# Protruder Optimization-Based Routing Protocol for Energy-Efficient Routing in Wireless Sensor Networks

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## ABSTRACT

WSNs find valuable application in monitoring purposes, but they suffer from energy-efficiency issues that affect the network lifetime. The energy-efficiency problem is addressed using the cluster head (CH) formation, data aggregation, and routing techniques. Therefore, an energy-aware routing algorithm named protruder optimization algorithm is proposed, which boosts the network lifetime through finding the optimal routing path. The proposed protruder optimization is developed with the hybridization of the wave propagator characteristics and weed characteristics in such a way that the global optimal convergence is boosted while selecting the optimal routing path. Moreover, the communication in the network through the optimal path is progressed through the optimal CHs selection based on fractional artificial bee colony optimization (FABC), and in turn, the energy minimization problem is aided with data aggregation process using sliding window approach that avoids retransmission of the data. The results of the proposed method are compared with the existing methods on the basis of its performance measures, such as energy, alive nodes, and throughput.

## KEYWORDS

Cluster Head Selection, Data Aggregation, Protruder Optimization, Routing Protocol, Wireless Sensor Networks (WSN)

## 1. INTRODUCTION

WSN is the research topic nowadays enabling several real-time operations, such as tracking the environmental conditions, climatic and weather conditions (LS ThisaraKandambige., 2018), effective traffic controlling (Deepak Rewadkar and DharmpalDoye., 2018) prevention of disasters, monitoring and recognizing the health care issues (EmanueleCannizzaro, *et al*., 2020; ChoudhuryandAvishek., 2021), industry and enterprises management, and video surveillance (Akyildiz, *et al.,* 2002; Mehra, *et al.,* 2020; Shyjith, *et al.,* 2020, Renjith Thomas and Dr. MJS. Rangachar., 2019). WSN is configured with a vast number of closely distributed nodes that collect and distribute the information detected from the environment(Loganathan, *et al.,* 2020).Both the physical and environmental factors are effectively regulated and sensed using the sensor nodes present in WSN and the users can gather information

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from the collected data(Shyjith, *et al.,* 2020). Such advantageous sensor nodes carry a small battery for performing different tasks like data communication and data processing that easily drain the energies in the nodes. Hence, the energy consumption should be minimized without affecting the behavior of the network and this aspectis a major concern in WSN as the huge energy loss reduces the lifetime of the networkleading to network failure (Pattnaik&Sahu, 2020; Li & Liu, 2009). Hence, the challenge relies on restraining the nodal energy while transmitting the data (Mehta &Saxena, 2020). Some of the well-organized algorithms such as clustering algorithms are also developed by various researchers to minimize the energyconsumed to improve the network's time(Soundaram&Arumugam 2020).

The clustering schemes employed in the WSNs enhance the longevity and the productivity of thenetwork(Pattnaik&Sahu, 2020). The clustering method divides all the sensor nodes in the form of logical groups and this cluster-based division is done to achieve scalability and energy efficiency in WSN(Mehta &Saxena, 2020). The main purpose of the clustering schemes is to choose the CHs among the categorized clusters and finallytotransmit the obtained information to the sink(Singh &Verma, 2017; Pattnaik&Sahu, 2020). For a long period, a single cluster node is made as coordinator for every nodewhich reduces the energyconsumedand as a result, the network lifetime is improvedgradually(Soundaram&Arumugam 2020). Due to these reasons, efficient energy-based routing is needed in WSN(Loganathan, *et al.,* 2020) such that this energy effective routing plays an important role in improving the lifetime of the network. The routing protocols are the set of rules which are used to create an appropriate path inbetween the current node and the base station or sink node(BS). Generally, the routing protocol is categorized into three types based on the network structuressuch as hierarchical, location-based, and flat. Hierarchical-based routing is found to be the best choice among all the three types for its performance in energy scalability and efficiency(Lotf, *et al.,* 2010). Routing based on the hierarchical structure is responsible forestablishing the clusters, with the CH as the controller of data gathering, accumulation, and distribution of data into the BS(Mehta &Saxena, 2020).

Moreover, the energy problems (KaladharGaddala and SangameswaraRaju P., 2019) prevail in the network due to the re-transmission of the data, which is handled by the data aggregation approaches, which aim at reducing the data packets by combining the detected data(Ahmed, *et al.,* 2016). The communication overhead can be reduced using thedata aggregation method that results in decreased redundancy and unnecessary transmission of data to the BS from the nodes, which provides a better solution for optimization of energy during transmitting the data (Akkaya, *et al.,* 2008).Rather than sending the data individually from separate nodes, the information obtained can be grouped at a specific node for minimizingthe data packets sent, and hence theaggregated data is centered in the CH. For obtaining an elongated lifetime of the WSN network, a clustering algorithm based on k-means is used (Ray & De, 2016). In hybrid WSNs, the reliability of theend-to-end path has to be enhanced in performance which is made possible through the use of a routing approach mentioned in (Zonouz, *et al.,* 2016; Nisha&Basha, 2020). LEACH protocol is the commonly employed energy-efficient protocol and in turn, swarm intelligence-based routing algorithm is the recent trend, which grabbed the researchers' interest (Mohajerani&Gharavian, 2016; Logambigai, *et al.,* 2018; Soundaram&Arumugam 2020).

The current research concentrates on an energy-aware routing protocol named asProtruder optimization algorithm based on the Multi-objective function. Initially, the CH selection is performed in the network using the FABC algorithm, which is the basic initiative for energy efficiency. The FABC algorithm utilizes the objective function based on minimizing the delay, intra-cluster distance,and energy consumption while maximizing the inter-cluster distance. Then, the data aggregation is done using the sliding window approach in the CH, which eliminates the duplicates in the transmitted data and in turn avoids retransmission. With the aid of the proposed routing algorithm, an energy-efficient routing path is chosen using the proposed Protruder optimization for communicating the aggregated data to the BS, which further improves the network lifetime.

The prime significance of the research includes:

- **Protruderoptimization:** The protruder optimization is an energy-aware routing algorithm, which is developed by integrating the standard characteristics of the IWO and WWO to inherit the advanced routing features during the communication.
- **Protruder optimization-based routing protocol in WSN:** When the routing in WSN is performed using the protrude optimization, the network lifetime is enhanced due to the selection of the optimal routing path for communication.

The organization of the manuscript is as follows - the review of the literature with the need for the development of an energy-aware routing protocol is illustrated in Section 2. The WSN system model and radio model are depicted in Section 3. The proposed routing algorithm based on Protruder optimization is explained in Section 4 and the result analysis is deliberated in Section 5. The conclusion and scope of the research are depicted in Section 6.

## 2. MOTIVATION

In this section, the conventional models are reviewed to portray the significance and limitations, which are considered as the motivation for developing new protocols for efficient routing in WSN. The open challenges for the research are detailed below.

### 2.1 Related Works

In this section, the evaluation of the existing literature is detailed. Pattnaik&Sahu, (2020)usedan EHO Greedy algorithm and fuzzy clustering approach for well-definedrouting in WSN, which promoted the lifetime of the networkthrough efficient energy utilization.However, the transmission delay was the main challenge reported in the network. Shyjith, *et al.,*(2020)used Rider-Cat Swarm Optimization (RCSO) algorithm for the communication in the network, which exhibited high throughput and restrained high energy through the efficient usage of the energy. However, there was a gradual dissipation in the energy level in consideration ofthe number of rounds and population size. Soundaram&Arumugam(2020) employed a spider monkey-based routing protocol that reduced the end-to-end delay, enhanced the network lifetime,andin turn, impacted much on the throughput, but the problem was regarding the control overhead.Mehta&Saxena, (2020) developed a fuzzy multi-criteria clustering and bio-inspired energy-efficient routing (FMCB-ER) to enhance the lifetime of the network and improve the operational time of the WSN applications. FMCB-ER methodwas useful both in the energy consumption as well as in the network lifetime enhancement. Loganathan, *et al.,*(2020) used an Energy-Aware Efficient Data Aggregation (EAEDAR) and Data Re-Scheduling with the incorporation of clustering techniques which provided ahigh throughput rate and enhanced energy efficiency. It alsoincreased thepacket delivery rate, reduced the delay, and enhanced the network lifetime, but the quality of the service-based factor is an open question. Bhajantri&Kumbar, (2020) employed the Bayesianclassifier approach that provides some advantages like improvement in scalability, less energy consumption, high network lifetime, and in addition, the computational overhead was minimized. The major issue experienced in the method was that the energy of the sensor node was affected when the number of nodes was increased. Nisha&Basha, (2020) used Triangular fuzzy-based spectral clustering that provided better performance in terms of reliability, energy consumption, and network lifetime. However, the network was exposed to malicious attacks, which resulted in data loss. Sankaralingam, *et al.,*(2020)usedenergy-aware decision Stump Linear Programming Boosting Node Classification based Data Aggregation (EADSLPBNCDA), which reduced the energy consumption, increased the network lifetime, and reduced the delay. However, there prevailed a problem regarding the redundancy during thedata aggregation process. Ahmed, *et al.,*(2016) employed a model namely, Cluster-based data aggregation, which reduced the average aggregation ratio, energy consumption, control overhead, and message overhead. The absence ofasuitable routing algorithm to feed the data from the cluster nodes to the BSwasthe major problem faced in this method.KashifNaseer Qureshi, *et al*., (2020) proposed a Gateway Clustering Energy-Efficient Centroid-based Routing Protocol (GCEEC) for WSN. This protocol selects and rotates the CH near the energy centroid position of the cluster. It results with better network lifetime, throughput, and energy consumption. However, the method needs further analysis with different environment like wireless body area networks, and sensor-based transportation systems. ChuanXu, *et al*., (2019) proposed an energy-efficient region source routing protocol for lifetime maximization in WSN using a energy efficient region source routing protocol (referred to ER-SR). It results with higher energy efficiency, and has moderate performance on packet delivery ratio, delivery delay, and network lifetime. However, the analysis is mainly focused on static networks and needs to analyze in mobile networks.

### 2.2 Problem Statement

The challenges in the research are enumerated below.

The main issue in the Assimilation of fuzzy clustering approach and EHO-Greedy Algorithm is that the cluster heads or the BS in the WSN experience a great challenge to execute the enormous amount of the information in the heterogeneous wireless sensor network as it is in the unprocessed form (Pattnaik&Sahu, 2020).

An Optimized and Dynamic Selection of Cluster Head Using Energy Efficient Routing Protocol in WSN (Shyjith, *et al.,* 2020), the throughput and the energy are reduced with respect to the increase in the population size. Hence, maintaining the population size is the hectic challenge encountered (Shyjith, *et al.,* 2020). This problem shall be managed through an effective cluster head selection algorithm.

The Triangular fuzzy-based spectral clustering routing (TF-SCR) experiences the problem of packet loss due to various malicious attacks. Hence, developing a secure routing to reduce packet loss is one of the main challenges encountered in TF-SCR (Nisha&Basha, 2020).

Reducing the redundancy which appears during the data aggregation process is the main challenge experienced in energy-aware decision stump linear programming boosting node classification based data aggregation in WSN (Sankaralingam, *et al.,* 2020). The problems identified during the data aggregation process include higher energy consumption, lesser network lifetime, more time consumption, less data aggregation accuracy, more delay, and so on. During continuous data aggregation from sensor nodes, the node, energy level gets reduced. This in turn reduces the network lifetime in WSN (Sankaralingam, *et al.,* 2020).

Data transmission is the major source of energy consumption, which causes network failure or reduces the network lifetime. So, it is essential to reduce the draining of energy while performing data transmission to enhance the lifetime of WSN. Energy-effective routing in WSN is one of the keys to enhancing the lifetime of thenetwork. The routing protocols need to create apath from the current SN to the BS or sink. In (Mehta &Saxena, 2020), a hierarchical routing protocol Fuzzy Multi-criteria Clustering and Bio-inspired Energy-efficient Routing (FMCB-ER) is used which finds the best route but it has the problem of converging to the local optimal minima.

## 3. SYSTEM MODEL OF WSN

WSN possesses $m$ normal nodes equipped with a BS which is represented as $M_C$ . Each sensor nodeis distributed uniformly within a maximum transmission range of $P_i$ and $Q_i$ meters and the individual sensor nodes are provided with a unique ID and are grouped as clusters for the communication in WSN. The BS is situated in the optimal location $\left\{0.5P_i, 0.5Q_i\right\}$ for collecting the data packets from the normal nodes while the location of the normal nodes is obtained using the coordinate values of

$P_S$ and $Q_S$. The transmission of data to the sink node from each sensor node is achieved using the CH-based routing techniqueto extend the network lifetime through energy conservation. Here, $H$ is the total nodes that are initiated as CHs ( $M_D$ ), which in other words refer to the grouping of the normal nodes as $H$ clusters, where the total normal nodes are equal to ( $m-H$ ). Additionally, for the $H$ number of CHs in the network, let us assume that there is $h$ number of sensor nodes in their respective clusters.Then the CHs $M_D$ gather the data from the normal nodes $M_M$ and communicate to the BS, $M_C$. After locating the network parameters, the distance between the $n^{th}$ normal nodes to the $k^{th}$ CH is derived as $f_{nk}$ and distance between the $k^{th}$ CH to $M_C$ is denoted as, $C_k$

### 3.1 Radio Model

Initially, all the sensor nodes present in the network hold initial energy denoted as '$\xi_0$' and the sensor nodes in the WSNs lose their energy upon the successive communication in thenetwork and these battery-operatedsensor nodes are not chargeable and require replacement. In free space, the data packets are transferred from $n^{th}$ normal node to the $k^{th}$ CH. Based on the distance between the receiver and transmitter, the process of transferring the data packets undergoes a multi-path fading as mentioned in (Heinzelman, *et al.,* 2002). All these data transferring mechanisms use TDMA protocol which enables all the nodes to access a common channel by dividing the channel into different time slots. Each node present in any cluster consists of a transmitter and receiver for transferring the data packets. The transmitters present in a node are equipped with radio electronics and power amplifiers that perform the energy dissipation process whereas the receivers possess the radio electronics which is responsible for the energy dissipation of the nodes. This energy dissipation is based on two modalities of the nodes namely, normal nodes and the CH (Rajeev Kumar & Dilip Kumar. 2016). The energy dissipation of a normal node transmitting '$U_V$' data bytes is,

$$\xi_d\left(M_M^t\right)=\begin{cases}\xi_{ect}*U_V+\xi_{xv}*U_V*\left\|M_M^t\_M_D^k\right\|^4 ; & \left\|M_M^t\_M_D^k\right\|\geq I_0\\ \xi_{ect}*U_V+\xi_{yu}*U_V*\left\|M_M^t\_M_D^k\right\|^2 ; & \left\|M_M^t-M_D^k\right\|<I_0\end{cases} \tag{1}$$

$$K_{I_0}=\sqrt{\frac{\xi_{yu}}{\xi_{xv}}} \tag{2}$$

where, $\xi_{ect}$ is the electronic energy, which depends on the modulation, filtration, amplification, and so on, and $M_M$, $M_D$ represent the normal sensor node and CH, respectively, $I_0$ denotes the initial distance and $\xi_{xv},\xi_{yu}$ describe the energy parameter of the power amplifier used in the transmitter, $\xi_{xv}$ denotes the energyin the free space and $\xi_{yu}$ is the multipath energy. The term $\left\|M_M^t-M_D^k\right\|$ is the distance between a normal node and CH available in the network.The electronic energy is given as,

$$\xi_{ect}=\xi_{trans}+\xi_{agg} \tag{3}$$

where $\xi_{trans}$ and $\xi_{agg}$ demonstrate the transmitter energy and the data aggregation energy of the nodes. The energy dissipation of the cluster head receiving '$U_V$' data bytes is,

$$\xi_d\left(M_D^t\right) = \xi_{ect} * U_V \tag{4}$$

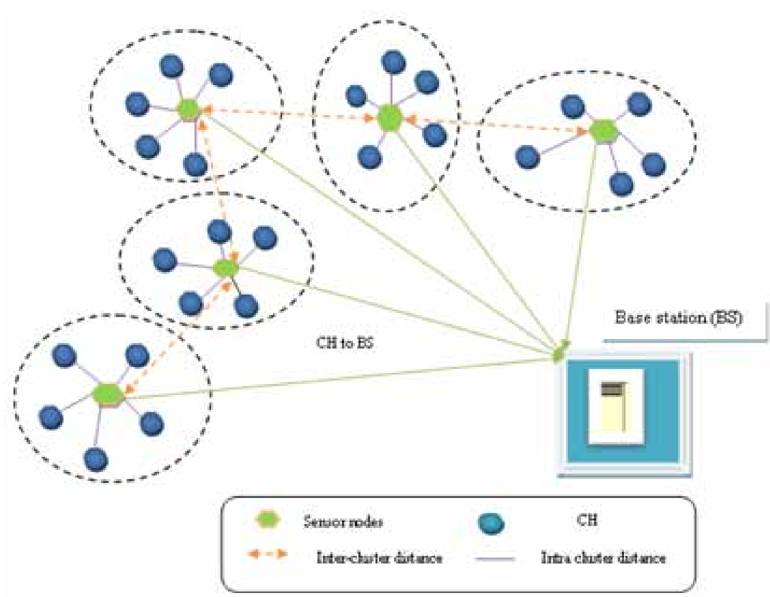
At the end of the communication, the energy levels of the normal sensor nodes and the cluster heads decays and hence, the remaining energies in the nodes and cluster heads are updated, which is formulated as follows.

$$\xi_{\gamma+1}\left(M_M^t\right) = \xi_\gamma\left(M_M^t\right) - \xi_d\left(M_M^t\right) \tag{5}$$

$$\xi_{\gamma+1}\left(M_D^t\right) = \xi_\gamma\left(M_D^t\right) - \xi_d\left(M_D^t\right) \tag{6}$$

where, $\xi_{\gamma+1}(M_M^t)$ is the updated energy of a sensor node and $\xi_{\gamma+1}(M_D^t)$ is the updated energy of the cluster head, $\xi_d(M_D^t)$ & $\xi_d(M_M^t)$ represent the dissipated energy by the receiver with respect to the CH and the member node, and $\xi_\gamma(M_M^t)$ & $\xi_\gamma(M_D^t)$ denotes the initial energies of the CH and member nodes.The data transferring prevails in the network until the network reaches a dead zone, which explains the completely drained nodes in the network.Forenabling energy-efficient communication in the network, CH selection strategies and an energy-aware routing protocol are required. Hence, CH selection is considered as the major step in the routing process, which is detailed in the upcoming section. Fig. 1 shows the system model of WSN.

**Figure 1. System model of WSN**



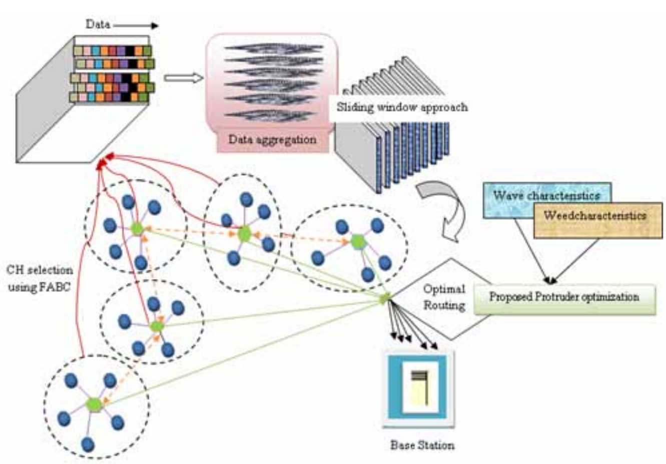
## 4. PROPOSED ROUTING ALGORITHM BASED ON PROTRUDER OPTIMIZATION IN WSN

In WSN, the energy-operated sensor nodes are prone to the unbalanced distribution of energy and high energy utilization, which are found to affect the network operation. Therefore, there is a need forCH selection and an efficient energy-aware routing algorithm, which ensures energy efficiency and prolongs the network life.In this research, a new routing algorithm, proposed asprotruder optimization is developed that enables smooth communication in the network through the selection of the optimal routing path. Additionally, the nodes are subjected to the CH selection and data aggregationto perform centralized routing thus, enabling the energy-efficient routing. Initially, the CH selection is done with the aid of FABC algorithm,which prolongs the network lifetime. In this process, sensor nodes under a cluster communicate the sensed data to the CH, which is then forwardedto the BS using the optimal path, selected using the proposed Protruder optimization. The FABC algorithm solves the exploration and exploitation problems encountered in selecting the CH. Moreover, there is an energy challenge associated with the re-transmission of the data between the CH and the BS, which is addressed using the data aggregation process for which the sliding window approach is employed that minimizes the duplicates of the transmitted data. The proposed protruder optimization holds the wave and weed characteristicsto enable the effective trade-off among the exploitation and exploration phases of optimization in such a way that the routing path is selected to provide minimal communication delay and thereby improves the network life.Fig. 2 shows the schematic diagram of the routing mechanism.

### 4.1 Cluster Head Formation and Data Aggregation

The nodes are placed in the sensor area and to assure energy efficiency, the clusters are formed with a CH for each cluster and in this research, the FABC algorithm (Kumar & Kumar, 2016) is utilized, which forms the optimal clusters in the network. The optimal placement of the nodes and CHs facilitate energy conservation as energy, distance, and delay are considered as asignificant criteria. The CH receives the information from all the nodes within the cluster, during which the CH loses its energy faster than other nodes in a cluster. The energy dissipation in the CH is handled effectively byconstantly updating theCHs in such a way that the node with the maximal energy and at an optimal distance to the BSbecomes the CH. The monitoring of the CH update process at the end of every transmission is governed by FABC. The FABC (Kumar & Kumar, 2016)renders better usability of the globally gathered information for improving the searching behavior and in turn, FABC plays a prominent role in enhancing the solution exploration capabilities in an allotted search space through solving the issues

Figure 2. Selection of an energy-aware routing using the proposed protruder optimization



in solution up-gradation using the best outcomes obtained in the earlier stages. Moreover, FABC further enhances the diverse nature of the evolution process. Due to the aforementioned advantages, FABC is used for solving the optimal CH selection problem by finding the shortest path between the CH and base station. The update rule used in FABC for locating the optimal cluster head is given as,

$$A_{n,k}^{\gamma+1} = \left[ \beta_A A_{n,k}^{\gamma} + \frac{1}{2} \beta_A A_{n,k}^{\gamma-1} + W_{n,k} \left( A_{n,k} - A_{l,k} \right) \right] \tag{7}$$

where, $A_{n,k}^{\gamma}$ is the $n^{th}$ food source of $k^{th}$ value in $\gamma^{th}$ iteration, $W_{n,k}$ is the random value generated, ranges between [-1,1], $k \in \left\{1,\ 2,\ 3 \ldots. \mathrm{H}\right\}$, and $l \in \{1,2,.....Z\}$ .Here, $\beta_A$ demonstrates the order of food derivative in the range of $0 \le \beta_A \le 1$ , $A_{n,k}^{\gamma+1}$ is the derivative version of the order $\beta_A = 1$ and $A_{n,k}^{\gamma+1}$ is referred as the new solution with respect to the best solution at theinstance $\gamma$ and $\left(\gamma - 1\right)$.

*Multi-Objective (MO) function:* The optimal CH is located based on the MO-function, which is derived based on the network parameters, such as energy, distance, and delay. It is interesting to understand that to assure the energy efficient selection of the CHs, the energy consumption should be minimal with less delay, and the intra-cluster distance should be minimal while maintaining the maximal distance between the inter-clusters. The multi-objective function is given by,

$$MO_1 = \frac{1}{4} \left[ r^d + \partial_1 (M_M^n, M_D^k) + \partial_2 (M_D^k, M_D^j) + \xi_{\gamma+1} (M_M^t) + \xi_{\gamma+1} (M_D^t) \right] \tag{8}$$

where, $r^d$ denotes the transmission delay, $\partial_1 (M_M^n, M_D^k)$ represents the intra-cluster distance, $\partial_2 (M_D^k, M_D^j)$ dignifies the inter-cluster distance, and $\xi_{\gamma+1} (M_M^t)$ specifies the energy of the member nodes, and $\xi_{\gamma+1} (M_D^t)$ represents the energy of the CH.

*Data aggregation in the Cluster heads using the Sliding window approach:* Once the CHs are optimally chosen using the FABC algorithm, data aggregation is performed in the CHs to remove the duplication of the gathered data and to avoid the data re-transmission. The main purpose of data aggregation is to maximize the energy efficiency of the nodes and in this work, thesliding window approach (Heinzelman, *et al.,* 2002) is utilized for removing the duplicates from the received data in the CH and this approach is mainly utilized for the packet-based data transmission in any network in high latency areas for providing reliabilityduring data transmission. Generally, during the data transmission, the CHs and BS wait for the acknowledgment message until when the next data communication waits, which increases the communication delay and performs the re-transmission, which is avoided in thecase of the sliding window approach.

### 4.2 Optimal Route Discovery in WSN Using the Proposed Protruder Optimization

The prime intention of proposed protruder optimization is to enable energy-efficient communication in the network without much transmission delay, extending the network lifetime. Initially, the CH selection is done using the FABC algorithm, from which the energy-efficient routing is initiated using the centralized routing. Though CH selection is the basic step in energy efficiency, data aggregation is done using the sliding window approach that further minimizes the energy consumption by avoiding the re-transmission of the gathered data. Finally, the aggregated data is communicated with the BS such that the gathered data is applied for applications like pattern recognition. The data communication is done through an optimal routing path that renders the extended life to the network such that the dead zone is prolonged and the selection of the optimal routing path is done using the protruder optimization based on the objectives, like minimal distance, minimaldelay,and minimal energy consumption while holding thehigher degree of the trust between the nodes during communication. The deepinsight into the algorithmic steps of the proposed Protruder optimization is explained below.

#### *4.2.1 Solution Encoding of the Proposed Optimization*

The solution encoding represents the optimal solution to be determined using the proposed protruder algorithm. In the solution encoding process, the optimal routing path to be selected using the proposed algorithm for establishing efficient communication is explained. The data is communicated from the source (CH) to its destination (BS) through the optimal route selected using the proposed Protruder optimization, which optimizes 1) the routing path through the minimal distance 2)the delay as well as the energy consumption of nodes thereby enhancing the network lifetime. Let us consider the source CH as, $SN_{CH}$ and the destination as $BS$ , where the intermediate nodes engaged in the routing varies between $j = 1,2,...,H$ , where $j \in k$ . The solution vector is represented in figure 3.

#### *4.2.2 Multi-Objective(MO) Function of the Protruder Optimization to Derive the Optimal Route for Communication*

The proposed protruder optimization selects the optimal route based on the MO function that is designed based on the network parameters, likedelay, distance, trust, network lifetime, and energy. The multi-objective function for optimal route discovery is given by,

$$MO_2 = \Re\kappa + \Re r^d + \Re\partial + \Re\xi_{\gamma+1} + \Re G' \tag{9}$$

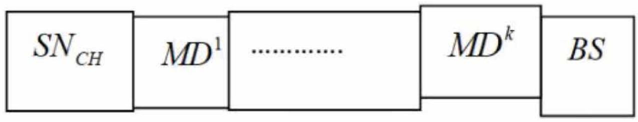
where, $\kappa$ denotes the network lifetime, $r^d$ is the delay, $\partial$ demonstrates the distance measurement in terms of both inter and intra-cluster distance, $\xi_{\gamma+1}$ denotes the energy of both the member and CH which is depicted in equations (5) and (6),and $G'$ denotes the trust of the network. $\Re$ is a constant parameter that varies between 0 and 1. The link lifetime of the network is formulated as given below.

$$\kappa = \frac{1}{m \times |M_D|} \sum_{n=1}^{m} \sum_{k=1,k\in n}^{|M_D|} \kappa'_{nk} \tag{10}$$

where, $m$ represents the total sensor nodes, $|M_D|$ denotes the CH, $\kappa'_{nk}$ denotes the link between $n^{th}$ normal node and $k^{th}$ CH. The link lifetime has to be effective for good communication and the delay is the time interval in the transmission and reception of data, which is formulated as,

$$r^d = \frac{\max_{k=1}^{H}(H_m^k)}{m} \tag{11}$$

**Figure 3. Solution Encoding**



where, $H_m^k$ represents the $k^{th}$ CH. The distance between the nodes and the corresponding CH is known as intra-cluster distance, which is calculated as,

$$\partial_1(M_M^n, M_D^k) = \sqrt{\frac{1}{2|M_D|} \sum_{\substack{n=1 \\ k\in 1,2,\ldots H}}^{m} (M_M^n, M_D^k)^2} \tag{12}$$

where $\partial_1(M_M^n, M_D^k)$ denotes the intra-cluster distance between the $n^{th}$ member node and the $k^{th}$ cluster head. The inter-cluster distance is defined as the distance between two CHs, belonging to two different clusters as formulated as,

$$\partial_2(M_D^k, M_D^j) = \sqrt{\frac{1}{|M_D|} \sum_{\substack{k=1 \\ j\in k}}^{H} (M_D^k, M_D^j)^2} \tag{13}$$

where $\partial_2(M_D^k, M_D^j)$ demonstrates the inter-cluster distance between the $k^{th}$ CH and $j^{th}$ CH node. The intra-cluster distance, delay, and energy consumption are minimal, while the inter-cluster distance is maximal for an optimal node to be a CH.In WSN, trust is an important factor as it confines the reliability and privacy in a communication process, without trust the communication is prone to many malicious attacks.

$$G' = \frac{N_1 + N_2}{2} \tag{14}$$

where $G'$ denotes the trust factor, $N_1, N_2$ denotes the direct and recent trust of the network.The direct trust is the trust of the CH $\left(M_D^k\right)$ with respect to the member node, $\left(M_M^n\right)$ that is given by,

$$N_1 = N_\rho^\gamma\left(M_D^k, M_M^n\right) = st_\rho^\gamma\left(M_D^k, M_M^n\right) \tag{15}$$

where $\rho$ demonstrates the transaction in the $\gamma^{th}$ interval, $M_D^k$ represents the CH, and $M_M^n$ denotes the member node. The recent trust depends on the recent features of the network which combines both the direct and indirect trust and is given below,

$$N_2 = \mu \times N_\rho^\gamma\left(M_D^k, M_M^n\right) + \left(1-\mu\right) \times N_\rho^{\gamma_1}\left(M_D^k, M_D^j\right) \tag{16}$$

where $N_\rho^\gamma\left(M_D^k, M_M^n\right)$ represents the direct trust and $N_\rho^{\gamma_1}\left(M_D^k, M_D^j\right)$ denotes the indirect trust.

### *4.2.3 Proposed Optimization Algorithm - Protruder Algorithm*

A routing protocol termedprotruder optimization algorithm is discussed in this section. It is obvious that the nodes suffer fromenergyloss in the communication process, which affects the network lifetime. Hence, an energy-aware routing protocol is required and the protruder optimization algorithm is proposed. The protrude optimization algorithm is developed by hybridizing the weed characteristics

(Misaghi&Yaghoobi, 2019) and wave propagator characteristics (Zheng, 2015)to inherit the higher degree of solution search-ability, resistibility, and adaptability. The inheritance of wave propagator characteristics and weed characteristics in the protruder optimization boosts the performance of the optimization byselecting the optimal route that extends the network lifetime in comparison with the other standard optimizations. The algorithmic explanations are given below:

1. Motivation

The prime intention in the development of the proposed Protruder optimization is to provide energy-efficient data communication in the network. As far as optimization is concerned, global optimal convergence to a solution is significant. Accordingly, the protruder optimization renders an optimal solution through inheriting the wave propagator characteristics, which is very well suitable for local exploration, but cannot make any significant impact on the global exploration and in addition, wave propagators end up with premature convergence. To avoid these problems, the weed characters are combined with the wave characters that provide a better trade-off between exploitation and exploration thereby boosting the chances of global optimal convergence. Thus, inspired by the characteristics of the wave and weed, the drawbacks of the waves are nullified with the features of the weed characters thereby increasing the diversification and intensification.

2. Mathematical design of the proposed protruder optimization

In this context, the algorithmic description step-wise is detailed with the successive steps, and it is significant to note that there are three phases:

- Wave propagation
- Refraction phase
- Crumbling phase

The in-depth description of the phases is detailed in the sub-sections below:

1. **Propagator Initialization:**The populations or solutions are randomly initialized in the first phase such that there are $\omega$ number of solutions and $E$ numbers of waves.The solutions are nothing, but the search agents arenamed as a propagator, which obtains the global minima, where the wavelength and fitness are inversely proportional to each other.Itis peculiar to note that the solutions of high fitness values exploit smaller regions, while those of the lower fitness values explore the larger regions. During initialization, the height is set to a maximum value and the wavelength is set to a constant value of 0.5.
2. **WavePropagation:** For the individual iterations, all the propagatorsproliferate in the search space at least once, which further generates the successive propagators.Thepropagator $S_n^{\gamma}$ proliferatesto produce a new solution $S_{\eta,wave}^{\gamma+1}$. The new solution $S_{\eta,wave}^{\gamma+1}$ generation follows:

$$S_{\eta,wave}^{\gamma+1} = S_{\eta}^{\gamma} + random\left(-1,1\right) \varphi\ J_{\eta} \tag{17}$$

where $\eta$ denotes the dimension of theoriginal wave,random $\left(-1,1\right)$ denotes the random numberthat is distributed uniformly in the range of $\left(-1,1\right)$, and $J_{\eta}$ is the length of the search space $\eta^{th}$ given by, $\left(1 \le \eta \le \upsilon\right)$.When a new position obtained after the propagation process is beyond a feasible range at that instance the propagator is reset to any random position within the range of $\left(-1,1\right)$. To boost the global convergence of protruder optimization, the weed characteristics are inherited in the equation (17). The standard algorithm following the wave characteristics has many challenges which are discussed below. The ability to solve exploitation problems is very poor and in addition, the best optimal solution among the population is not used in this method. The algorithm holds many random parameters, which tends to decrease the performance and limit the operation of accurate global coverage to the whole search space available. Moreover, the standard algorithm cannot bring additional improvements until the process is terminated and the main problem is that it cannot balance the exploitation and exploration problems. The above-mentioned factors are taken into consideration that affects the process negatively and some of the shortcomings include integration at an early stage, local optimum trapping, and the low population diversity. Hence, the characteristics of the weed are integrated with the wave characteristics in such a way that the protruder optimization, which is the combination of the weed and wave characteristics boost the exploitation and exploration abilities through designing new operators or redesigning the existing operators with an adaptive value.With the aid of the adaptive value, the problem of local optimum trapping for the multimodal wave functions are solved and additionally, the propagation operator is made effective, which achieves balance between exploration and exploitation problems. The update equation that describes the weed characteristics is modelled as,

$$S_{\eta,\,weed}^{\gamma+1} = \sigma(\gamma) * S_{\eta}^{\gamma} + (S_{best}^{t} - S_{\eta}^{\gamma}) \tag{18}$$

The update equation for evaluating the position of the propagators is based on the equation given below,

$$S^{\gamma+1} = 0.5\, S_{\eta,\,weed}^{\gamma+1} + 0.5\, S_{\eta,\,wave}^{\gamma+1} \tag{19}$$

Equation (19) that inherits the hybridization of the characteristics is derived from (Binu&Kariyappa, 2020) which facilitates the hybridization of weeds and wave characteristics in the proposed Protruder optimization that renders the effective diversification and intensification through balancing the trade-off between the exploration and exploitation, towards convergence to the global optimal solution. Substitute the equation (17) and (18) in equation (19), we get,

$$S^{\gamma+1} = 0.5\left[S_{\eta}^{\gamma} + random\left(-1,1\right)\, \varphi\ J_{\eta}\right] + 0.5\left[\sigma(\gamma) * S_{\eta}^{\gamma} + (S_{best}^{t} - S_{\eta}^{\gamma})\right] \tag{20}$$

$$S^{\gamma+1} = 0.5\left[S_{best}^{t} + random\left(-1,1\right)\, \varphi\ J_{\eta} + \sigma(\gamma) * S_{\eta}^{\gamma}\right] \tag{21}$$

Equation (21) is the proposed equation holding the features of wave and weed characteristics in the proposed Protruder optimization. The protruder optimization updates the position of the propagator based on the best solution in the previous instance, random number, and the current position of the propagator. Consider a propagator that moves from thedeep search space of the low fitness region to the shallow search space of thehigh fitness region that increasestheheight of the wave and a decrease in wavelength. Consider that $L\left(S^{\gamma+1}\right) > L\left(S^{\gamma}\right)$ then, $S^{\gamma}$ is replaced with $\left(S^{\gamma+1}\right)$ and again the height is set to maximum value or else $S^{\gamma}$ is retained.Theformula for finding wavelength of the propagator '$S$' is given by,

$$\varphi = \varphi O^{-\left(L\left(S^{\gamma}\right)-L_{\min}+\delta\right)/\left(L_{\max-}L_{\min}+\delta\right)} \tag{22}$$

where $L_{\max,}L_{\min}$ is the maximal and minimal fitness value, $O$ represents the wavelength reduction coefficient, and $\delta$ demonstrates a small positive number. This equation denotes that the higher fitness solutions have little wavelength values and are propagated in smaller wavelength regions.

3. **Refraction:** During the generation of the propagator, there is a possibility for the refraction of the propagator when a ray is not inclined perpendicular to iso-bath such that the refraction occurs when the heights of the propagator are reduced to zero. The position of the propagator after refraction is given by,

$$S_{\eta}^{\gamma+1} = z\left[\left(\frac{S_{\eta}^{\gamma^*}+S_{\eta}^{\gamma}}{2}\right),\left(\frac{S_{\eta}^{\gamma^*}-S_{\eta}^{\gamma}}{2}\right)\right] \tag{23}$$

where $S_{\eta}^{\gamma^*}$ denotes the best solution among many other solutions obtained so far, $z(\mu,\sigma)$ represents the Gaussian random number with mean $\mu$ and standard deviation $\sigma$. A propagator which is not enhanced even after much continuous propagationtends to lose its momentum and finally the wave is distorted and in turn, one shall confess that the new propagator position is a mid-position between the original location and best-knownlocation of the propagator and their absolute difference is considered as the standard deviation of the new propagator.After refraction, the propagator height is set to maximum and the wavelength of $S_{\eta}^{\gamma+1}$ is given by,

$$\varphi^{'} = \varphi.\frac{L\left(S^{\gamma}\right)}{L\left(S^{\gamma+1}\right)} \tag{24}$$

where $\varphi^{'}$ represents the wavelength of the wave after and before refraction, and $L(S^{\gamma})$ & $L(S^{\gamma+1})$ denotes the function of the normal and new propagators, respectively.

4. **Crumbling:** Crumbling is the local search operator which is employed when a propagator jumpsdeeper in water where the depth lies below the threshold such that the crest of the propagator extends beyond the propagator celerity. During this instance, the propagator crest turns out more steeper, and finally, the propagators are broken into many other solitary propagators. This crumbling operation is done on the propagators that are capable of finding the best optimal solution.At each dimension $\eta$, a solitary wave $S_{\eta}^{\gamma+1}$ generated is,

$$S_{\eta}^{\gamma+1} = S_{\eta}^{\gamma} + z\left(0,1\right).\theta J_{\eta} \tag{25}$$

where $\theta$ denotes the crumbling coefficient.

5. **SolutionUpdate:** If any propagator is better than the best possible location then the best location is modifiedwith the new solution or otherwise the best solution in the previous instances retained. In other words,oncea solution better than $S_{\eta}^{\gamma^*}$ is found then, the position $S_{\eta}^{\gamma^*}$ is updated or else $S_{\eta}^{\gamma^*}$ is retained.
6. **Termination:** The steps are repeated for the maximal number of solutions until the global optimal solution is obtained. The pseudo-code of the proposed protruder optimization is presented in algorithm 1.

**Table 1. Algorithm - pseudocode for the proposed Protruder optimization**

| **Sl. Pseudocode for the proposed Protruder optimization** |
|---|
| 1 Input: $S_{\eta}^{\gamma}$ |
| 2 Output: $S_{\eta}^{\gamma^*}$ |
| 3 Random Initialization of population E of $\omega$ **waves (solution)** |
| 4 For the maximal Iterations, do |
| 5 for all $S^{\gamma} \in E$ **do** |
| 6 Update the position $S^{\gamma+1}$ **based on eqn. (21).** |
| 7 if $L\left(S^{\gamma+1}\right) > L\left(S^{\gamma}\right)$ |
| 8 { |
| 9 if $L\left(S^{\gamma+1}\right) > L\left(S^{\gamma^*}\right)$ **then** |
| 10 { |
| 11 Break $S^{\gamma+1}$ **based on eqn. (25)** |
| 12 Update $S^{\gamma^*}$ **with** $S^{\gamma+1}$ |
| 13 Replace $S^{\gamma}$ **with** $S^{\gamma+1}$ |
| 14 else |
| 15 Decrease $S^{\gamma}.ht$ **by one** |
| 16 } |
| 17} |
| 18 if $S^{\gamma}.ht = 0$ **then** |
| 19 { |
| 20 Refract $S^{\gamma}$ with a new $S^{\gamma+1}$ based on eqn. (23) and (24) |
| 21 Updatethe wavelength based on eqn. (22) |
| 22 } |
| 23 Return $S^{\gamma^*}$ |

## 5. RESULTS AND DISCUSSION

This section elucidates the results and discussion of the protruderoptimization-based routing algorithm for creating an energy-aware routing protocol. To justify the efficacy of the protruder optimization, the performancebased on the network energy, throughput, and severalalive nodes are executed. Furthermore,acomparative analysis is performed with the conventional methods to justify the performance of the proposed method.

### 5.1 Experimental Setup

The proposed protruder optimization-based energy-aware system is implemented usingPython and the system configuration of the implementation includes PYTHON 2.7.X, 3.6.X software running in Windows 7 or later, MacOS, and Linux Operating system with 4GB RAM.

### 5.2 Simulation Results

This section briefly enumerates the network simulation using the proposed protruder optimization algorithm. For improving the network lifetime of the nodes, an optimal route is chosen by the proposed protruder optimization. The CH selection methods enable the selection of the CHs in the network and the centralized routing is initiated in the network for energy-efficient data routing. At first, the nodes are distributed in the sensing environment, for which the CH selection algorithm, FABC is applied for cluster formation. During the routing process, when the data packets are transmitted from the CH to the BS, the nodal energy tends to decrease thus, minimizing the size of the nodes in the network. The results obtained from the proposed protruder optimization for 100 nodes are depicted in figure 4.

The results obtained from the proposed protruder optimization for 200 nodes are demonstrated in figure 5.

### 5.3 Comparative Methods

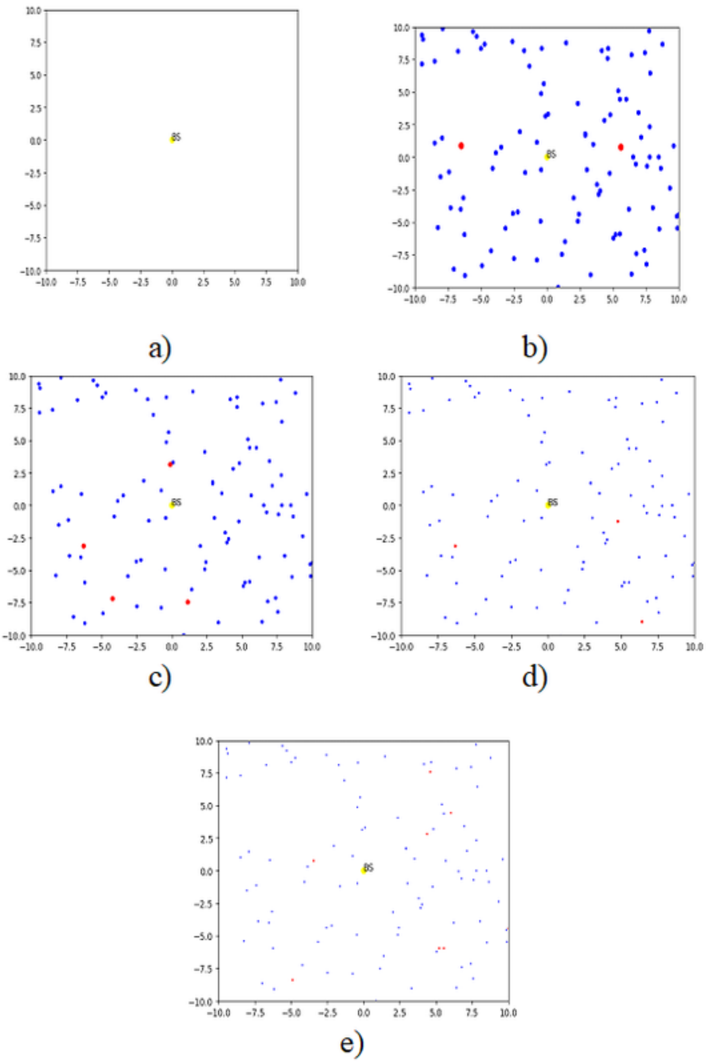
The methods used for the comparison includes Artificial Bee Colony (ABC)(Karaboga&Basturk, 2008) + proposed protruder optimization, ABC [26]+ Invasive Weed Optimization (IWO) (Misaghi&Yaghoobi, 2019), Fractional Artificial Bee Colony (FABC) (Kumar & Kumar, 2016) +Water Wave Optimization (WWO) (Zheng, 2015), TOPSIS + Fuzzy Multi-criteria clustering and Bio-inspired energy efficiency routing (FMCB-ER)(Mehta &Saxena, 2020), Genetic Spider Monkey Optimization(GMSO)+Spider Monkey Optimization (SMO) (Soundaram&Arumugam 2020), O-SEED + Rider-Cat Swarm Optimization (RCSO)(Shyjith, *et al.,* 2020), which are compared with the developed method.

### 5.4 Performance Measures

The metrics used for the discussion with the comparative methods with the proposed model are described below:

- **Alive nodes:** The number of active nodes at the final stage of the transmission process yields the alive nodes. The best method obtains the maximal number of alive nodes**.**
- **Average energy:** The amount of energy left on each nodeafter the communication process is the average energy of the network. In WSN, the energy is considered as a very important factor since it defines the network lifetime and the formulation of energy is represented in equations (5) and (6).
- **Throughput:** Throughput is defined as the amount of the service given by the network protocol to the service renders. In order to perform energy-aware routing, the best method should provide a high throughput rate.

**Figure 4. Simulationarea with 100 nodes, a) Round_0, b) Round_50, c) Round_100, d) Round_200, and e) Round_300**



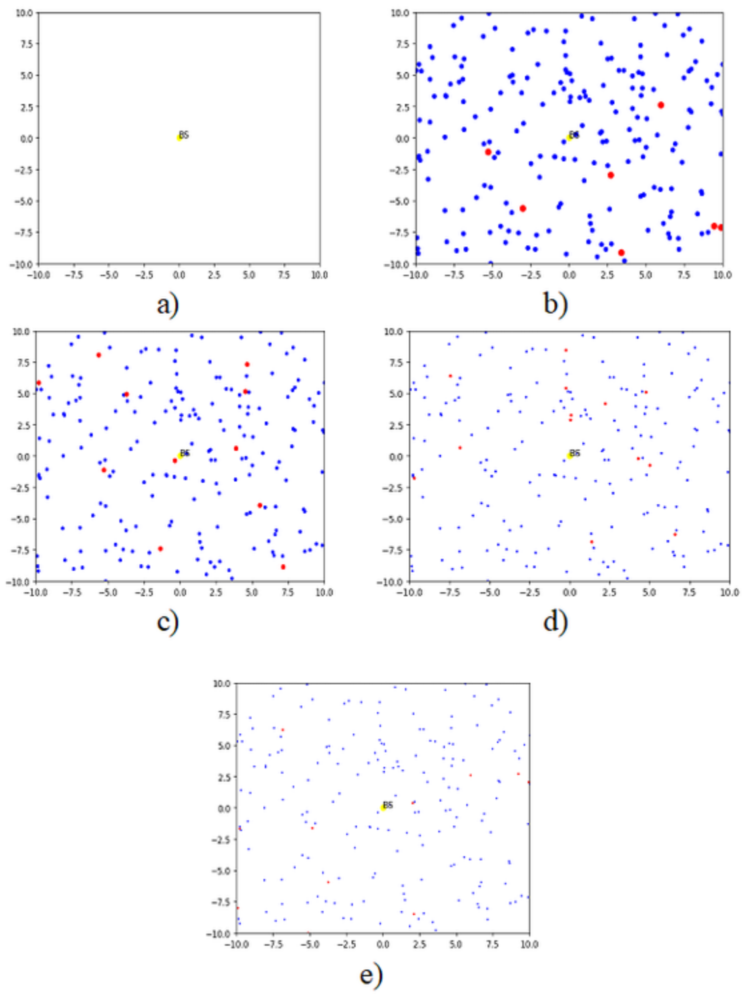

## 5.5 Analysis of the Comparative Methods

The comparative analysis of the protruder routing model with 50, 100, 150, and 200 nodes in the network is done based on a number of active nodes, normalized network energy and throughputin order to reveal the significance of the proposed model.

1. Analysis with 50 nodes

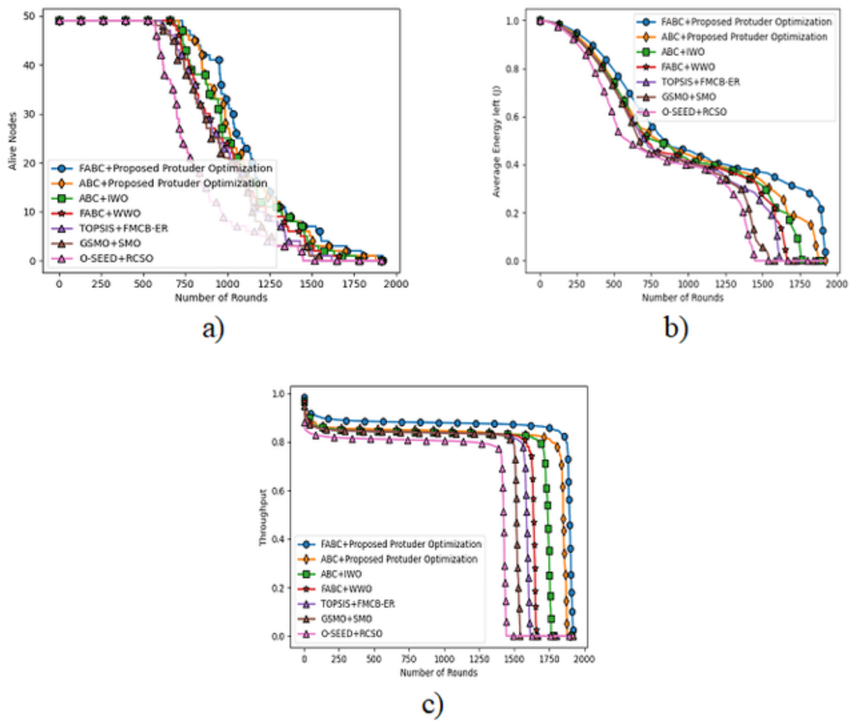
Figure 6 shows the analysis of the proposed method with 50 nodes. The comparative analysis in terms of alive nodes, network energy and throughput of the methods is depicted in figure 6 a), b), and c), respectively.At 800 rounds, the alive nodes available for the ABC + proposed protruder optimization, ABC + IWO, FABC +WWO, TOPSIS +FMCB-ER, GSMO +SMO, and O-SEED +RCSO are45, 38, 38, 36, 35, and 19respectively.On the other hand, the FABC + proposed protruder optimization

**Figure 5. Simulation area with 200 nodes, a) Round_0, b) Round_50, c) Round_100, d) Round_200, and e) Round_270**



holds 46 alive nodes at the end of 800 rounds, this shows the efficacy of the proposed method. At1000 rounds, the total network energy forABC + proposed protruder optimization, ABC + IWO, FABC +WWO, TOPSIS +FMCB-ER, GSMO+SMO, O-SEED+RCSO are0.441466J, 0.421185J, 0.415324J, 0.410627J, 0.404966J and 0.398477J respectively and for the FABC+proposedprotruder optimization, the available energy is 0.458781J, which is 3.77% better than ABC + proposed protruder optimization,8.19% better than ABC + IWO, 9.46% better than FABC +WWO,10.48% better than TOPSIS +FMCB-ER, 11.72% better than GSMO+SMO, and 13.14% better than O-SEED+RCSO. At 1000 rounds, the performance of 50 nodes in terms of throughput for the methods, such as the ABC + proposed protruder optimization, ABC + IWO, FABC +WWO, TOPSIS +FMCB-ER, GSMO +SMO, O-SEED +RCSO are 0.846056bps, 0.838857bps, 0.838443bps, 0.837444bps, 0.837362bpsand 0.804913bps respectively, whereas the proposed FABC+ proposed protruder optimization acquired the throughput of 0.879119 bps. This proves that the proposed methodhashighest throughput and O-SEED +RCSO has a least throughput. Thus, the proposed method shows an improved result when compared with other conventional methods.

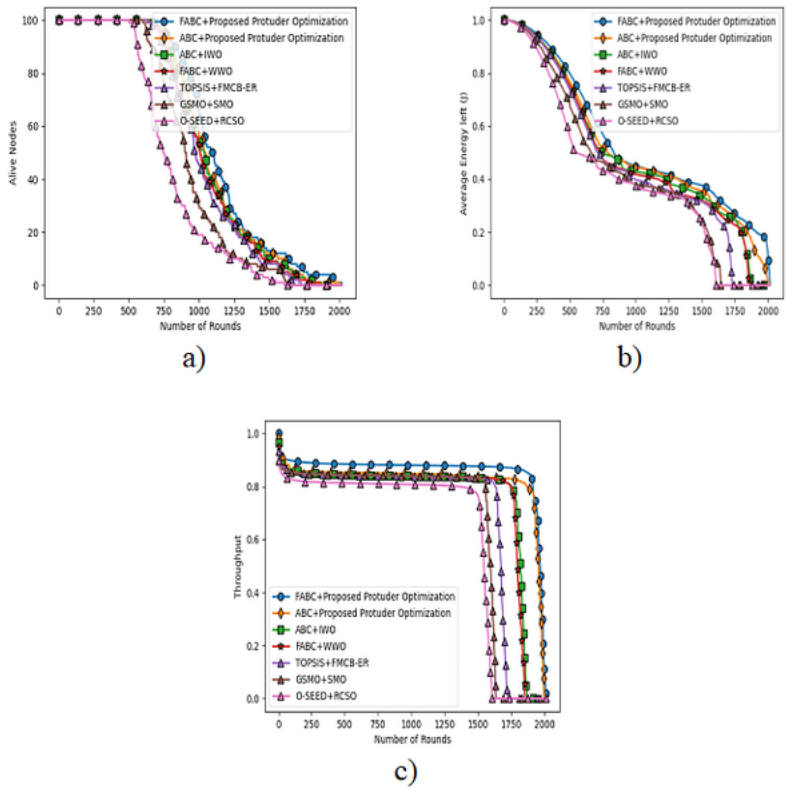
**Figure 6. Comparative analysis with 50 nodes, a) active nodes, b) average energy remaining in the nodes, and c) throughput**




2. Analysis with 100 nodes

Figure 7 shows the comparative analysis of the proposed method with 100 nodes in the simulation area. The comparative analysis in terms of alive nodes, network energy, and throughput of the method is depicted in figure 7 a), b), and c), respectively. At 900 nodes, the comparative analysis of 100 nodes in terms of alive nodes for the ABC + proposed protruder optimization, ABC + IWO, FABC +WWO, TOPSIS +FMCB-ER, GSMO +SMO, and O-SEED +RCSO are 75, 67, 66, 64, 51, and 30 respectively, which is illustrated in figure 7 a) and for the number of alive nodes for FABC+ proposed protruder optimization is 84, which shows the efficacy of the proposed method. At 500 rounds, the network energy of ABC + proposed protruder optimization, ABC + IWO, FABC +WWO, TOPSIS +FMCB-ER, GSMO +SMO, and O-SEED +RCSO is 0.768459 J, 0.753918 J, 0.75313 J, 0.737484 J, 0.685742 J, and 0.564397 Jrespectively and the network energy for the FABC + proposed protruder optimization is 0.799423 J as shown in figure 7b). The network energy of the proposed method is 3.87% better than ABC + proposed protruder optimization, 5.69% better than ABC + IWO, 5.79% better than FABC +WWO, 7.75% better than TOPSIS +FMCB-ER, 14.22% better than GSMO +SMO, and 29.40% better than O-SEED +RCSO.The analysis indicates that the FABC+ proposed protruder optimization renders effective performance in terms of energy compared with the other conventional methods. At 700 rounds, the throughput of ABC + proposed protruder optimization, ABC + IWO, FABC +WWO, TOPSIS +FMCB-ER, GSMO +SMO, and O-SEED +RCSO is 0.850222 bps, 0.841919 bps, 0.841186 bps, 0.841115 bps, 0.840911 bps, and 0.810027 bps respectively, while for the FABC + proposed protruder optimization, the throughput is 0.881896 bps. Thus,from the analysis FABC + proposed protruder optimization has the highest throughput.

**Figure 7. Comparative analysis of 100 nodes in terms of a) alive nodes, b)network energy and c) throughput**

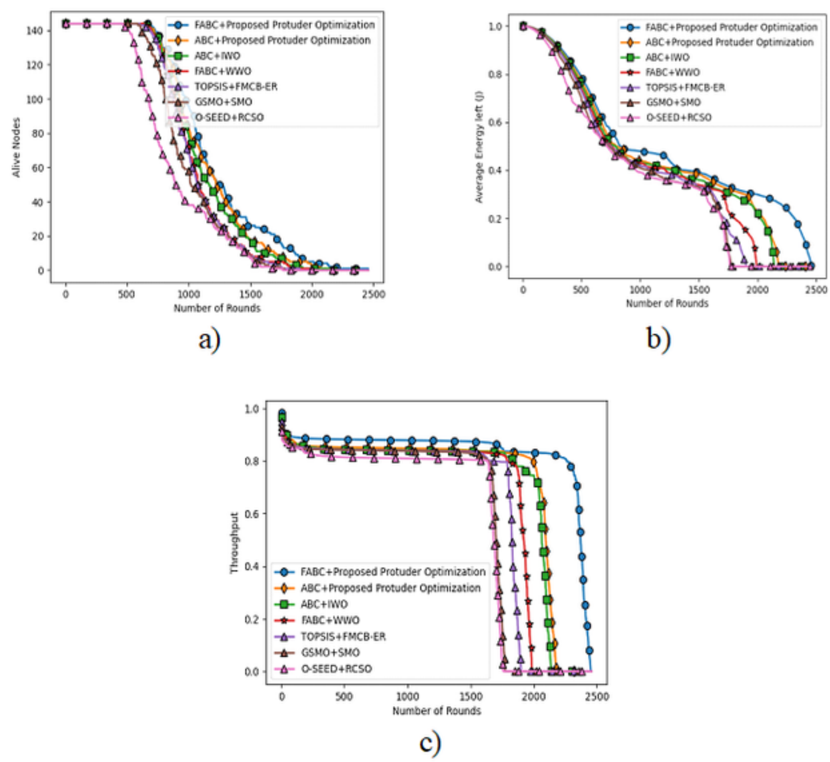



Next to FABC + proposed protruder optimization, ABC + proposed protruder optimization produces the highest throughputwheras, O-SEED +RCSO produces the lowest throughput.

3. Analysis with 150 nodes

Figure 8 shows the comparative analysis of the proposed method with 150 nodes. The comparative analysis in terms of alive nodes, network energy, and throughput of the method is depicted in figure 8 a), b), and c) respectively. At 700 rounds, the available alive nodes for the ABC + proposed protruder optimization, ABC + IWO, FABC +WWO, TOPSIS +FMCB-ER, GSMO +SMO, O-SEED +RCSO are 141, 141, 141, 139, 130 and 93respectively and in case of the FABC+proposedprotruder optimization, the available alive nodes are 143, which shows the advantage of the proposed method. At 1500 rounds, the performance of the ABC + proposed protruder optimization, ABC + IWO, FABC +WWO, TOPSIS +FMCB-ER, GSMO +SMO, and O-SEED +RCSO in terms of network energy are 0.382948 J, 0.359638 J, 0.339054 J, 0.331068 J, 0.327427 Jand0.319821 J respectively, while for the FABC + proposed protruder optimization, the energy is 0.390341 J, which is 1.89% better than ABC + proposed protruder optimization, 7.86% better than ABC + IWO, 13.14% better than FABC +WWO, 15.19% better than TOPSIS +FMCB-ER, 16.11% better than GSMO +SMO, and 18.06% better than O-SEED +RCSO.Figure 8c) represents the comparative analysis in terms of throughput at 1100 rounds. The throughput for the ABC + proposed protruder optimization, ABC + IWO, FABC +WWO, TOPSIS +FMCB-ER, GSMO +SMO, and O-SEED +RCSO are 0.847693 bps, 0.840433 bps, 0.839072 bps, 0.83873 bps, 0.837542 bpsand 0.809171 bps respectively, while

**Figure 8. Comparative analysis of 150 nodes in terms of a) alive nodes, b) network energy and c) throughput**

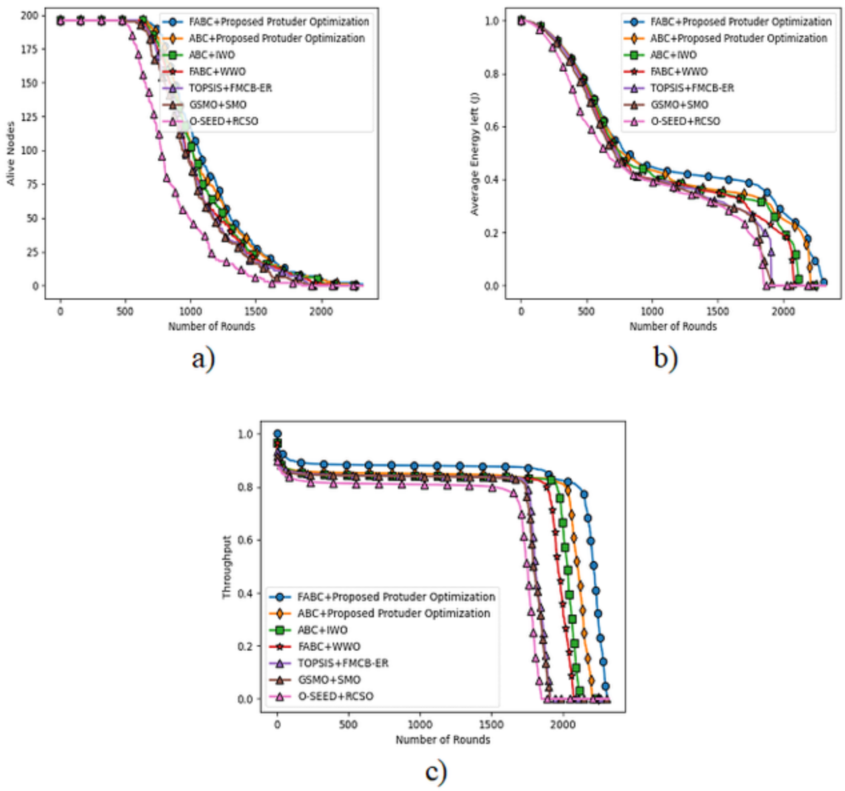



the FABC + proposed protruder optimization acquired the throughput of 0.878441 bps. The analysis proves that the FABC + proposed protruder optimization showsasignificant improvement in the performance and O-SEED +RCSO shows lowest throughput value when compared with the other conventional methods.

4. Analysis with 200 nodes

Figure 9 shows the comparative analysis of the proposed method with 200 nodes. The performance analysis in terms of alive nodes, network energy, and throughput of the method is depicted in figure 9 a), b), and c) respectively. At 1200 rounds, the available alive nodes for the ABC + proposed protruder optimization, ABC + IWO, FABC +WWO, TOPSIS +FMCB-ER, GSMO +SMO, and O-SEED +RCSO are 69, 60, 52, 49, 47, and 19 respectively, while the FABC + proposed protruder optimization shows the available alive nodes to be 74. The comparative analysis for network energy at 1300 rounds for the ABC + proposed protruder optimization, ABC + IWO, FABC +WWO, TOPSIS +FMCB-ER, GSMO +SMO, O-SEED +RCSO are 0.37705 J, 0.37112 J, 0.369185 J, 0.365875 J, 0.350853 J and 0.343708 J respectively and the network energy for the FABC+ proposed protruder optimization is 0.418152 J at 1300 rounds, which is 9.83% better than ABC + proposed protruder optimization, 11.24% better than ABC + IWO, 11.71% better than FABC +WWO, 12.50% better than TOPSIS +FMCB-ER, 18.06% better than GSMO +SMO, and 16.09% better than O-SEED +RCSOwhich indicates the superiority of the proposed method. At 1600 rounds, the analysis of ABC + proposed protruder optimization, ABC + IWO, FABC +WWO, TOPSIS +FMCB-ER, GSMO +SMO, and O-SEED +RCSO in terms of throughput is 0.841921 bps, 0.83611 bps, 0.835606 bps,

**Figure 9. Comparative analysis of 200 nodes in terms of a) alive nodes, b) network energy and c) throughput**




0.834412 bps, 0.831307 bps and 0.78802 bps respectively, while the FABC + proposed protruder optimization acquired the throughput is 0.875394 bps, which shows that theproposed method has higher throughput and O-SEED +RCSO has lower throughput and next to O-SEED +RCSO, GSMO +SMO has the lowest throughput and thus the performance of the proposed method is far better than the conventional methods.

## 5.6 Comparative Discussion

This section portrays the discussion of the methods employed for the design of an energy-aware routing protocol. The discussion depictsthe performance evaluation of the nodes in terms of alive nodes, energy-left in the nodes and throughput at various levels.Table 2 shows the comparative discussion of the methods with 50 nodes at 1000 rounds

The performance improvement of the FABC+ proposed protruder optimization in terms of energy with 50 nodes when compared with ABC+ proposed protruder optimization, ABC + IWO, FABC +WWO, TOPSIS +FMCB-ER, GSMO +SMO, and O-SEED +RCSO are 3.9222%,8.9262%,10.4634, 11.7269,13.2888 and 15.1336 respectively. From the table, it is inferred that with 200 nodes in the network, the available alive nodes for ABC + proposed protruder optimization, ABC + IWO, FABC +WWO, TOPSIS +FMCB-ER, GSMO +SMO, and O-SEED +RCSO are 69,60,52,49,47, and 19 respectively. On the other hand, for FABC+ proposed protruder optimization, the available alive nodes are 74 at the end of the transmission process which indicates the efficacy of the proposed method. In case of 150 nodes, the energy left at the end of ABC + proposed protruder optimization, ABC + IWO, FABC + WWO, TOPSIS + FMCB-ER,GSMO +

**Table 2. Comparative discussion of the methods with 50 nodes at 1000th round**

| Methods | Alive nodes | | | | Energy left | | | | Throughput | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | With 50 nodes | With 100 nodes | With 150 nodes | With 200 nodes | With 50 nodes | With 100 nodes | With 150 nodes | With 200 nodes | With 50 nodes | With 100 nodes | With 150 nodes | With 200 nodes |
| FABC + proposed protruder optimization | 32 | 66 | 56 | 74 | 0.458781 | 0.449126 | 0.462025 | 0.425546 | 0.879119 | 0.879661 | 0.877803 | 0.878331 |
| ABC [26]+ proposed protruder optimization | 27 | 57 | 55 | 69 | 0.441466 | 0.444602 | 0.414025 | 0.38738 | 0.846056 | 0.847622 | 0.846823 | 0.84779 |
| ABC (Misaghi&Yaghoobi, 2019) + IWO (Kumar & Kumar, 2016) | 25 | 54 | 46 | 60 | 0.421185 | 0.428907 | 0.407981 | 0.386421 | 0.838857 | 0.839612 | 0.839885 | 0.838852 |
| FABC (Kumar & Kumar, 2016)+WWO (Zheng, 2015) | 23 | 54 | 32 | 52 | 0.415324 | 0.418517 | 0.407273 | 0.384679 | 0.838443 | 0.838902 | 0.838477 | 0.838837 |
| TOPSIS +FMCB-ER (Mehta &Saxena, 2020) | 23 | 45 | 32 | 49 | 0.410627 | 0.39827 | 0.38826 | 0.371423 | 0.837444 | 0.838839 | 0.838055 | 0.838358 |
| GSMO +SMO (Soundaram&Arumugam 2020) | 21 | 30 | 29 | 47 | 0.404966 | 0.381488 | 0.367777 | 0.369625 | 0.837362 | 0.838396 | 0.8366 | 0.837625 |
| O-SEED +RCSO (Shyjith, *et al.*, 2020) | 8 | 19 | 28 | 19 | 0.398477 | 0.377773 | 0.359186 | 0.352406 | 0.804913 | 0.806999 | 0.808449 | 0.806587 |

SMO, and O-SEED + RCSOare 0.414025,0.407981,0.407273,0.38826,0.367777, and 0.359186 respectively, similarly for the FABC+ proposed protruder optimization, the energy left is 0.462025. With 200 nodes, the throughput for the ABC + proposed protruder optimization, ABC + IWO, FABC +WWO, TOPSIS +FMCB-ER, GSMO +SMO, and O-SEED +RCSO are 0.84779, 0.838852, 0.838837, 0.838358, 0.837625 and 0.806587 respectively. On the contrary, the throughput is 0.878331 for FABC+ proposed protruder optimization. From the above results obtained from the table, it is clear that the FABC+ proposed protruder optimization achieves improved performance in comparison with the conventional methods. This method reduces the packet loss, retransmission of data as well as performing centralized routing which provides energy-efficient routing, further boosts the network performance. This shows that the FABC+ proposed protruder optimization achieves better performance in terms of alive nodes, energy left and throughput when compared with other existing methods.

## 6. CONCLUSION

The lifetime of the WSNis affected due to the issues in energy efficiency.Thus, the research on the energy-aware routing protocol is implemented and analyzed in this paper, where a novel protruder optimization is proposed.This method is developed with the prime intention of designing energy-efficient routing protocol for smooth communicationin the network so that the delay and energy consumption is lowered.Thesignificant step used in this research is the CH selection for which the FABC algorithm is used in such a way that further communications to the BS are made effective through the optimal CHs. Finally, the proposed protruder optimization is proposed for the optimal route discovery based on the Multi-objective function so that the lifetime of the network is extended with an enhanced communication experience.The comparative analysis is done in order to prove the effectiveness of the proposed protruder algorithm based on alive nodes, throughput, and average energy left.The comparative analysis proves that the proposed method is superior over the other conventional methods with alive nodesof 74,throughput of 0.879661 bps, and energy energyleft of 0.462025J respectively.It needs more consideration for finding the optimal transmission power for each sensor node while clustering. In case if two nodes are close to each other, low transmission power is enough to communicate with each other. Therefore, the power level should be high enough for transmission, but should be as low as possible to save energy.Thus, this will be considered as a future work.Also, in the future, the development of highly advanced energy-efficient algorithms is developed for making the different real-time applications easy and more feasible.

## CONFLICTS OF INTEREST

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## REFERENCES

Ahmed, R. Z., Biradar, R. C., & Chaudhari, S. S. (2016). Cluster-based data aggregation for pest identification in coffee plantations using wireless sensor networks. *Computers & Electrical Engineering*, *56*, 591–607.

Akkaya, K., Demirbas, M., & Aygun, R. S. (2008). The impact of data aggregation on the performance of wireless sensor networks. *Wireless Communications and Mobile Computing*, *8*(2), 171–193.

Akyildiz, I. F., Su, W., Sankarasubramaniam, Y., & Cayirci, E. (2002). A survey on sensor networks. *IEEE Communications Magazine*, *40*(8), 102–114.

Avishek, C. (2021). Predicting cancer using supervised machine learning: Mesothelioma. *Technology and Health Care*, *29*(1), 45–58.

Bhajantri, L.B., & Kumbar, B.G. (2020). Cluster-Based Data Aggregation in Wireless Sensor Networks: A Bayesian Classifier Approach. *Evolutionary Computing and Mobile Sustainable Networks*, 971-980.

Binu, D., & Kariyappa, B.S. (2020). Rider Deep LSTM Network for Hybrid Distance Score-based Fault Prediction in Analog Circuits. *IEEE Transactions on Industrial Electronics, 1*, 9.

Cannizzaro, E., Cirrincione, L., Mazzucco, W., Scorciapino, A., Catalano, C., Ramaci, T., Ledda, C., & Plescia, F. (2020). Night-Time Shift Work and Related Stress Responses: A Study on Security Guards. *International Journal of Environmental Research and Public Health*, *17*(2).

Chythanya, K. R., Kumar, K. S., Yadav, B. P., Madhuri, P. M., & Mothe, R. (2020). Routing and data aggregation in wireless sensor networks by using clusters, In proceedings of Input Output Processor Conference Series. *Materials Science and Engineering*, *981*(2), 022051.

Gaddala, K., & Raju, P. S. (2019). Enhanced Self Adaptive Bat Algorithm for Optimal Location of Unified Power Quality Conditioner, Journal of Computational Mechanics. *Power System and Control*, *2*(3), 28–38.

Heinzelman, W. B., Chandrakasan, A. P., & Balakrishnan, H. (2002). An application-specific protocol architecture for wireless microsensor networks. *IEEE Transactions on Wireless Communications*, *1*(4), 660–670.

Kandambige, L. S. T. (2018). Indigenous Adaptations to Climatic Variation in Agricultural Activities: A Study Based on the Dry Zone of Sri Lanka. In IRCHSS-2018 and Faculty of Humanities and Social Sciences. University of Sri Jayewardenepura.

Karaboga, D., & Basturk, B. (2008). On the performance of artificial bee colony (ABC) algorithm. *Applied Soft Computing*, *8*(1), 687–697.

Kumar, R., & Kumar, D. (2016). Multi-objective fractional artificial bee colony algorithm to energy aware routing protocol in wireless sensor network. *Wireless Networks*, *22*, 1461–1474.

Li, M., & Liu, Y. (2009). Iso-map: Energy-efficient contour mapping in wireless sensor networks. *IEEE Transactions on Knowledge and Data Engineering*, *22*(5), 699–710.

Logambigai, R., Ganapathy, S., & Kannan, A. (2018). Energy–efficient grid–based routing algorithm using intelligent fuzzy rules for wireless sensor networks. *Computers & Electrical Engineering*, *68*, 62–75.

Loganathan, D., Balasubramani, M., & Sabitha, R. (2020). Energy Aware Efficient Data Aggregation (EAEDAR) with Re-scheduling Mechanism Using Clustering Techniques in Wireless Sensor Networks. *Wireless Personal Communications*, 1–17.

Lotf, J. J., Hosseinzadeh, M., & Alguliev, R. M. (2010). Hierarchical routing in wireless sensor networks: a survey. *Proceedings of IEEE 2010 2nd International Conference on Computer Engineering and Technology, 3*.

Mehra, P. S., Doja, M. N., & Alam, B. (2020). Fuzzy based enhanced cluster head selection (FBECS) for WSN. *Journal of King Saud University-Science*, *32*(1), 390–401.

Mehta, D., & Saxena, S. (2020). Hierarchical WSN protocol with fuzzy multi-criteria clustering and bio-inspired energy-efficient routing (FMCB-ER). *Multimedia Tools and Applications*, 1–34.

Min, J.-K., Ng, R. T., & Shim, K. (2015). Aggregate query processing in the presence of duplicates in wireless sensor networks. *Information Sciences*, *297*, 1–20.

Misaghi, M., & Yaghoobi, M. (2019). Improved invasive weed optimization algorithm (IWO) based on chaos theory for optimal design of PID controller. *Journal of Computational Design and Engineering*, *6*(3), 284–295.

Mohajerani, A., & Gharavian, D. (2016). An ant colony optimization based routing algorithm for extending network lifetime in wireless sensor networks. *Wireless Networks*, *22*(8), 2637–2647.

Nisha, U. N., & Basha, A. M. (2020). Triangular fuzzy-based spectral clustering for energy-efficient routing in wireless sensor network. *The Journal of Supercomputing*, *76*(6), 4302–4327.

Pattnaik, S., & Sahu, P.K. (2020). Assimilation of fuzzy clustering approach and EHO Greedy algorithm for efficient routing in WSN. *International Journal of Communication Systems, 33*(8), e4354.

Qureshi, K. N., Bashir, M. U., Lloret, J., & Leon, A. (2020). Optimized Cluster-Based Dynamic Energy-Aware Routing Protocol for Wireless Sensor Networks in Agriculture Precision. *Journal of Sensors*. Advance online publication. doi:10.1155/2020/9040395

Kumar, R., & Kumar, D. (2016). Multi-objective fractional artificial bee colony algorithm to energy aware routing protocol in wireless sensor network. *Wireless Networks*, *22*, 1461–1474.

Ray, A., & De, D. (2016). Energy efficient clustering protocol based on K-means (EECPK-means)-midpoint algorithm for enhanced network lifetime in wireless sensor network. *IET Wireless Sensor Systems*, *6*(6), 181–191.

Rewadkar, D., & Doye, D. (2018). Traffic-aware Routing Protocol in VANET using Adaptive Autoregressive Crow Search Algorithm. *Journal of Networking and Communication Systems*, *1*(1), 36–42.

Sankaralingam, S. K., Nagarajan, N. S., & Narmadha, A. S. (2020). Energy aware decision stump linear programming boosting node classification based data aggregation in WSN. *Computer Communications*.

Shyjith, M. B., Maheswaran, C. P., & Reshma, V. K. (2020). Optimized and Dynamic Selection of Cluster Head Using Energy Efficient Routing Protocol in WSN. *Wireless Personal Communications*, 1–23.

Singh, R., & Verma, A. K. (2017). Energy efficient cross layer based adaptive threshold routing protocol for WSN. *AEÜ. International Journal of Electronics and Communications*, *72*, 166–173.

Soundaram, J., & Arumugam, C. (2020). Genetic spider monkey based routing protocol to increase the lifetime of the network and energy management in WSN. *International Journal of Communication Systems*, *33*(14), e4525.

Thomas, R., & Dr.Rangachar, M. J. S. (2019). Fractional Rider and Multi-Kernel-Based Spherical SVM for Low Resolution Face Recognition. *Multimedia Research*, *2*(2), 35–43.

Xu, C., Xiong, Z., Zhao, G., & Yu, S. (2019). An Energy-Efficient Region Source Routing Protocol for Lifetime Maximization in WSN. *IEEE Access : Practical Innovations, Open Solutions*, *7*, 135277–135289.

Zheng, Y.-J. (2015). Water wave optimization: A new nature-inspired meta-heuristic. *Computers & Operations Research*, *55*, 1–11.

Zonouz, A. E., Xing, L., Vokkarane, V. M., & Sun, Y. L. (2016). Hybrid wireless sensor networks: A reliability, cost and energy-aware approach. *IET Wireless Sensor Systems*, *6*(2), 42–48.

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