Adaptive Optimization for Optimal Mobile Sink Placement in Wireless Sensor Networks

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Abstract: *In recent years, Wireless Sensor Networks (WSN) with mobile sinks has attracted much attention as the mobile sink roams over the sensing field and collects sensing data from sensor nodes. Mobile sinks are mounted on moving objects, such as people, vehicles, robots, and so on. However, optimal placement of the sink for the effective management of the WSN is the major challenge. Hence, an adaptive Fractional Rider Optimization Algorithm (adaptive-FROA) is developed for the optimal placement of mobile sink in WSN environment for effective routing. The adaptive FROA, which is the integration of the adaptive concept in the FROA, operates based on the fitness measure based on distance, delay, and energy measure of the nodes in the network. The main objective of the research work is to compute the energy and distance. The proposed method is analyzed based on the metrics, such as energy, throughput, distance, and lifetime of the network. The simulation results reveal that the proposed method acquired a minimal distance of 24.87m, maximal network energy of 94.54 J, maximal alive nodes of 77, maximal throughput of 94.42 bps, minimum delay of 0.00918s, and maximum Packet delivery ratio (PDR) of 87.98%, when compared with the existing methods.*

***Keywords*:** *Mobile sink, wireless sensor network, fractional concept, rider optimization algorithm, routing.*

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1. Introduction

Routing in Wireless Sensor Networks (WSN) using the conventional protocols fails to address the global intrusion detection issues when a large number of deployed sensor nodes are employed. WSN has inherent characteristics, such as processing capability, limited energy, storage, and high dynamic network, which makes it challenging to develop a routing protocol [13]. For sending the data to a particular base station multiple sources are required [11]. These multiple sources deplete the energy from the nodes near the sink and they die eventually. This leads to the partitioning of the network, known as the energy hole problem or hotspots [14]. The hotspot problem is solved by balancing the load in the sensor nodes using the mobile sink [15]. This prolongs the network lifetime and achieves uniform energy consumption. Other problems associated with mobile sinks are their frequent requirement to update the current position information that leads to high energy consumption. It is impossible to find the routing path as the sensor network are dynamic due to the mobile sink [18].

The traditional protocols support mobile sink but have poor data delivery and large energy consumption [19]. Mobile geocasting protocols supports macro- and micro-mobility, where the current position is updated by the leader sink of the mobile group and the data is delivered by the source [10]. The structured architecture is categorized into two: flat and hierarchical network. Hierarchical networks have cluster and chain architecture. The commonly used protocol for Hierarchical networks is Power Efficient Gathering In Sensor Information Systems (PEGASIS) [1] and Low Energy Adaptive Clustering Hierarchy (LEACH) [17]. In a flat network, the sensors collaborate performing the task of sensing. The routing protocols used for a flat network include gossiping, rumor routing, flooding, sensor protocols for information via gradient-based routing, directed diffusion, and negotiation Sensor Protocols for Information via Negotiation (SPIN) [12, 16].

The main intention of this paper is to develop an optimization algorithm for the optimal placement of nodes in the WSN environment. Initially, the WSN environment is transformed to the cell network, which is the virtual grid of a uniformly sized cell that depends on the sensor nodes. The second step is the cluster-head selection using a Fuzzy C-Means Clusterin sparse-(FCM) algorithm. After the cluster selection, the sink is placed optimally in the WSN environment using Fractional Rider Optimization Algorithm adaptive-(FROA), which is the integration of adaptive concepts in FROA. The fitness measure for the optimal placement of the sink is based on the energy, delay, and distance measure of the nodes in the network.

The organization of the paper is as follows: section 1 describes the routing protocol; section 2 reviews the existing methods of the routing protocol. Section 3 deliberates the proposed method, section 4 describes the results and discussion of the proposed method and finally, section 5 concludes the paper.

2. Literature Survey

The literature survey of the routing protocol is discussed in this section. Yarinezhad and Sarabi [22] developed a routing protocol for the mobile sinks. Although this method consumed only minimum time for the transmission of data and it supported multiple sinks, it had a minimum network lifetime. Sharma S *al.* [18] developed a rendezvous-based routing protocol to address the end-to-end latency and energy-efficiency. A rendezvous region and a tree were formed in the middle of the network. This method had good end-to-end latency, energy consumption, and network lifetime. Wang *et al.* [20] modelled a particle swarm optimization-based clustering algorithm using the mobile sink for WSN. In this method, a virtual clustering technique was performed using a particle swarm optimization algorithm. This method had improved the network performance. Wang *et al.* [21] designed an Ant Colony Optimization (ACO) algorithm. This method provided a good result in finding the optimal traversal path and it had a prolonged wireless sensor network lifetime.

2.1. Challenges

The major challenges of the research are given below:

- The infeasibility of the mobile sink to visit all the nodes within the given time causes data packet drop, which in turn results in memory overflow or other constraints. Even though there is a chance of reaching the sensor nodes regardless of the memory overflow, it is a hectic challenge for larger networks [22].
- The data forwarding process causes the sensor near the sink node to suffer from large traffic loads, which leads to large energy consumption [18].
- The routing protocol should possess energy-efficient routing with minimal time for delivering the sensed data. The Line-Based Data Dissemination (LBDD) method has minimal end-to-end latency but has low energy-efficiency and the grid-based energy-efficient routing method has good energy-efficiency but has low latency [20, 21].

3. Proposed Method of Mobile Sink Placement in the Network Area Using a Novel Optimization Algorithm

The network performance is enhanced and the energy crisis is met by the optimal placement of the sink nodes in WSN. Figure 1 shows the block diagram of the proposed adaptive FROA method. Initially, the WSN environment with battery-operated sensors is formed into a cell network by Voronoi partition. From the cell, an effective cluster head is selected using the Sparse FCM strategy. Finally, the proposed adaptive-FROA helps in the optimal placement of the mobile sinks. The fitness measures, such as energy and distance are used for the optimal placement of the sink. Thus, the lifetime of the network is extended by conserving the energy effectively.

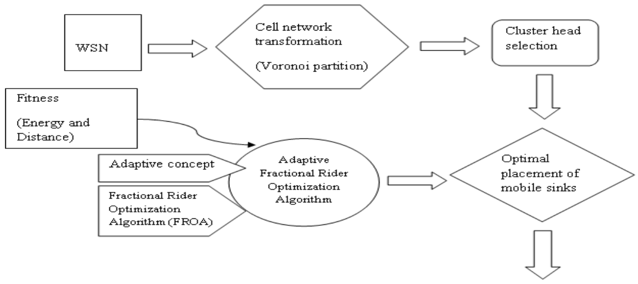


Figure 1. Block diagram of proposed adaptive FROA method.

3.1. Formation of the Cell Network using Voronoi Partitions

Initially, the Voronoi partitioning [5] transforms the WSN area into a cell network, which establishes the optimal partitions in the WSN environment. The Voronoi regions are expressed as, $V_W(1\leq W\leq X)$;, such that there is a X number of cells in partitioned areas, generated using the points $p_1,\ldots, p_X$. Further, the cell network is subjected to cluster head selection and the individual cells share a cluster head with other cells in the cell network.

3.2. Sparse-FCM for Cluster Head Selection

The sparse-FCM algorithm [4] is used for cluster head selection to address the issues related to high-dimensional data clustering. The cluster head selection algorithm is based on sparse regularizations, which are integrated into the FCM algorithm to establish the sparseFCM. The cluster centroid formed by the sparse-FCM is expressed as,

$$d=\{d_1,d_2,\ldots,d_n,\ldots,d_j\} \tag{1}$$

Where j represents the number of cluster centroids in the network. Assume the data matrix $L_b=k_{uv}^b=\Re^{p\times q}$ with a total of q attributes and p number of data points; $(1\leq u\leq p)$ and $(1\leq u\leq q)$. The size of b^{th} the data matrix is $[p\times q]$, and the rows and columns in L_b are denoted as, $k_u^b\in\Re^q$ $k_b^b\in\Re^p$ and. The algorithm is grouped based on the minimum distance between the cluster centroid and the individual data point [4]. The algorithmic steps of the sparse-FCM algorithm are given as follows:

1. *Initialization*: in the first step, the weights and the attributes are initialized.

$$x = x_1^f = x_2^f = \ldots = x_q^f = \frac{1}{\sqrt{q}} \tag{2}$$

2. *Update the partition matrix*: the attribute weights x and the cluster centers P are set, such that $\varepsilon(\Re)$ is minimized,

$$P_{mr} = \begin{cases} \frac{1}{O_r}; if\ I_{mr} = 0\, and\, O_r = card\{h : I_{mr} = 0\} \\ 0; if\ I_{mr} \neq 0\, but\, I_{mn} = 0\ for\, some\, n; n \neq r \\ \frac{1}{\sum_{n=1}^{j} \left(\frac{I_{mr}}{I_{nr}}\right)^{\left(\frac{1}{s-1}\right)}}; otherwise \end{cases} \tag{3}$$

Where $card(J)$ represents the cardinality of Ja set. The distance measure used in sparse-FCM is given as,

$$I_{mr} = \sum_{r=1}^{j} x_h (Z_{mr} - Z_{rh})^2 \tag{4}$$

The distance measure is the distance between the cluster center and the individual data point and the data point with minimal distance is grouped under the same cluster.

3. *Update the cluster center P*: let x and $\Re$ be set and $\varepsilon(d)$ is minimized if

$$d_{rh} = \begin{cases} 0 & ; \quad if\ x_h = 0 \\ \frac{\sum_{n=1}^{j} W_{mr}^{s} . Z_{mh}}{\sum_{r=1}^{j} W_{mr}^{s}} & ; \quad if\ x_h \neq 0 \end{cases} \tag{5}$$

Where, $\Re$ is the dissimilarity measure; the objective function of the h^{th} feature is denoted as, x_h; s is the weight component that controls the membership sharing between the cluster centroids; r=1,…,j and h=1,…q.

4. *Compute the class*: the class value F_W is computed with fixed clusters d={d_1, d_2,…, d_g,…d_j} and membership W.
5. *Terminate*: until the stopping criterion is attained, iteration is repeated. The stopping criterion is given as,

$$\frac{\sum_{w=1}^{q} |x_w^* - x_w^f|}{\sum_{w=1}^{q} |x_w^f|} < 10^{-4} \tag{6}$$

3.3. Optimal Placement of The Sink Node in The Cell Network

The cluster head is chosen using effective energy-constraint such that the network life is extended to yield improved performance. The sink node is placed optimally using the proposed adaptive-FROA, which is the integration of the adaptive concept in FROA. The FROA concept is developed by integrating the fractional concept [3] in ROA [2]. The concept of ROA is based on the concept of the riders in the race moving towards a target and this optimization is based on imaginary ideas and concepts. More specifically, ROA operates in the fictional computing environment. In this algorithm, the riders aim at reaching the destination, and the one leading the search is named as a leading rider. The riders, such as bypass, follower, over-taker, and attacker are involved in the optimization process. With the proper management of the accelerator, gear, steering, and brake, the rider reaches the destination, which enables the rider to change the position. The rider with a high success rate is declared as the winner. In FROA, the position of the bypass rider is modified based on the fractional concept, while in adaptive FROA, the optimization parameters are updated adaptively adding numerous advantages in addition to the fractional merits in ROA.

3.3.1. Solution Encoding

The binary vector representation of the optimal solution is termed solution encoding. The solution size depends on the number of cells in the cell network. The size of the solution for a m number of cells is, [1×m] and the location of the sink is referred to as, ‘1’ or ‘0’ in the corresponding cell. The location of the sink in the corresponding cell is referred to as ‘1’. Figure 2 shows the solution vector for either ‘0’ or ‘1’.

1	*2*	……………………	*m*

Figure 2. Solution representation.

3.3.2. Fitness Measure

The fitness is calculated using the energy and distance as shown in Equation (7).

$$F = \frac{1}{2} \times [\varepsilon . \mathrm{E} + \alpha . \lambda + \mu . \lambda_{\mathrm{sinw}}] \tag{7}$$

Where, E and λ refers to the energy and the distance. The major constraint of the battery operated nodes is the energy [8]. The energy in the nodes and the cluster heads are updated as,

$$E_{\tau+1}(J_v) = E_\tau(J_v) - E_{dis}(J_v) \tag{8}$$

$$\eta_{r+1}(I_i) = \eta_r(I_i) - \eta_{dis}(I_i) \tag{9}$$

At instant τ, the energy and the cluster head of the normal node are represented as, $E_\tau(J_v)$ and $\eta_r(I_i)$ at the instant r, the dissipated energies of normal node and cluster head are given as, $E_{dis}(J_v)$ and $\eta_{dis}(I_i)$. Until all the nodes are dead, the update continuous. The distance measure is based on,

$$\sigma = \frac{1}{3}[\sigma_1, \sigma_2, \sigma_3] \tag{10}$$

Where, σ_1 is the minimum distance between the n^{th} cluster head and sink node, σ_2 is the distance between the v^{th} nodes and j^{th} cluster head in the particular cluster, and σ_3 is the distance between the adjacent cells in the cell network.

3.3.3. Adaptive Fractional Rider Optimization Algorithm for Locating the Mobile Sink in the Cell Network

The proposed adaptive FROA helps in determining the optimal location of the sink node and the algorithmic steps are given as below:

1. *Initialization*: let, *W*be the four rider groups and the randomly initialized position of the riders [2] is,

$$W_\tau = \{W_{a,b}^\tau\}; 1 \le a \le T; 1 \le b \le B \tag{11}$$

Where, $W_{a,b}^\tau$ is the solution of the a^{th} rider of b^{th} position at an instant τ, *B* refers to the position of the rider, and *B* is the riders' position. The total riders *R*are equal to *W*, which is the sum of riders in individual rider groups, bypass riders *B*, followers *F*, over takers *O*, and attackers *A*.

2. *Determine the success rate*: the winner is decided based on the success rate, which is calculated based on the fitness measure.
3. *Determining the leading rider*: the leading rider is the rider with maximal success rate and the leading rider changes with time.
4. *Riders' position*: *T*he rider updates the position of the follower, bypass rider, overtaker, and the attackers. The position of the bypass rider is updated randomly irrespective of the position of the leader as,

$$W_{\tau+1}(a+b) = (\rho+\psi-1)\, W_\tau(a,b) + \frac{1}{2}\times\rho\times W_{\tau-1}(a,b) + \frac{1}{6}\times(1-\rho)\times W_{\tau-2}(a,b) + \frac{1}{24}\times\rho\times(1-\rho)(2-\rho) W_{\tau-3}(a,b) \tag{12}$$

Where, $W_{\tau-1}(a,b)$, $W_{\tau-2}(a,b)$, and $W_{\tau-3}(a,b)$ are the best position of a^{th} rider in the previous iterations and these solutions are used for updating the position of the rider in the present iteration. The benefits of the proposed method are exhibited in this section, where the adaptive concept is integrated with the attacker equation of FROA. The term ρ is updated as,

$$\rho = \left(\frac{I_{curr} - I_{\min}}{I_{\max} - I_{\min}}\right)\omega_1 + \left(\frac{1 - D(W_\tau, W_{\tau-1})}{N_f}\right)\omega_2 \tag{13}$$

Where, N_f is the normalized factor, $I_{\max}$ is the maximum iteration, I_{mix} is the minimum iteration, I_{curr} is the current iteration. ω_1, ω_2 are the weights at interval [0, 1]. $D(W_\tau, W_{\tau-1})$ is the distance between W_τ and $W_{\tau-1}$.

5. *Compute the success rate*: as soon as the position update terminates, the rider with maximal success rate is finalized as the winners.
6. *Update the parameters of the rider*: with the activity counter the parameters, such as steering angle and gear are updated. Finally, the optimal solution is derived based on the maximal value of the success rate.
7. *Riding Off-time*: the iteration is repeated till the off-time $\tau_{\max}$, until the optimal solution is derived.

4. Results and Discussion

The result and discussion of the proposed adaptive-FROA method for routing protocol in WSN are discussed in this section.

4.1. Experimental Setup

The proposed adaptive-FROA is implemented in the NS2 simulator using nodes based on the number of the simulation rounds, which varies from 0 to 2000. Table 1 shows the experimental setup of the proposed method.

Table 1. Experimental setup.

Parameters	Value
Antenna type	Omni Antenna
Initial receiving power	0.395
Initial sending power	0.660
Initial idle power	0.035
Initial energy	40.1J
Number of rounds	0 to 2000
Packet size	512
Number of nodes	100
Time of simulation end	100

4.2. Performance Metrics

The performance of the proposed method is analyzed based on the metrics, such as energy, the lifetime of the network, distance, and throughput of the nodes, which are the important metrics used for optimal mobile sink placement in WSN. Also, many existing related research papers used these metrics for the performance evaluation. Network energy is the remaining energy in the node that measures the network lifetime. The network lifetime is the total number of active nodes or alive nodes in a simulation environment. The distance is the total distance traveled by the sink node and throughput is the total number of bits transmitted in a second. The delay defines total time to transmit the data packets. The Packet Delivery Ratio (PDR) is defined as the number of packets successfully received with respect to the total packet sent.

4.3. Comparative Methods

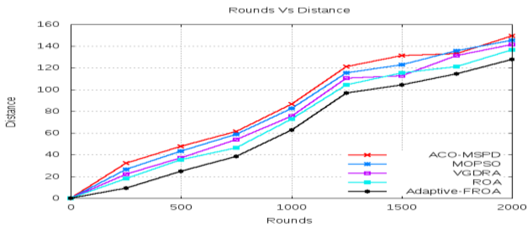
The performance of the proposed Adaptive-FROA is compared with the existing methods, such as Ant Colony Optimization-based Mobile Sink Path Determination (ACO-MSPD) [9], Multi-Objective Particle Swarm Optimization (MOPSO) [6], Virtual Grid-based Dynamic Routes Adjustment Scheme (VGDRA) [7], and Rider Optimization Algorithm (ROA) [2].

4.4. Comparative Analysis

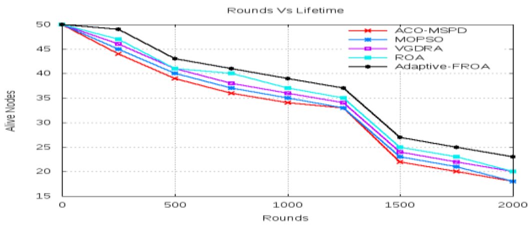
The comparative analysis is based on the number of rounds in the presence of 50 and 100 users based on the performance metrics

4.4.1. Analysis Using 50 Nodes

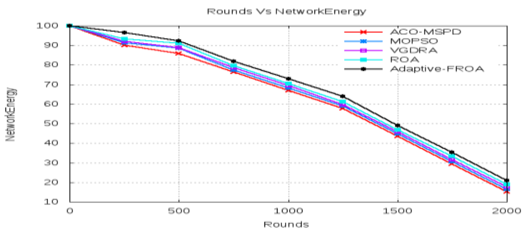
Figure 3 explains the comparative analysis of the simulation rounds with 50 nodes.



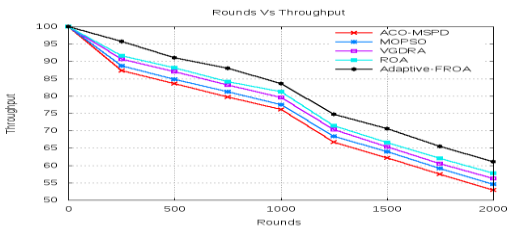
a) Distance.



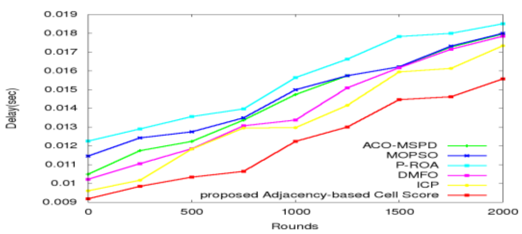
b) Lifetime.



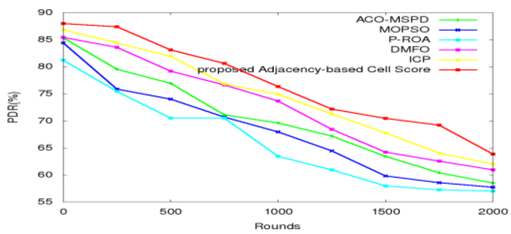
c) Network energy.



d) Throughput.



e) Delay.



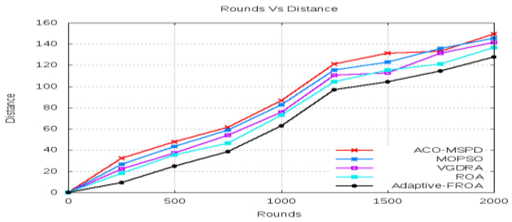
f) Packet delivery ratio.

Figure 3. Comparative analysis using 50 nodes.

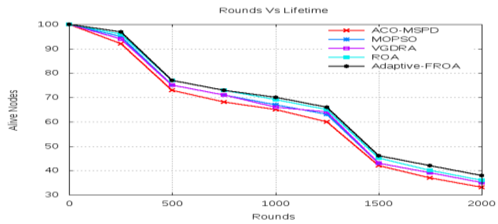
Figure 3-a) demonstrates the analysis based on distance. The distance of the mobile sinks at round 500 for the proposed adaptive FROA and the existing methods, such as ACO-MSPD, MOPSO, VGDRA, and ROA is 30.35m, 40.49m, 38.71m, 35.98m, and 35.42m respectively. The analysis of the alive nodes for varying rounds is depicted in Figure 3-b). The number of alive nodes at round 500 for the proposed adaptive-FROA and the existing methods, such as ACO-MSPD, MOPSO, VGDRA, and ROA is 43, 39, 40, 41, and 41, respectively. Figure 3-c) explains the analysis of network energy with varying rounds. At round 500, the network energy for the proposed adaptive-FROA and the existing methods, such as ACO-MSPD, MOPSO, VGDRA, and ROA is 92.39J, 85.94J, 88.49J, 88.72J, and 91.03J respectively. The analysis of the throughput for varying rounds is depicted in Figure 3-d). At round 500, the throughput of the proposed adaptive FROA and the existing methods, such as ACO-MSPD, MOPSO, VGDRA, ROA is 91.03bps, 83.58bps, 84.87bps, 87.00bps, and 88.07bps respectively. Figure 3-e) explains the analysis of delay with varying rounds. At round 500, the delay for the proposed adaptive FROA and the existing methods, such as ACO-MSPD, MOPSO, VGDRA, and ROA is 0.0122s, 0.0127s, 0.0135s, 0.0118s, 0.118s and 0.0103s respectively. The analysis of the PDR for varying rounds is depicted in Figure 3-f). At round 500, the PDR for the proposed adaptive-FROA and the existing methods, such as ACO-MSPD, MOPSO, VGDRA, and ROA is 76.92%, 93.99%, 70.53%, 79.18%, 81.89%, and 83.08%, respectively.

4.4.2. Analysis Using 100 Nodes

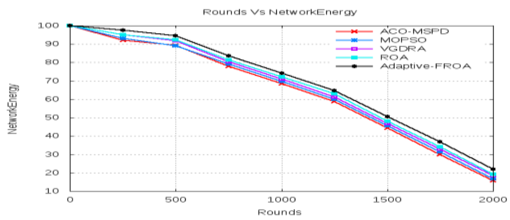
Figure 4 demonstrates the comparative analysis with 100 nodes. Figure 4-a) demonstrates the analysis based on distance and the distance of the mobile sinks at round 500 for the proposed adaptive FROA and the existing methods, such as ACO-MSPD, MOPSO, VGDRA, and ROA is 24.87m, 47.90m, 43.23m, 36.92m and 35.42mrespectively. The analysis of the alive nodes for varying rounds is depicted in Figure 4-b). The number of alive nodes at round 500 for the proposed adaptive FROA and the existing methods, such as ACO-MSPD, MOPSO, VGDRA, and ROA is 77, 73, 75, 75, and 77, respectively. Figure 4-c) explains the analysis of network energy with varying rounds. At round 500, the network energy for the proposed adaptive FROA and the existing methods, such as ACO-MSPD, MOPSO, VGDRA, and ROA is 94.54J, 89.22J, 88.95J, 91.81J, and 92.17J respectively. The analysis of the throughput for varying rounds is depicted in Figure 4-d). At round 500, the throughput of the proposed adaptive FROA and the existing methods, such as ACO-MSPD, MOPSO, VGDRA, and ROA is 94.42bps, 86.13bps, 87.74bps, 89.38bps, and 91.25bpsrespectively. Figure 4-e) explains the analysis of delay with varying rounds. At round 500, the delay for the proposed adaptive FROA and the existing methods, such as ACO-MSPD, MOPSO, VGDRA, and ROA is 0.0176s, 0.0170s, 0.0158s, 0.0164s, 0.0167s and 0.0134s respectively. Figure 4-f) explains the analysis of PDR with varying rounds. At round 500, the PDR for the proposed adaptive FROA and the existing methods, such as ACO-MSPD, MOPSO, VGDRA, and ROA is 78.63%, 68.05%,81.05%, 80.15%, 78.38%, and 83.70% respectively.



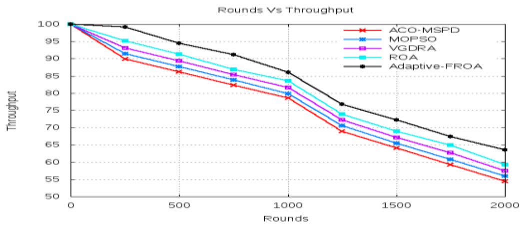
a) Distance.



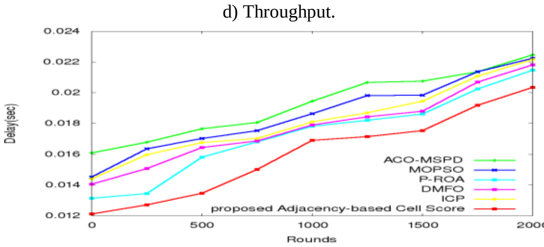
b) Lifetime.



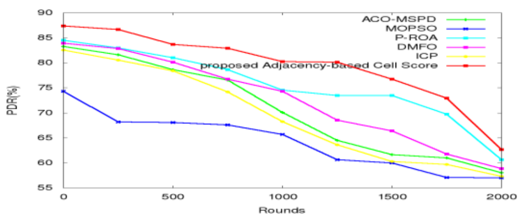
c) Network energy.



d) Throughput.



e) Delay.



f) PDR.

Figure 4. Comparative analysis using 100 nodes.

5. Conclusions

The research aimed at the optimal placement of nodes in the WSN environment for effective routing. Here, an adaptive Fractional Rider Optimization Algorithm (adaptive-FROA) optimization algorithm is developed. The adaptive adaptive FROA is the integration of adaptive concept in the Fractional Rider Optimization Algorithm. The uniformly-sized cells are obtained by Voronoi partitions and the cluster head is selected by the sparse-FCM algorithm. Once the clusters are formed, the sink is optimally placed in WSN using the adaptive-FROA m. The sink nodes are optimally placed, which is duly based on the fitness measures, such as distance, delay, and energy of the nodes in the network. The performance of the network is an analysis using 50, 100, and 150 nodes based on the performance metrics, which acquired a minimal distance of 24.87m, maximal network energy of 94.54J, maximal alive nodes of 77, and maximal throughput of 94.42 bps, minimum delay of 0.00918s, and maximum PDR of 87.98%. This method can be further enhanced by developing hybrid optimizations to handle mobile sinks.

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