussion in terms of average values:

The proposed FEWO method's performance is compared with other existing standard optimization algorithms after implementing them in our WSN scenario. The average values of performance parameters like delay, energy and throughput are mentioned in table 3 and table 4 with several nodes that are 50 and 100.

Table 3. Comparison of FEWO algorithm with other optimization methods in terms of average values for 50 nodes

Parameters	Number of nodes = 50					
	GA	PSO	DE	ACO	EWO	FEWO
Delay (sec)	0.276512	0.40213	0.48252	0.32681	0.22015	0.082910
Energy (J)	0.179173	0.146672	0.13750	0.184522	0.220343	0.330175
Throughput (%)	64.86866	68.35754	72.41174	77.81489	85.79964	87.80326

Table 4. Comparison of FEWO algorithm with other optimization methods in terms of average values for 100 nodes

Parameters	Number of nodes = 100					
	GA	PSO	DE	ACO	EWO	FEWO
Delay (sec)	0.547308	0.486158	0.715442	0.537612	0.374691	0.208665
Energy (J)	0.165354	0.202258	0.124864	0.153053	0.232226	0.216422
Throughput (%)	60.0141	67.10725	71.97621	77.66661	85.35704	88.57683

5. Conclusion

This paper presents the comparative analysis of the FEWA optimization method to integrate earthworm optimization algorithms with fractional calculus. The fractional derivative is used for calculating the position of the final earthworm after the two reproduction systems. By selecting the proportional constant 0.64 and the population size 30, the proposed Fractional Earth Worm Optimization algorithm (FEWA) is implemented in the WSN environment with 100 nodes and 100×100 square meter area with a sink node centre. The simulated results prove that the proposed algorithm gives better minimization for standard optimization functions. Further, the performance parameters like the number of alive nodes, residual energy, delay and throughput for the FEWO algorithm is compared with earlier reported optimization algorithms in the literature. This analysis shows that the implemented algorithm can perform well compared to the other standard optimization algorithms used in cluster head and routing techniques in wireless sensor networks. This work can be extended by implementing any hybrid optimization algorithm with multi-objective methods to further improve energy efficiency and network lifetime. The future extension of this research is to develop a hybrid optimization algorithm with fractional calculus. It would be interesting to recognize missing sensor data values in real-time environmental data using higher-order tensor completion models.

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