Energy efficient data transmission using multiobjective improved remora optimization algorithm for wireless sensor network with mobile sink

Anil Kumar Jemla Naik[1], Manjunatha Parameswarappa[1], Mohan Naik Ramachandra[2]
[1]Department of Electronics and Communication Engineering, Jawaharlal Nehru National College of Engineering, Shivamogga, India
[2]Department of Electronics and Communication Engineering, Sri Dharmasthala Manjunatheshwara Institute of Technology, Ujire, India

Article Info

Article history:

Received Mar 4, 2023
Revised May 3, 2023
Accepted Jun 4, 2023

Keywords:

Average residual energy
Multiobjective ant colony optimization
Multiobjective improved remora optimization algorithm
Network lifespan
Wireless sensor networks

ABSTRACT

A wireless sensor network (WSN) is a collection of nodes fitted with small sensors and transceiver elements. Energy consumption, data loss, and transmission delays are the major drawback of creating mobile sinks. For instance, battery life and data latency might result in node isolation, which breaks the link between nodes in the network. These issues have been avoided by means of mobile data sinks, which move between nodes with connection issues. Therefore, energy aware multiobjective improved remora optimization algorithm and multiobjective ant colony optimization (EA-MIROA-MACO) is proposed in this research to improve the WSN's energy efficiency by eliminating node isolation issue. MIRO is utilized to pick the optimal cluster heads (CHs), while multiobjective ant colony optimization (MACO) is employed to find the path through the CHs. The EA-MIROA-MACO aims to optimize energy consumption in nodes and enhance data transmission within a WSN. The analysis of EA-MIROA-MACO's performance is conducted by considering the number of alive along with dead nodes, average residual energy, and network lifespan. The EA-MIROA-MACO is compared with traditional approaches such as mobile sink and fuzzy based relay node routing (MSFBRR) protocol as well as hybrid neural network (HNN). The EA-MIROA-MACO demonstrates a higher number of alive nodes, specifically 192, over the MSFBRR and HNN for 2,000 rounds.

Corresponding Author:

Anil Kumar Jemla Naik
Department of Electronics and Communication Engineering, Jawaharlal Nehru National College of Engineering
Shivamogga, India
Email: anilkumarj@jnnce.ac.in

1. INTRODUCTION

Wireless sensor networks (WSNs) have become a major interesting area for many researchers due to their importance in internet of things (IoT) environments [1]. WSNs are made up of a huge amount of independent wireless sensing nodes that are placed in a specific region to analyze environmental or physical factors such as power consumption, temperatures, humidity, vibration, sound, pollution, or motion, among other things [2]. Sensor nodes gather environmental information and transmit it to a sink or base station via direct or multi-hop communications [3]. A sink node is a mobile or stationary node that connects the WSN to a communication network [4]. WSNs provide a broad range of uses to several industries, including agriculture, tsunami detection, environmental and ecosystem monitoring, ocean boarding alarms, and smart grids [5]–[7]. The sensor nodes are operated by energy-limited batteries, therefore, the replacement of batteries will be difficult because of the high cost and huge amount of sensors [8]. Such a huge amount of interlinked sensors creates a network that is utilized for data transmission and reception at the time of communication [9]. Since WSNs have no organized structure, they are simpler and quicker to construct than other WSNs. WSNs would not need centralized management and it is configured independently. Seismic, low-rate magnetic, thermal, and optical sensors, are examples of wireless sensors [10]. The primary goals of WSNs include lowering the energy utilization of sensor nodes while increasing the network's lifetime [11]. Energy restrictions are a very important concern in advanced technologies, particularly in the WSN environment, because they reduce the network lifetime of the whole WSN system [12]. Due to the nature of WSNs, sensors must interact to convey information to the sink, because sensor energy is confined while transferring information and receiving information from the sink which consumes more energy in the intermediary nodes. As a result, there is a need to design an efficient method to extend the lifetime of the WSN network [13].

Clustering reduces long-distance communication among nodes and sinks, which results in reduced energy depletion of nodes. The crucial objective of clustering is to improve the network's lifetime. In addition to increased lifetime, clustering improves load balancing and decreases data packet collision [14]. Clustering divides the network into subgroups, each with its head. Cluster heads (CHs) gather sensor node information and transmit it to the sink node directly or through another CHs. To handle the transmitting and receiving activities, cluster heads must be energy-efficient [15]. Using several approaches, the researchers have previously done only a few studies that were only partially reliable as they had more limitations. So, to improve the CHs energy efficiency, energy aware multiobjective improved remora optimization algorithm and multiobjective ant colony optimization (EA-MIROA-MACO) is proposed. Here, the proposed EA-MIROA-MACO is used for the clusters head selection and MACO is used for identifying the efficient routing path. Here, some of the existing works are described here, Mirania and Sharma [16] proposed a mobile sink-based improved energy efficient routing scheme utilizing cluster coordinator node for reducing node energy as well as extending network lifetime. The procedure began by dividing the network into similar clusters with a cluster coordinator node (CCO) and a balanced distribution of nodes. The MATLAB programming language was used to generate the expected model's outputs. The suggested model demonstrated that whenever the network size was lower and the mobile sink proceeds on a smaller path, the network was more efficient and had a maximal lifetime. The number of nodes decreased significantly at each radius. While compared to various radii, the sink moved around a relatively small radius, whereas the greater radius-based network had a high energy consumption. Gupta *et al.* [17] suggested a hybrid red deer algorithm-black widow optimization approach (RDA-BWO) to accomplish an EE data transmission. Initially, utilizing the combination of five characteristics, RDA-based CH selection allocated one CH for every cluster. Next, BWO-based mobile sink (MS) position estimation and precise path prediction was used to determine the current mobile sink position and route data packets along the shortest route. Because of the suggested RDA-based CH selection in the network, the throughput of the suggested RDA-BWO approach was increased consistently. As a result, nodes simply sent the packets for longer periods, which considerably improved the network's throughput factor. The suggested RDA-BWO comprised the maximum amount of rounds at various phases of dead nodes (DNs). This was due to less amount of energy flow created by optimized CH selection as well as intra-cluster communication.

Kumaran and Nagarajan [18] suggested a mobile sink and fuzzy based relay node routing (MSFBRR) protocol to preserve the energy consumed by the sensor nodes. A fuzzy system was implemented that utilizes distance and energy among CH as well as relay node input data to select the suitable relay node. Additionally, the mobile sink node collected the information from the relay node and forwarded it to the MS. The network lifespan of the suggested technique was significantly longer than the other prior techniques due to the cluster head selection procedure and communication among the CH and sink node utilizing a multi-hop connection to pass the collected data. However, the amount of active nodes in the MSFBRR was reduced, which implied that the network performed in an exemplary way. Gowda and Jayasree [19] suggested a novel hybrid neural network-based energy-efficient routing technique depending on rendezvous points (RPs) for increasing network lifespan and lowering energy consumption. The most significant change (MSC) technique was used to cluster the network effectively, and then a bald eagle search (BES) optimization was used to choose the optimum CHs for each cluster. Furthermore, in the hierarchical techniques, RPs were constructed for each CH depending on the local data. At last, the hybrid graph theoretical approach (GTA) determined the best route for energy efficiency. The suggested method employed a mobile sink instead of a static sink, where the WSNs' lifespan was increased. A minor variation in a single input impacted the whole network, hence, the neural networks were complex to represent statistically. Yalçin and Erdem [20] proposed a novel mobile clustering routing protocol for heterogeneous WSNs depending on thermal exchange optimization (TEO-MCRP). TEO-MCRP was an evolutionary approach for the selection of CHs in a network that incorporated the fitness metrics such as the node's average energy, distance to MS, and multiple adjacent nodes in the target function. Furthermore, the suggested technique employed numerous fitness criteria, such as the remaining and average CH energy, as well as the amount of nodes in a cluster, while determining the MS mobile path. The suggested technique detected the optimal CH with the MS pathway by providing a shorter and more stable solution through the TEO approach. Because the data loss, as well as transmission delays, were high in broad area networks, the TEO-MCRP method consumed more energy. A process of adaptive hierarchical clustering and routing based on maximum bottleneck energy routing (MBER) from a node to the sink has been presented by Al-Jumaili and Karimi [21]. Instead of favoring the neighboring node with the highest energy, this approach supports the routes with the highest energy. The suggested MBER reduces the likelihood of a dead node while a packet was being sent to sink. Depending on the application, data fusion has been used in various levels due to the hierarchical nature of MBER to transfer the supplementary data from every node to sink. But in this study, the only factor taken into consideration was the data transfer condition.

The contributions are stated below:

- With the goal to enhance the WSN's network lifetime, an energy-efficient CH selection as well as routing approaches have been created. Whereas, EA-MIROA-MACO is designed to identify suitable CHs, thereby reducing nodes energy consumption.
- Then, the efficient path through the CHs is achieved utilizing EA-MACO. Reducing energy utilization as well as enhancing packet delivery are facilitated by identifying the shortest path along with mitigating node failures.

The following sections of the remaining paper are organized as follows: section 2 provides a comprehensive description of the proposed EA-MIROA-MACO. The proposed multi-objectives of ROA are explained in section 3. Section 4 discusses the outcomes of the EA-MIROA-MACO, while section 5 concludes the research.

2. EA-MIROA-MACO METHOD

The information regarding the mobile sink that functioned under the WSN architecture is made clear in this part. The architecture of a WSN with a movable sink is shown in Figure 1. The sensor node sends the data to the knowledge base (sink) in a clustering method. Monitoring a relatively large region of interest (RoI) relies on the clustering design. The data is generated by the sensor node and transmitted to the CH, which sends it to the sink for further processing and storage. This monitoring applications control the sink's movement. The mobile sink acts as a data carrier, traveling throughout the network to collect data packets from the sensor nodes. The mobile sink moves regularly inside the network to visit data collection points (CPs) and collects each and every data packets. Conferring to this, the mobile sink distributes over the center of CPs.

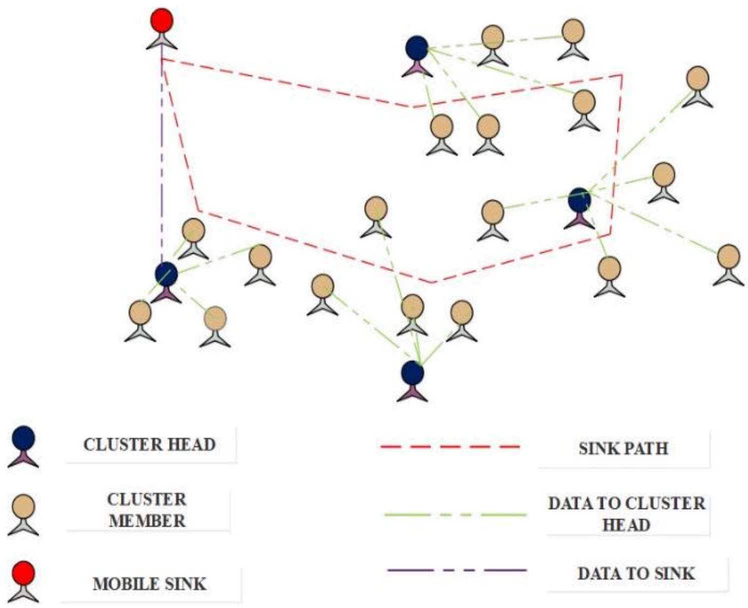

Figure 1. Architecture of WSN with mobile sink

The number of clusters created can be determined based on the RoI size. Data is gathered by the CH from each of its CM and sent to the sink. The sensor nodes CH along with cluster member (CM) should be taken into consideration even though the sink has a prosperity of resources because they are small embedded machines powered by rechargeable batteries. The node chosen as a CH should extend its lifetime as well to prevent energy hole issues. Because the amount of data exchanged and the distance between the sender and receiver may both be limited, the node's energy consumption can be decreased. Therefore, based on the sink mobility, the CM passes data to CH.

2.1. Sensor initialization

The network begins by randomly placing the sensors, and then the CHs selection is done utilizing MIROA. The WSN generates clusters after selecting the CHs. Then the MACO is used to determine the path from the transmitter CH to the MS. The upcoming sub-sections broadly explain the CH and route selection process. Figure 2 depicts the process/flowchart of the EA-MIROA-MACO method in this research.

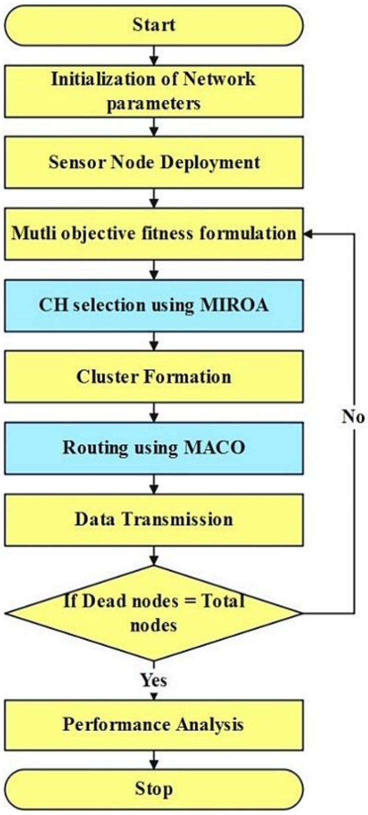

Figure 2. Flowchart of proposed method

2.2. CH selection using MIROA

The rain optimization algorithm (ROA) is a metaheuristic optimization method that mimics the remora fish behavior. To escape from enemy invasion and preserve energy, remoras join themselves to sailfish, whales, or other species to locate food. As a result, ROA employs various sailed fish optimizer (SFO) and whale optimization algorithm (WOA) formulae while updating locations. If there is no requirement to change the host, they will perform host feeding. In this case, the normal ROA is transformed into MIRO to reduce the WSN's energy consumption [22].

2.2.1. Representation and initialization

The primary solutions in MIRO termed remora fish, contain the collection of potential sensors which need to be chosen as CH. Every remora solution is begun with random node ID ranging from 1 to N, where N is the amount of nodes. Assume the i^{th} MIRO remora fish as $Z_i = (Z_{i,1}, Z_{i,2}, \dots, Z_{i,d})$, wheras, d states as every solution's dimension. $Z_{i,pos}$ is the posture of the remora fish, and the random node position from the WSN sensors is $1 \leq pos \leq d$.

2.2.2. Iterative process

a. SFO strategy

Whenever the remora is bound on the sailfish, its looks like as though the remora moves together with the sailfish. The formulas of the solvent freeze out (SFO) technique are enhanced depending on the elite approach, then the following equations are given, where ct represents prevalent iteration number, ${Z_{Best}}^{ct}$ defines prevalent best position, ${Z_{rand}}^{ct}$ is the remora's prevalent random posture [22].

$$Z_i^{ct+1} = {Z_{Best}}^{ct} - \left(rand \times \left(\frac{{Z_{Best}}^{ct} + {Z_{rand}}^{ct}}{2}\right) - {Z_{rand}}^{ct}\right) \quad (1)$$

2.2.3. Experience attack

Whenever the remora is leap on the hosts, they travel in a narrow range by surrounding the hosts to determine whether the host wants to be changed. This procedure is equivalent to the acquisition of experience. The following is the statistical computation formula, where Z_{ppg} states as remora's past generation posture of, Z_{tm} states as remora's tentative movement, $randn$ states as random number with normal distribution in [0 to 1].

$$Z_{tm} = Z_i^{ct} + (Z_i^{ct} + Z_{ppg}) \times randn \quad (2)$$

$$f(Z_i^{ct}) < f(Z_{ppg}) \quad (3)$$

$$H(i) = round(rand) \quad (4)$$

The remora examines either to change host after brief movement range as stated in (3), as well as the equation for switching host is given in (4). The initial value of $H(i)$ is either 0 or 1, specifies the hosts used by remora. The sailfish is consumed if $H(i)$ matches 0, conversely, when $H(i)$ matches 1, it indicates the consumption of the whale. Additionally, both Z_i^{ct} and Z_{ppg} have fitness values denoted as $f(Z_i^{ct})$ and $f(Z_{ppg})$ respectively and the rounded function is represented as round [22].

2.2.4. WOA strategy

Whenever a whale is assumed as a host, the remora travels in a rhythm with the specified host. The following is the computation formula, where, the distance between the optimal and present locations prior the updation is defined as *DT*, *ec* defined as constant with approximate value (2.7182), *MT* defined as maximum iteration count, whereas la stated as linear drop between [-2, 1] during iteration [21].

$$Z_i^{ct+1} = DT \times ec^r \times cos(2\pi a) + Z_i^{ct} \quad (5)$$

$$DT = |{Z_{Best}}^{ct} - Z_i^{ct}| \quad (6)$$

$$r = rand \times (a - 1) + 1 \quad (7)$$

$$la = -\left(1 + \frac{ct}{MT}\right) \quad (8)$$

2.2.5. Host feeding

The host feeding phase is a subset of the exploitation phase, as well as the range for the search process, is limited. The remora will seek food near the hosts. The following is the statistical computation formula, where the remora's moving distance is sated as *RA*, which proportional to host's as well as remora's volume. In ROA, to define the remora's location, the remora factor *C* is employed and given as 0.1. To imitate the remora's volume, *RV* is employed, also to mimic the host volume, *RB* is employed [22].

$$Z_i^{ct+1} = Z_i^{ct} + RA \quad (9)$$

$$RA = RB \times (Z_i^{ct} - C \times Z_{Best}) \quad (10)$$

$$RB = 2 \times RV \times rand - RV \quad (11)$$

$$RV = 2 \times \left(1 - \frac{ct}{MT}\right) \quad (12)$$

3. PROPOSED MULTI-STRATEGIES FOR ROA

3.1. Host-switching method

ROA determines whether the host wants to be changed after an experience attack. The following optimization concepts are offered in this research based on the abovementioned remora's foraging behavior, where Z_{new} defined as new solution, k as random factor, as well as β stated as constant in this work with a value of 0.2. The distance between two random solutions is stated by step. ${Z_{r1}}^{ct}$ and ${Z_{r2}}^{ct}$are 2 randomly generated solutions. The fitness value of Z_{new} is defined by $f(Z_{new})$.

$$Z_{new} = Z_i^{ct} + k \times step\ if\ rand < LP \tag{13}$$

$$k = \beta \times (1 - rand) + rand \tag{14}$$

$$step = {Z_{r1}}^{ct} - {Z_{r2}}^{ct} \tag{15}$$

$$LP = 0.5\left(2 - \frac{ct}{MT}\right) \tag{16}$$

$$f(Z_i^{ct}) < f(Z_{new}) \tag{17}$$

LP states as decreasing factor ranges [1 to 0.5] which is utilized to regulate the frequency with which new solutions are generated [22]. Using (13), the aforementioned method creates a fresh solution based on the present solution and then analyses the fitness value of the new solution as well as the current solution (17). If the fitness value of a new solution is higher, the solution's updating procedure will be modified [23].

3.2. Multi-objective fitness formulation

Residual energy ($fmet_1$), neighbor node distance ($fmet_2$), sink distance ($fmet_3$), CH balance factor ($fmet_4$) as well as node centrality ($fmet_5$) are the fitness measures utilized to select an optimum CH. The multiobjective MIROA's fitness is calculated as given in (18), where $\alpha_1, \alpha_2 \ldots. \alpha_5$ are the weight parameters that are assigned to every fitness measure/metric. The following are the MIRO fitness measures:

- The sensor selected as CH is the one with the highest remaining energy. The residual energy computation is expressed by (19). Where E_{CH_i} is the remaining energy of the i^{th} CH.

$$f = \alpha_1 \times fmet_1 + \alpha_2 \times fmet_2 + \alpha_3 \times fmet_3 + \alpha_4 \times fmet_4 + \alpha_5 \times fmet_5 \tag{18}$$

$$fmet_1 = \sum_{i=1}^{d} \frac{1}{E_{CH_i}} \tag{19}$$

- The neighbor distance and sink distance are expressed by (20) and (21). Where the CM_j states the intra CMs count for cluster j; $dt(N_i, CH_j)$ states the distance between i^{th} node as well as j^{th} CH whereas $dt(CH_i, BS)$ states the distance among the i^{th} CH and MS.

$$fmet_2 = \sum_{j=1}^{d} \left(\sum_{i=1}^{CM_j} dt(N_i, CH_j)/CM_j\right) \tag{20}$$

$$fmet_3 = \sum_{i=1}^{d} dt(CH_i, MS) \tag{21}$$

- The CH balancing factor represented in (22) is regarded to maintain the cluster, which assists in energy balancing in WSN. Where AN denotes the overall count of alive nodes.

$$fmet_4 = \sum_{i=1}^{d} \frac{AN}{d} - CM_j \tag{22}$$

- Node centrality is defined as the value that characterizes a sensor based on its distance from neighbor sensors by the dimension of the network, as given in (23).

$$fmet_5 = \frac{\sqrt{\left(\sum_{rk \in NCR(CH_i)} DTct^2(CH_i, rk)\right)/NCR(CH_i)}}{Network\ dimension} \tag{23}$$

Where the $NCR(CH_i)$ specifies the amount of nodes in i^{th} CH's clustering range. The fitness indicators stated above are utilized to choose relevant CHs from regular nodes. To determine whether the CH has sufficient energy, the energy is utilized since a low-energy CH leads to loss of information. To increase the WSN's energy efficiency, the CH balance variables as well as distance are used, resulting in a longer network life span. Furthermore, to improve the connectivity among the CM as well as CH, node centrality is applied.

3.3. Cluster generation

In cluster generation, the CMs are assigned to CHs from MIRO. According to the distance as well as residual energy, the cluster is produced, wherein the potential function is considered at the time of cluster formation given in (24). As a result, according to (23), along with the highest residual energy as well as the shortest travel distance, the sensors are assigned to CH.

$$Potential\ function\ (N_i) = \frac{E_{CH}}{DT(N_i,CH)} \tag{23}$$

3.4. Routing using ACO

Based on the energy model, the network node's energy consumption is proportional to the transmission distance. To manage node energy usage and enhance energy consumption, an optimized ACO is employed to build inter-cluster routing [24]. Choosing the probability transfer function for a CH is determined as (24).

$$P_{ij}^{A} = \begin{cases} \frac{\tau_{ij}^{\alpha_{ant}}(t)\times\eta_{ij}^{\beta_{ant}}(t)}{\sum_{s\epsilon allowed_A}[\tau_{is}^{\alpha_{ant}}(t)\times\eta_{is}^{\beta_{ant}}(t)]} & s\ \epsilon\ allowed_A \\ 0 & s\ \notin\ allowed_A \end{cases} \tag{24}$$

As indicated in (24), ant A is at CH *(i)* at time t, and the probability of choosing CH (*j*) as the next hop is P_{ij}^{A}. The pheromone intensity among cluster heads *i* and *j* at time *t* is given by $\tau_{ij}(t)$ and η_{ij} is the motivating factor for the path-searching process. The pheromone weight is α_{ant}, as well as the heuristic weight is β_{ant}. The next hop CH set is referred as $allowed_A$ and is selected by CH *A*. The heuristic value from CH (*i*) to the following hop CH (*j*) is computed as (25):

$$\eta_{ij} = \varphi_1 \frac{e^{E_{j-remain}}}{d_{ij}} + \varphi_2 \frac{1}{N_j(2-\cos\theta)} \tag{25}$$

where $E_{j-remain}$ denotes the next hop CH (*j*)'s remaining energy, d_{ij} is the distance between CH (*i*) and CH (*j*), N_j is the number of members of the j^{th} cluster, and θ is the angle formed between the line from CH *i* to the MS. The weight coefficients are φ_1 and φ_2. The heuristic values, as shown in (25), contain a distance term, an energy term, as well as an angle term. The (26) characterizes the pheromone updating model. Where *v* denotes the pheromone volatility coefficient and $v\Delta\tau_{ij}(t) =$ the pheromone increments.

$$\tau_{ij}(t+1) = (1-v)\tau_{ij}(t) + v\Delta\tau_{ij}(t) \tag{26}$$

3.4.1. Local pheromone changes

The front ant travels from CH (*i*) to CH (*j*), updating the local pheromone by the (27). Where, Q_{loc} is the pheromone intensity in the locale. The local pheromone updated rule considers the next hop's remaining energy along with the distance between CH (*i*) and the next hop CH (*j*). This not just assures that the following hop has sufficient data forwarding capability, but also minimizes transmission distance and increases energy consumption.

$$\Delta\tau_{ij}^{A} = Q_{loc} \frac{E_{j-remain}}{d_{ij}} \tag{27}$$

$$\Delta\tau_{ij}^{A} = Q_{glob} \frac{E_{min}}{c_v \times L_{ant}} \tag{28}$$

$$c_v = \frac{E_\sigma}{E_\mu} \tag{29}$$

3.4.2. Updates on global pheromone

Returning to the source node, the backward ant accomplishes the update of the global pheromone. (28) depicts the updating procedure, where, E_{min} is the minimal energy of nodes in the path, i.e. the energy of the path's bottleneck node, L_{ant} denotes the length of the path covered by the ant A, Q_{glob} is the global pheromone concentration, and c_v is the coefficient of variation which is utilized to estimate data dispersion, minimum coefficient of variation and less data dispersion [25]. These are employed in the global pheromone updation process to maintain a much more balanced energy of the nodes in the path. Updating the global pheromone, based on (28), needs to consider the energy of the bottleneck nodes in the network, along with the path's energy balance, which could significantly increase the performance of inter-cluster routing. Because of the path's length L_{ant}, cluster heads nearer to the MS may conduct more transmitting operations, which efficiently balance the energy consumption of the network node [26].

4. RESULT AND DISCUSSION

4.1. Simulation environment

The proposed EA-MIROA-MACO technique is implemented and simulated utilizing the MATLAB R2020a tool. The computer is powered by an i5 CPU with 6 GB of RAM. This EA-MIROA-MACO simulation model consists of 200 sensor nodes distributed in a 900×900 m area. The location of MS is always random, and the sensors are initialized with 1 J of energy. Table 1 lists the simulation parameters examined for this study. Mobile sinks that travel along fixed paths (in all directions) with a constant speed are utilized to address isolated node difficulties in large-scale WSNs. As a result, the data collecting strategy enhances communication between sensor nodes and BS while also decreasing the energy consumption of fixed nodes.

Table 1. Simulation parameters

Parameter	Value
Size of network	900×900 m
Node count	200
Location of MS	random
Initial energy	1 J
Transmitter energy	50 mJ/bit
Energy of free space model	10 pJ/bit/m^2
Energy of power amplifier	0.0013 pJ/bit/m^4
Size of packet	4,096 bits

The major goal is to incorporate mobile sinks into a WSN that will be used in 900×900 m sized areas. Random connectivity in a WSN is caused by random node placement, and this can lead to significant fluctuation in important WSN performance indicators like data latency and battery life, which results in node isolation. Mobile data sinks, however, which move between nodes with connection issues, help to solve these issues. The primary goal of this study was to evaluate the utilization of mobile sinks in this manner. The ongoing research discovered that, in most cases, using a suitable route to resolve the delay in node communication.

4.2. Performance analysis

The EA-MIROA-MACO's performance is evaluated using energy consumption, packets to MS, alive and dead nodes, throughput, and network life span. The EA-MIROA-MACO is contrasted to the traditional methodologies which includes low energy adaptive clustering hierarchy (LEACH), which gains a measurable level of sensor network lifespan by matching the node energy consumption. Centralized LEACH (C-LEACH) is a type of cluster protocol, where CHs are chosen based on centralized base station. Distributed energy efficient clustering (DEEC), which is a cluster-based solution for multi-level as well as two-level energy heterogeneous WSN. In, developed DEEC (D-DEEC), CHs are chosen based on probability. Threshold distributed energy efficient clustering (T-DEEC), which chooses the CHs from greater energy nodes, thus enhancing energy efficiency as well as network lifespan.

4.2.1. Alive and dead nodes

Nodes having enough energy to distribute data is defined as alive nodes. Whereas the difference among the amount of nodes as well as the amount of alive nodes is referred as dead nodes. Particularly, a dead node consumes all of its energy while communicating. Figures 3 and 4 depict the performance of alive and dead nodes in EA-MIROA-MACO as well as those in LEACH, C-LEACH, DEEC, D-DEEC and T-DEEC. According to the findings such as in 2,000 rounds, the alive nodes for EA-MIROA-MACO, LEACH, C-LEACH, DEEC, D-DEEC and T-DEEC are 192, 0, 0, 0, and 0 respectively. As a result, EA-MIROA-MACO has a higher amount of alive nodes than, T-DEEC, DEEC, as well as LEACH. To reduce the amount of energy consumed by several sensors, the energy efficient CH as well as route finding is utilized, results more alive nodes.

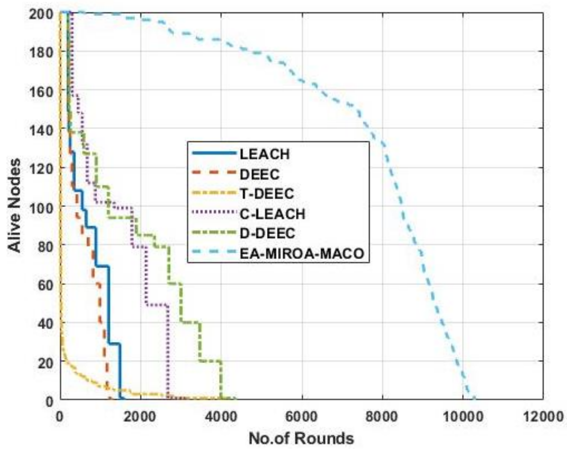

Figure 3. Alive nodes vs no. of rounds

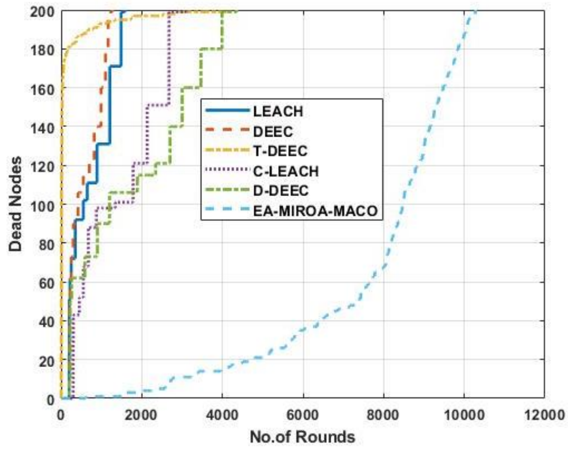

Figure 4. Dead nodes vs no. of rounds

4.2.2. Residual energy

Residual energy (RE) is the current value of energy in a node after it has received or transmitted routing packets. Figure 5 depicts a residual energy comparison of EA-MIROA-MACO, LEACH, C-LEACH, DEEC, D-DEEC and T-DEEC. This research shows that the EA-MIROA-MACO has higher residual energy than the LEACH, C-LEACH, DEEC, D-DEEC and T-DEEC. To achieve cluster balance, the optimum CH selection of EA-MIROA-MACO along with CH balancing factor is employed, which assists in reducing energy usage. Furthermore, the MACO's shortest path finding is employed to reduce node energy consumption.

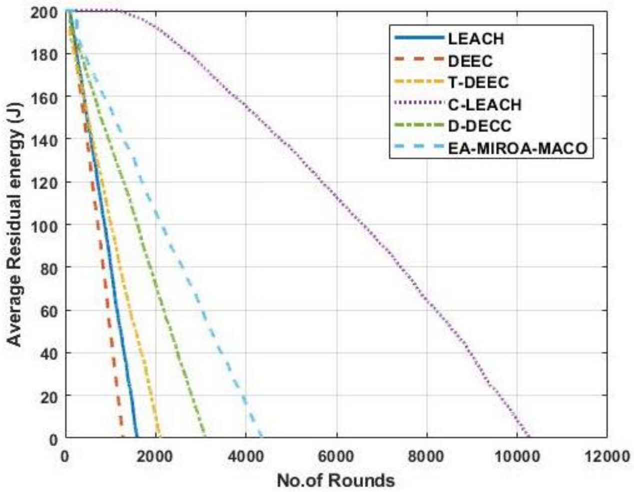

Figure 5. Average RE vs no. of rounds

4.2.3. Total energy consumption

In WSNs, energy plays as important aspect of improving network performance. Sensing, processing, and receiving data consumes the required energy for the respective process. Figure 6 depicts the comparison between the proposed EA-MIROA-MACO with LEACH, C-LEACH, DEEC, D-DEEC and T-DEEC in terms of total energy consumption (EC). According to the graph, the proposed EA-MIROA-MACO consumed less energy than the existing LEACH, C-LEACH, DEEC, D-DEEC and T-DEEC approaches.

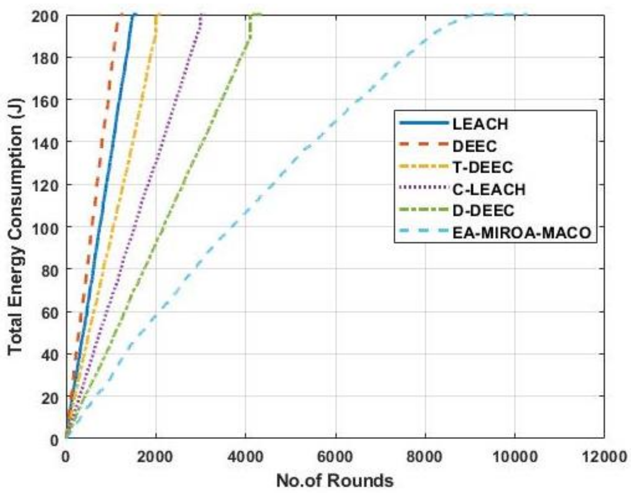

Figure 6. Total EC vs no. of rounds

4.2.4. Network lifespan

The period that nodes are active when transferring data packets is defined as Network life span. The network life span is calculated utilizing three separate parameters: first node die (FND), half node die (HND), and last node die (LND). Figure 7 depicts the lifespan performance of EA-MIROA-MACO with LEACH, C-LEACH, DEEC, D-DEEC and T-DEEC. According to the graph, the EA-MIROA-MACO has a longer life span than the LEACH, C-LEACH, DEEC, D-DEEC and T-DEEC. The use of EA-MIROA-MACO to develop energy-efficient CH selection and routing increases life span.

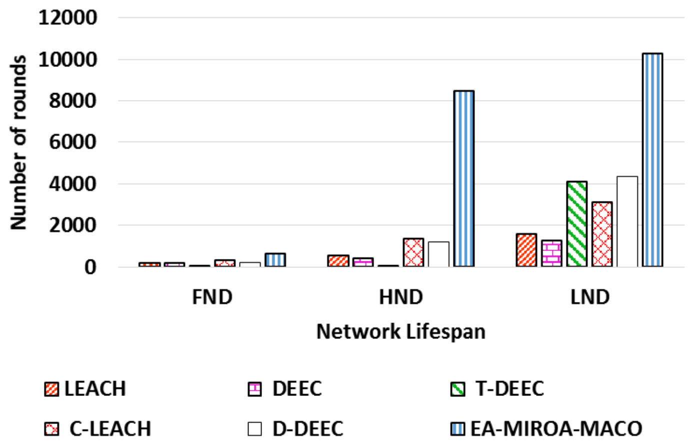

Figure 7. Comparison of network lifespan

4.3. Comparative analysis

This section provides a comparative analysis of the EA-MIROA-MACO. Existing studies, such as MSFBRR [18] and HNN [19], are utilized to assess the effectiveness of the EA-MIROA-MACO. Two alternative cases are examined while analyzing the EA-MIROA-MACO. In case 1, nodes are given an initial energy of 1 J, whereas nodes in case 2 are given an initial energy of 0.5 J. In Tables 2 and 3 the EA-MIROA-MACO is compared to the MSFBRR [18] for case 1. For case 2, the EA-MIROA-MACO is compared to the HNN [19], as shown in Table 4. Based on Tables 2, 3 and 4, it is clear that the EA-MIROA-MACO outperforms the MSFBRR [18] and HNN [19].

Table 2. Comparative analysis of case 1

Parameters	Methods	No. of rounds			
		500	1,000	1,500	2,000
Alive nodes	MSFBRR [18]	200	198	120	40
	EA-MIROA-MACO	200	200	197	192
Dead nodes	MSFBRR [18]	0	2	80	160
	EA-MIROA-MACO	0	0	3	8
Average residual energy (J)	MSFBRR [18]	185	160	115	38
	EA-MIROA-MACO	200	200	197.5	192.2
Total energy consumption (J)	MSFBRR [18]	15	40	85	162
	EA-MIROA-MACO	15.16	28.76	45.53	58.32

Table 3. Network lifespan of case 1

Parameters	Methods	No. of rounds
FND	MSFBRR [18]	1,010
	EA-MIROA-MACO	616
HND	MSFBRR [18]	1,650
	EA-MIROA-MACO	8,466
LND	MSFBRR [18]	2,300
	EA-MIROA-MACO	10,280

Table 4. Comparative analysis of case 2

Parameters	Methods	No. of nodes				
		100	200	300	400	500
Energy consumption (mJ)	HNN [19]	0.1	0.3	0.5	0.7	0.78
	EA-MIROA-MACO	0.09	0.25	0.42	0.66	0.71
PDR (%)	HNN [19]	99.5	99	97.9	96	94.4
	EA-MIROA-MACO	99.89	99.01	98.90	98.00	96.34
Network lifetime (Rounds)	HNN [19]	5,990	5,700	5,500	5,300	5,100
	EA-MIROA-MACO	9,000	8,000	7,900	7,700	6,500
E2E delay (sec)	HNN [19]	0.5	1.2	1.7	2.9	3.9
	EA-MIROA-MACO	0.2	0.9	1.0	2.1	2.9
Throughput (Mbps)	HNN [19]	0.99	0.96	0.90	0.86	0.79
	EA-MIROA-MACO	0.99	0.98	0.97	0.96	0.94
Packet loss ratio (%)	HNN [19]	0.5	1.5	2.1	5.5	5.9
	EA-MIROA-MACO	0.2	1.0	1.5	2.9	4.2

Figure 8 shows the graphical comparison of dead nodes count. In the Figure 8, the dead nodes comparisons are calculated on existing MSFBRR [18] and HNN [19] for 2,000 rounds. Overall, it clearly shows that proposed EA-MIROA-MACO has achieved less dead node count of 8 at 2,000 rounds. While the existing MSFBRR [18] and HNN [19] has attained 160 and 179 respectively for 2,000 rounds.

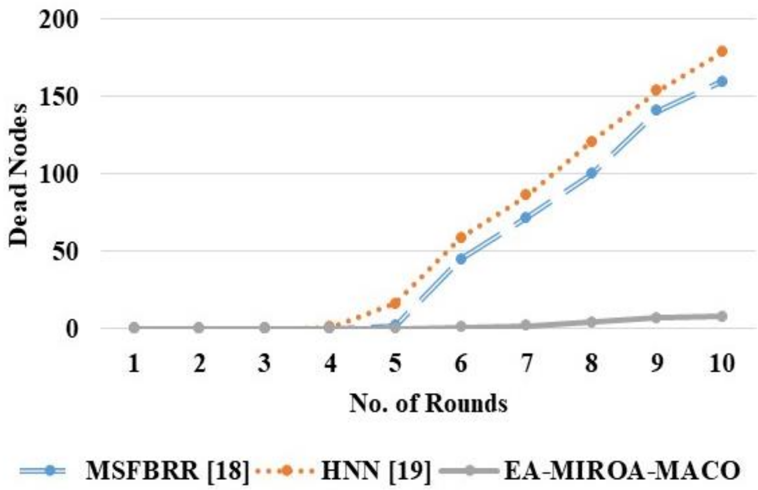

Figure 8. Graphical comparison of dead nodes

5. CONCLUSION

Nodes get isolated in a WSN created by poorly designed distributed clustering algorithms as a result of randomly chosen CHs. Therefore, in this research, EA-MIROA-MACO is developed to enhance the energy efficiency of WSNs. The developed MIRO is used to choose optimum CHs, followed by the MACO which is utilized to determine the path from the transmitter CH to the destination. The detection of CH with the minimum neighbor nodes and the shortest sink distance is utilized to reduce the energy spent by the nodes. Following that, the clusters are balanced by using the CH balancing factor in the MIRO, which assists in reducing the energy spent by the nodes. The MACO is utilized to establish reliable data transmission in WSN and selects the shortest path with the fewest node degrees. Based on the data, it is determined that the EA-MIROA-MACO outperforms the MSFBRR, HNN, LEACH, C-LEACH, DEEC, D-DEEC and T-DEEC. The alive nodes of EA-MIROA-MACO for 2,000 rounds are 192, which is higher than LEACH, C-LEACH, DEEC, D-DEEC and T-DEEC. In the future, to improve security, the novel security-efficient routing protocol will be implemented in WSNs.

REFERENCES

[1] J. Lu, K. Hu, X. Yang, C. Hu, and T. Wang, "A cluster-tree-based energy-efficient routing protocol for wireless sensor networks with a mobile sink," *The Journal of Supercomputing*, vol. 77, no. 6, pp. 6078–6104, 2021, doi: 10.1007/s11227-020-03501-w.

[2] N. Moussa, D. Benhaddou, and A. E. B. E. Alaoui, "EARP: an enhanced ACO-based routing protocol for wireless sensor networks with multiple mobile sinks," *International Journal of Wireless Information Networks*, vol. 29, no. 1, pp. 118–129, Mar. 2022, doi: 10.1007/s10776-021-00545-4.

[3] S. K. S. L. Preeth, R. Dhanalakshmi, and P. M. Shakeel, "An intelligent approach for energy efficient trajectory design for mobile sink based IoT supported wireless sensor networks," *Peer-to-Peer Networking and Applications*, vol. 13, no. 6, pp. 2011–2022, Nov. 2020, doi: 10.1007/s12083-019-00798-0.

[4] S. Yalçın and E. Erdem, "BTA-MM: burst traffic awareness-based adaptive mobility model with mobile sinks for heterogeneous wireless sensor networks," *ISA Transactions*, vol. 125, pp. 338–359, Jun. 2022, doi: 10.1016/j.isatra.2021.06.027.

[5] M. R. Y. M. and D. U. B. Mahadevaswamy, "Energy efficient routing in wireless sensor network based on mobile sink guided by stochastic hill climbing," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 10, no. 6, pp. 5965–5973, Dec. 2020, doi: 10.11591/ijece.v10i6.pp5965-5973.

[6] V. B. Christopher and J. Jasper, "Jellyfish dynamic routing protocol with mobile sink for location privacy and congestion avoidance in wireless sensor networks," *Journal of Systems Architecture*, vol. 112, Jan. 2021, doi: 10.1016/j.sysarc.2020.101840.

[7] S. Roy, N. Mazumdar, and R. Pamula, "An energy and coverage sensitive approach to hierarchical data collection for mobile sink based wireless sensor networks," *Journal of Ambient Intelligence and Humanized Computing*, vol. 12, no. 1, pp. 1267–1291, Jan. 2021, doi: 10.1007/s12652-020-02176-8.

[8] M. Srinivas and T. Amgoth, "EE-hHHSS: energy-efficient wireless sensor network with mobile sink strategy using hybrid Harris hawk-salp swarm optimization algorithm," *International Journal of Communication Systems*, vol. 33, no. 16, Aug. 2020, doi: 10.1002/dac.4569.

[9] A. Singh and A. Nagaraju, "Low latency and energy efficient routing-aware network coding-based data transmission in multi-hop and multi-sink WSN," *Ad Hoc Networks*, vol. 107, Oct. 2020, doi: 10.1016/j.adhoc.2020.102182.

[10] S. Tabatabaei, "Provide energy-aware routing protocol in wireless sensor networks using bacterial foraging optimization algorithm and mobile sink," *PLOS ONE*, vol. 17, no. 3, Mar. 2022, doi: 10.1371/journal.pone.0265113.

[11] U. K. Nannapanenia, U. Srilakshmia, A. Sravyaa, and K. Tejaswia, "Cluster-based collection point energy efficient routing protocol for the mobile sink in wireless sensor network," *International Journal of Future Generation Communication and Networking*, vol. 13, no. 2, pp. 787–796, 2020.

[12] R. Ashween, B. Ramakrishnan, and M. Milton Joe, "Energy efficient data gathering technique based on optimal mobile sink node selection for improved network life time in wireless sensor network (WSN)," *Wireless Personal Communications*, vol. 113, no. 4, pp. 2107–2126, Aug. 2020, doi: 10.1007/s11277-020-07309-y.

[13] M. Naghibi and H. Barati, "EGRPM: energy efficient geographic routing protocol based on mobile sink in wireless sensor networks," *Sustainable Computing: Informatics and Systems*, vol. 25, Mar. 2020, doi: 10.1016/j.suscom.2020.100377.

[14] V. Chauhan and S. Soni, "Mobile sink-based energy efficient cluster head selection strategy for wireless sensor networks," *Journal of Ambient Intelligence and Humanized Computing*, vol. 11, no. 11, pp. 4453–4466, Nov. 2020, doi: 10.1007/s12652-019-01509-6.

[15] F. H. El-Fouly, A. B. Altamimi, and R. A. Ramadan, "Energy and environment-aware path planning in wireless sensor networks with mobile sink," *Sensors*, vol. 22, no. 24, Dec. 2022, doi: 10.3390/s22249789.

[16] S. K. Mirania and K. Sharma, "Mobile sink based improved energy efficient routing algorithm using cluster coordinator node in wireless sensor network," *International Journal of Electrical and Electronic Engineering and Telecommunications*, vol. 10, no. 5, pp. 355–361, 2021, doi: 10.18178/ijeetc.10.5.355-361.

[17] P. Gupta, S. Tripathi, and S. Singh, "RDA-BWO: hybrid energy efficient data transfer and mobile sink location prediction in heterogeneous WSN," *Wireless Networks*, vol. 27, no. 7, pp. 4421–4440, Oct. 2021, doi: 10.1007/s11276-021-02678-z.

[18] R. Senthil Kumaran and G. Nagarajan, "Mobile sink and fuzzy based relay node routing protocol for network lifetime enhancement in wireless sensor networks," *Wireless Networks*, vol. 28, no. 5, pp. 1963–1975, Jul. 2022, doi: 10.1007/s11276-022-02960-8.

[19] C. S. Gowda and P. V. Y. Jayasree, "Rendezvous points based energy-aware routing using hybrid neural network for mobile sink in wireless sensor networks," *Wireless Networks*, vol. 27, no. 4, pp. 2961–2976, May 2021, doi: 10.1007/s11276-021-02630-1.

[20] S. Yalçın and E. Erdem, "TEO-MCRP: thermal exchange optimization-based clustering routing protocol with a mobile sink for wireless sensor networks," *Journal of King Saud University-Computer and Information Sciences*, vol. 34, no. 8, pp. 5333–5348, Sep. 2022, doi: 10.1016/j.jksuci.2022.01.007.

[21] M. Al-Jumaili and B. Karimi, "Maximum bottleneck energy routing (MBER)-an energy efficient routing method for wireless sensor networks," in *2016 IEEE Conference on Wireless Sensors (ICWiSE)*, Oct. 2016, pp. 38–44, doi: 10.1109/ICWISE.2016.8187759.

[22] S. Konduru and M. Sathya, "Remora optimization algorithm-based optimized node clustering technique for reliable data delivery in VANETs," *International Journal of Intelligent Networks*, vol. 3, pp. 74–79, 2022, doi: 10.1016/j.ijin.2022.07.002.

[23] C. Wen *et al.*, "Modified remora optimization algorithm with multistrategies for global optimization problem," *Mathematics*, vol. 10, no. 19, Oct. 2022, doi: 10.3390/math10193604.
[24] X. Xiao and H. Huang, "A clustering routing algorithm based on improved ant colony optimization algorithms for underwater wireless sensor networks," *Algorithms*, vol. 13, no. 10, Oct. 2020, doi: 10.3390/a13100250.
[25] D. L. Reddy, P. C., and H. N. Suresh, "Merged glowworm swarm with ant colony optimization for energy efficient clustering and routing in wireless sensor network," *Pervasive and Mobile Computing*, vol. 71, Feb. 2021, doi: 10.1016/j.pmcj.2021.101338.
[26] Z. Wang, H. Ding, B. Li, L. Bao, Z. Yang, and Q. Liu, "Energy efficient cluster based routing protocol for WSN using firefly algorithm and ant colony optimization," *Wireless Personal Communications*, vol. 125, no. 3, pp. 2167–2200, Aug. 2022, doi: 10.1007/s11277-022-09651-9.

BIOGRAPHIES OF AUTHORS

Anil Kumar Jemla Naik completed B.E. and M.Tech. in Electronics and Communication Engineering from VTU, currently working as Assistant Professor in Electronics and Communication Department, JNN College of Engineering, Shivamogga, Karnataka, India from past 12 years and pursuing Ph.D. in the field of wireless sensor networks from VTU, Belagavi, Karnataka, India. He published 4 papers in national and international journals. He can be contacted at email: anilkumarj@jnnce.ac.in.

Manjunatha Parameswarappa completed B.E. and M.Tech. in Electronics and Communication Engineering and completed his Ph.D. from IIT Bombay in 2012. Working as Professor and Dean (Academics) in JNN College of Engineering, Shivamogga, Karnataka, India with teaching experience of more than 30 years and his research area are wireless sensor networks, signal processing, image processing. He produced 4 Ph.D. and currently guiding 8 Ph.D. students. He published more than 30 research papers both in national and international journals. He can be contacted at email: manjunath_p@jnnce.ac.in.

Mohan Naik Ramachandra completed B.E. and M.Tech. in Electronics and Communication Engineering and completed his Ph.D. from VTU Belagavi in 2022. Working as Assistant Professor in Sri Dharmasthala Manjunatheshwara Institute of Technology, Ujire-574 240 and affiliated to Visvesvaraya Technological University, Belagavi, Karnataka, India, with teaching experience of more than 15 years and his research area are cryptography, network security, cloud security, IoT, wireless sensor networks, image processing. He published more than 10 research papers both in national and international journals. He can be contacted at email: mohannaik@sdmit.in.