ENHANCED QOS ENERGY-EFFICIENT ROUTING ALGORITHM USING DEEP BELIEF NEURAL NETWORK IN HYBRID FALCON-IMPROVED ACO NATURE-INSPIRED OPTIMIZATION IN WIRELESS SENSOR NETWORKS

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Abstract: Wireless sensor networks (WSNs) have recently acquired prominence in a variety of applications such as remote monitoring and tracking. Since it is virtually hard to recharge the nodes in their remote deployment, also, the transmission of data from nodes to the base station requires a significant amount of energy. Thus, our research proposes a routing protocol, namely hybrid falcon-improved ACO Nature-Inspired Optimization using a deep learning model to reduce energy consumption while increases the network lifetime. In the developed model, initially, the falcon optimization technique is utilized to locate the best possible cluster heads in the quickest possible time. Furthermore, to improve the quality of service in routing optimization a new improved ACO has been proposed in which linear flexible operator and the premier operator are used to increasing the iteration speed. Finally, the optimum route is obtained through DBNN based on predicted energy. As a result, our proposed model gives a lifetime as 121 s and energy consumption as 0.041 J at 500 rounds when compared to the baseline approaches. Therefore, our proposed approaches provides better routing and improves the QoS as well as the energy consumption which increases the longevity of mobile nodes.

Key words: *wireless sensor network, optimum routing protocol, ant colony optimization (ACO), deep belief neural network, cluster head, base station, energy consumption*

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1. Introduction

Wireless sensor networks (WSNs) were mostly comprised of multiple sensor nodes (SNs) having minimal energy. WSNs have been placed at random over an area to

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gather different categories of air exposures as well as transmit information towards the base station enabling tracking and also detection activities [1]. Sensor nodes are usually fitted along with sensor types, including acoustical pressure, movement, images, chemical, climate, pressure, heat, as well as optical sensors, among others. Due to the obvious diversity of sensor nodes, WSNs offer a vast array of applications spanning from wellness to military, security, and agriculture, including human daily lives.

WSN is an appealing development domain for academics as well as enterprises desiring enhanced communication systems that also offer a high level of QoS (quality of service) [2], necessities for energy efficiency, security, and durability in communication.

Despite its broad application, WSN suffers from several common constraints, such as restricted energy sources, processing speed, memory, and transmission bandwidth, as a consequence, sensor network effectiveness concerning QoS as well as network lifespan are degraded [3–9]. Furthermore, it is prevalently declared that the greatest prominent, for one, the shortcoming of WSNs seems to be the considerably shorter lifespan of its sensor nodes owing to stringent energy limitations. It is since perhaps the batteries that often send electricity to sensor nodes are sometimes difficult to repair or recharge since sensor nodes are frequently located in difficult spots. The fundamental cause for sensor node operation and, as a result, the increasing elimination of the overall lifespan of WSNs is their limited energy sufficiency.

As a result, obtaining energy savings is a significant concern for WSNs' proper operation [10]. Here's why energy discrepancies should be minimized at any of the sensor node protocol stack's five tiers. In actuality, a sensor node tends to spend most of its energy on wireless connections, with only a small total invested in sensing and data processing [11]. As a result, several research efforts are underway to preserve energy at the protocol stack's network layer by achieving energy-efficient route design and reliable data transfer between sensor nodes and the BS. Recognizing how to use constrained resources efficiently, attain congestion control between many access points [12], and extend the topology's lifespan as much as possible is a critical challenge in WSNs [13–15], particularly given a certain energy routing algorithms also can dramatically cut energy usage and lengthen the service lifetime of WSNs [16–18]. Creating many tactics for various reasons is a difficult endeavor.

Data compilation, grouping, routing, positioning, defect diagnosis, task management, and event monitoring as well as other issues must be addressed by WSN designers. As a result, various research interactions to preserve energy at the protocol stack's network layer by achieving energy-efficient route creation and reliable data transfer between sensor nodes and the BS. When researchers create protocols and hardware designs for SNs, optimal battery energy usage should be a top priority. Numerous routing methods had also been established to optimize the energy efficiency of a sensor network. WSN routing algorithms' central objective is to lessen the energy utilization for sensor nodes [19–24]. To network system functional for an extended period, the sensor network developer must consider all of the sensor node's energy consumption issues when routing data. Previous sustainable routing strategies emphasize clustering as well as choosing particular nodes to regulate data flow thus prolonging WSN lifetime.

These operations heavily rely on specified numerical configurations, which seem to be cost-prohibitive to construct as well as consume a great deal of energy. The low-energy responsive clustering hierarchal structure networking technology divides sensor nodes grouped and leverage advanced clustering head nodes; nevertheless, their flexibility to modify network topology with diverse sizes makes WSNs vulnerable to overcrowding and indeed unfeasible. As a result, novel techniques to resolve these difficulties are required [25–30]. Multiple designs have been explored in an endeavor to enlarge the network's lifetime. A clustered configuration with wireless sensor nodes has been discovered to lower the amount of energy needed by individual nodes. In this clustered architecture, adjacent nodes are allowed to form clusters.

Each cluster selects one node with a large energy reserve to serve as the cluster head. When cluster-heads are overloaded, their energy reserves decrease quickly, ending in the cluster's destruction. Because of the sensor nodes' remote deployment, data loss caused by these hotspots may be so severe that it cannot be recovered. Recently, machine learning-related mechanisms have assisted in addressing the limitations of traditional energy-efficient routing in WSNs [31], offering a diverse as well as an adaptable framework when interacting with information plus computation to address complex problems which closely fit the criteria for designing effective routing techniques within WSNs [32,33]. In this research, we combine the clustered architecture with the deep learning idea to determine the most energy-efficient route and thereby enhance network QoS. However, the existing energy-efficient routing techniques only focus on the energy basis, which doesn't focus on the execution speed and the QoS requirements in the same work, and also they haven't focused on the computational complexity of the used algorithms [34–36]. To overcome the above gaps, a novel hybrid falcon-improved ACO nature-inspired optimization using the deep learning model is developed to consider all the factors such as execution speed, QoS, and energy efficiency to identify the perfect optimum route within wireless sensor networks. The contribution of the proposed approach is as follows:

- Initially, the falcon optimization approach is being utilized to choose the cluster head also with residual energy, and greatest count of neighbor nodes, the greatest inter-cluster distance, the greatest intra-cluster range, as well as the minimum distance first from the base station.
- Moreover, to enhance the QoS in routing optimization, a new improved ant colony optimization has been proposed in which a linear flexible operator and the premier operator are used to increasing the iteration speed and the signals build with the rise of evolution time.
- Finally, the optimum route is evaluated by a deep belief neural network from the predicted energy.

The remainder of this paper is assembled as follows: Section 2 is a summary of the previous research. The proposed hybrid falcon improved ACO nature-inspired optimization employing a deep learning model is described in Section 3. Section 4 explains the acquired results, and Section 5 brings the paper to close.

2. Literature survey

Multiple research has been conducted to bring down the quantity of energy essential to activate wireless sensor networks.

Daneshvar et al. [37] introduced a unique clustering technique predicated on the grey wolf optimization as well as a one-term fitness function. This proposed approach further lowers energy usage by skipping the cluster construction phase in cycles where the present clustering is adequate. Relay selection has been demonstrated to optimize energy utilization while trying to balance energy usage among CHs as well as relays, consequently preventing quick energy degradation of remote nodes from BS. It is indeed unsuitable for failure-critical applications since the protocol has a fault tolerance mechanism.

Augustine et al. [38] developed a cluster head (CH) choosing mechanism premised just on Taylor kernel fuzzy c-means methodology, which is a variant of the Taylor series' kernel-based fuzzy c-means algorithm. The created algorithm selects the cluster head predicated on a selection process as well as the tolerance factor, which would be influenced by energy, proximity, as well as trust. The calculation difficulty, on the contrary, is greater.

Vinitha et al. [39] devised a cat–salp swarm algorithm (C-SSA), that helps determine the relevant stages in routing evolution, as just an energy-efficient routing approach. The CHs participate in multi-hop routing, and the optimal pathways are chosen to rely on that presented hybrid optimization, which chooses the optimal hops predicated on energy restrictions which include energy, latency, inter-cluster distance, connection longevity, and distance. However, their quality of service (QoS) has still not been examined.

Suresh Kumar et al. [40] established an E-ALWO algorithm, which incorporates EWMA, ALO, as well as WOA. This proposed methodology splits overall routing operation into three main phases: installation, steady-state, as well as route management. Mostly in lack of an attack scenario, the recommended method's average effectiveness in regards to latencies, durability, residual energy as well as throughput. However, the quality of service (QoS) is ignored.

Daniel et al. [41] introduced a TSBOA technique, which has been created by integrating both tunicate swarm model with the butterfly optimization method. As a consequence, this CH is chosen considering objective criteria including inter-cluster distance, node energy usage, anticipated energy, connection lifespan, intra-cluster distance as well as latency. A deep LSTM classifier has been utilized to anticipate energy by taking into account node baseline energy. This suggested TSBOA outperformed the competition in characteristics such as residual energy and throughput. The execution speed, on the other hand, has not been considered.

Rathore et al. [42], proposed an energy-efficient cluster head selection through a relay approach for wireless sensor networks. The cluster head's objective is influenced by node distance and node energy. By providing the shortest path relay node concept, the cluster head selection intends to minimize energy consumption and improve the longevity of the networking. The determined trajectory cluster is launched to achieve normal energy depletion because the energy consumption increases when only a few sub-cluster nodes are significantly loaded. For enhanced outcomes in the future, the author incorporates these methods with fuzzy and bio-inspired approaches.

Yadav et al. [43], introduced a new energy-aware CH selection framework for hierarchical routing in WSN and a hybrid optimization technique. Additionally, energy, distance, delay, and quality of service (QoS) are taken into account when choosing a CH. A new hybrid optimization approach particle distance updated sea lion optimization (PDU-SLnO) algorithm, which combines the features of sea lion optimization (SLnO) and particle swarm optimization (PSO) algorithm, is introduced for selecting the perfect CH.

Chauhan et al. [44], proposed to identify the best cluster head in a heterogeneous wireless sensor network using a diversity-driven multi-parent evolutionary algorithm with adaptive non-uniform mutation. The effectiveness of the suggested method is examined using classical benchmark functions, and the findings are contrasted with those of current techniques. This approach is also validated on a heterogeneous wireless sensor network using the multi-objective optimization challenge of cluster head selection. Several significant real-world issues like signal processing and fault diagnosis can be tackled using the suggested DDMPEA with ANUM. DDMPEA and ANUM should also be used with other efficient techniques from other metaheuristics, such as SCA and SSA.

Sengathir et al. [45], presented a hybrid modified artificial bee colony and firefly algorithm (HMABCFA)-based cluster head selection for assuring energy stabilization, latency minimization, and inter-node distance reduction to increase network lifetime. To create a new position that can replace the position that is not updated during the scout bee phase of ABC, this suggested HMABCFA incorporates the advantages of the firefly optimization technique. By incorporating the firefly optimization method into the ABC algorithm, the clustering process is protected against the limitations of fast convergence, slow convergence, and the potential for being caught at the local point of optimality. The improved viable dimensions for boosting the process of exploitation and exploration are greatly improved by the updated ABC-based clustering method. To analyze them against the planned HMABCFA system, spotted hyena optimization and simulated annealing clustering technique are scheduled to be developed in future.

From the above-related works, we can conclude that the existing works have some limitations. To overcome the above-mentioned limitations a new method has to be innovated to consider all the performance factors.

3. Hybrid falcon-improved ACO nature-inspired optimization using deep learning model

Developing a stable, low-power routing strategy with wireless sensor networks (WSNs) is indeed a massive undertaking. Despite breakthroughs in wireless sensor networks (WSN), optimal energy usage is still required to extend the network lifetime. Thus to overcome this, the novel hybrid falcon-improved ACO nature-inspired optimization using deep learning model is introduced. Initially, the falcon optimization technique has been utilized to choose the cluster head, employing residual energy, the greatest count of neighbor nodes, inter-cluster distance, as well as intra-cluster distance. Additionally, to enhance the overall quality of service for routing optimization, a novel upgraded ant colony optimization has been developed, when the linear flexible operator, as well as the premier operator, were employed to enhance iteration speed and select the shortest route in Wireless sensor networks. As a result, the number of ants taking this path is growing. Finally, for accurate information, all ants will focus on the optimum route, where the neural network uses a deep belief network to predict energy. Hence the optimal route has been evaluated. The process of falcon–improved ACO is as follows:

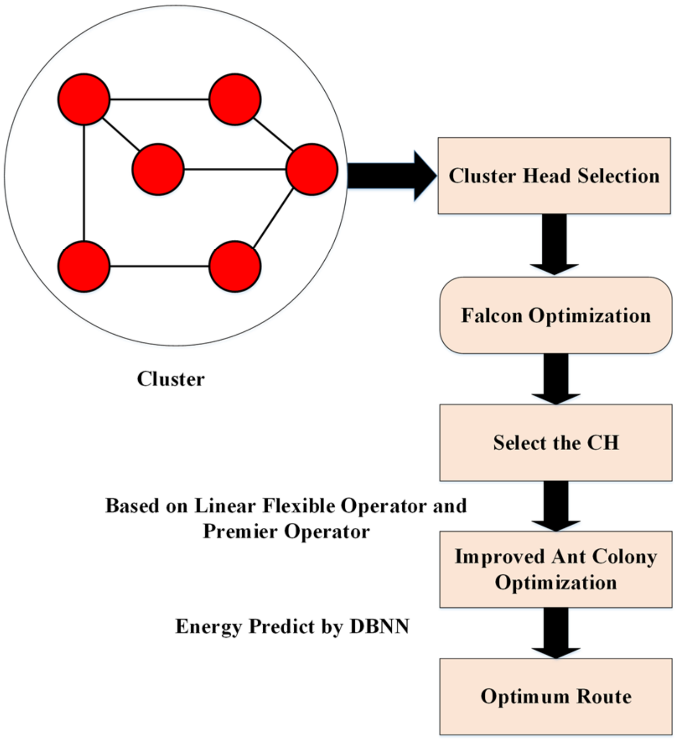

Fig. 1 *Structure of the proposed approach.*

3.1 Falcon optimization technique

WSNs appear to be wireless networks of connected sensor nodes that communicate with one another to acquire more about their environment. From this perspective of this, it is crucial to create a stable, low-power routing method for wireless sensor networks. However, the existing energy-efficient routing strategies, only concentrate on the energy basis and do not concentrate on the execution speed and QoS requirements in the same work, nor have they concentrated on the computational complexity of the used algorithms. To locate the cluster head nodes, our research utilized the falcon optimization technique, which takes into account constraints such as residual energy, the number of neighbor nodes with the greatest amount of energy, the inter-cluster distance, and the intra-cluster distance, and the distance from the base station. The foregoing constraints are adjusted by a falcon to catch the best possible cluster heads in the quickest possible time in a viable cluster. The proposed falcon optimization technique (FOT) mathematical formulation to replicate the actions of a falcon searching for prey is described as follows.

The falcon optimization technique (FOT) relies mostly on the falcon's spiral movement. Within wireless sensor networks, this falcon approach is enticed to attack cluster head nodes while cruises to find the largest count of neighbor nodes, the distance of inter-cluster, distance of intra-cluster, as well as lowest distance. Fig. 2 depicts the attack as well as cruise vectors in 2D space.

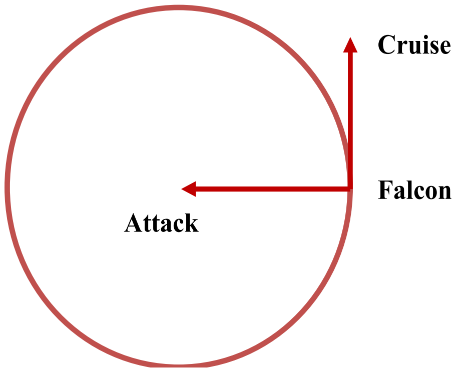

Fig. 2 *Spiral motion of falcon.*

In each iteration falcon k chooses its cluster head nodes of some other falcon f at arbitrary then revolves around the optimal spot visited thus far via a falcon f. This falcon k can also choose to circle its memory, giving us $k \in \{1, 2, 3, \ldots, m\}$.

Falcon is capable of memorizing the cluster head nodes, in each iteration, a single falcon chooses a destination cluster node first from the collect's memory. Attack, as well as cruise, were then computed with respect to the cluster node of choice. If an updated location (as determined by attack plus cruise) seems greater than that of the prior position within memory, then memory gets upgraded. To assist the falcon to explore the area more effectively, we utilized a stochastic one-to-one mappings approach whereby each falcon picks their clustered node randomly from the memory of every other flock member inside the iteration. This is important to realize that the cluster node chosen is not the nearest or farthest distant. In this strategy, every memory cluster head node is assigned or mapped toward a distinct falcon. Every falcon then does the cluster head node as well as a cruise on the chosen target.

The cluster head selection can be represented using a vector that starts at the falcon's current location and ends at the location of the cluster node in the falcon's memory. Eq. (1) can be used to compute the cluster head vector for falcon k.

$$\mathbf{c}_k = \mathbf{y}_f^* - \mathbf{y}_k, \tag{1}$$

where $\mathbf{c}_k$ is falcon k's cluster head vector, $\mathbf{y}_f^*$ is falcon f's the best location of visited cluster head, and $\mathbf{y}_k$ is falcon k's the current position of the cluster head which directs the population of falcon toward the most-visited locations. The cluster head node vector is used to determine the maximum number of neighbor nodes, the distance of inter-cluster, the distance of intra-cluster, as well as the vector of shortest distance.

The cruising vector was perpendicular to the cluster head node vector and tangent to the circle. This cruise might alternatively be thought of as the falcon's linear speed regarding such a cluster head node. Every cruise vector is within the tangent hyperplane towards the circular in m-dimensions; consequently, to evaluate the cruise vector, we should first evaluate the tangent hyperplane's formula. An equation of a hyperplane over m-dimensions may be computed utilizing an arbitrary point from a hyperplane and a perpendicular vector to that hyperplane called the normal vector of the hyperplane. Eq. (2) depicts the scalar formulation of the hyperplane equations for the m-dimensional area.

$$g_1 y_1 + g_2 y_2 + \cdots + g_m y_m = \sum_{l=1}^{m} g_l y_l = d, \tag{2}$$

where $\mathbf{g} = [g_1, g_2, \ldots, g_m]$ is the normal vector, $\mathbf{y} = [y_1, y_2, \ldots, y_m]$ is the variables vector, $\mathbf{q} = [q_1, q_2, \ldots, q_m]$ is the hyperplane arbitrary point and $d = \mathbf{g} \cdot \mathbf{q} = \sum_{l=1}^{m} g_l q_l = 1$. If we consider $\mathbf{y}_k$ (the falcon's location k) as a randomized point there in hyperplane as well as $\mathbf{c}_k$ (the cluster head node vector) as the normal of the hyperplane, we can demonstrate the hyperplane to which $\mathbf{c}_k^t$ (the falcons cruise the shortest route vector in iteration t) belongs using Eq. (3).

$$\sum_{l=1}^{m} c_l y_l = \sum_{l=1}^{m} c_l^t y_l^*, \tag{3}$$

where $\mathbf{c} = [c_1, c_2, \ldots, c_m]$ is the cluster head node vector, $\mathbf{y} = [y_1, y_2, \ldots, y_m]$ is the decision variables vector, and $\mathbf{y}^* = [y_1^*, y_2^*, \ldots, y_m^*]$ is the location of the selected cluster head node. Determine the maximum number of neighbor nodes, the distance of inter-class, distance of inter-cluster, the distance of intra-cluster as well as the vector of shortest distance for this falcon within this hyperplane since that a cruise hyperplane per falcon k during iteration, t has been derived. We use the accompanying method to establish an arbitrary m-dimensional target destination A just on a cruise hyperplane with falcon k.

Step 1: As the fixed variable, choose one of the m variables at random. The index of the selected variable is denoted by n. This should be noted that perhaps the static variable cannot be picked from variables there in the cluster head node vector $\mathbf{c}_n$, who have a zero matching element. Another rationale behind this is that whenever the coefficient of such a variable in Eq. (2) becomes equal to zero, its hyperplane lies parallel to a certain variable's axis, and also that variable might take either value provided a randomized mixture of some other $m - 1$ variable.

Step 2: Apart from the nth variable, which is fixed, assign random values to all the variables.

Step 3: Employing the Eq. (4), assess the value of such fixed variable

$$a_n = \frac{d - \sum\limits_{l,l\neq n} c_l}{c_n}, \tag{4}$$

where a_n seems to be the nth element of a target point $\mathbf{a}$, c_l would be the lth component of a cluster node vector $\mathbf{c}_l$, d indicates the right-hand side of Eq. (2), c_n stands the nth component of such cluster node vector $\mathbf{a}_k$, while k denotes the index of such fixed variable. A random target point of the cruise hyperplane is computed. Eq. (5) depicts a broad depiction of the cruise hyperplane's target point.

$$\begin{aligned}\mathbf{a}_k \quad = \quad & \Bigg[a_1 = random, a_2 = random, \ldots, \\ & a_n = \frac{d - \sum\limits_{l,l\neq n} c_l}{c_n}, \ldots, a_m = random \Bigg].\end{aligned} \tag{5}$$

The target point has indeed been identified, its cruise vector for such falcon k during iteration t might well be obtained. All constituents of the determined target point were arbitrary integers between zero and one. It's indeed necessary to recognize that cruise vector leads its falcon populace away from the memory sites, stressing the FOT exploration stage.

A falcon's displacement consists of an attack and a vector. The step vector for falcon k in iteration t is defined by Eq. (6).

$$\Delta \mathbf{y}_k^t = \mathbf{s}_1 q_c^t \frac{\mathbf{c}_k}{\|\mathbf{c}_k\|} + \mathbf{s}_2 q_a^t \frac{\mathbf{a}_k}{\|\mathbf{a}_k\|}, \tag{6}$$

where q_c^t is the cluster node coefficient in iteration t and q_a^t is the cruise coefficient in iteration t. The random vectors $\mathbf{s}_1$ and $\mathbf{s}_2$ have elements in the range [0,1]. The cluster node and cruise vectors' Euclidean norms, $\|\mathbf{c}_k\|$ and $\|\mathbf{a}_k\|$, are derived using Eq. (7).

$$\|\mathbf{c}_k\| = \sqrt{\sum_{l=1}^{m} c_l^2}, \quad \|\mathbf{a}_k\| = \sqrt{\sum_{l=1}^{m} a_l^2}. \tag{7}$$

During iteration $t+1$, a falcon's location was merely derived by attaching the step vector from iteration t towards the locations.

$$\mathbf{y}^{t+1} = \mathbf{y}^t + \Delta \mathbf{y}_k^t. \tag{8}$$

If a falcon's newfound place k is much more suitable than that of the location in that memory, this same falcon's memory is updated to reflect that latest place. Instead, the memory is maintained, but the falcon still discovers its new position. In the most recent iteration, each falcon first randomly selects a cluster node from the population to circle the latter's most-frequented location. Then, each falcon quantifies its cluster head node vector, the highest possible number of neighbor nodes, the distance between clusters, the distance within clusters, as well as very short distances. Finally, each falcon determines its step vector and the new location for the following iteration. Until one or both of the termination conditions were satisfied, each loop was repeated. The cluster head node coefficient q_c^t and the shortest route coefficient q_a^t are two coefficients in Eq. (6) that govern how well the cluster node, as well as shortest route vectors, influence this same step vector.

Algorithm 1 Falcon optimization algorithm.

```
Initialize the population of falcon
Evaluate fitness function by using improved ACO
Initialize population memory
Initialize q_c^t and q_a^t
for each iteration t do
  Update q_c^t and q_a^t
  for each falcon k do
    Randomly select a prey from the falcon's memory
    Calculate attack vector c_k by Eq. (1)
    if the attack vector's length is not equal to zero then
      Calculate cruise vector a_k (Eq. (2)–(5))
      Calculate step vector Δy_k^t (Eq. (6)–(8))
      Update position (Eq. (8))
      Evaluate fitness function for the new position
      if fitness is better than the fitness of the position falcon's memory then
        Replace the new position with the position in the falcon's memory
      end if
    end if
  end for
end for
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With wireless sensor networks, each chosen cluster head would be an input towards the subsequent procedure of choosing the optimal route.

3.2 Enhanced ant-colony optimization method

To tackle the QoS routing challenge for WSNs, another optimization approach predicated on advanced ACO is presented. Wherein the linear adjustable operator as well as the premier operator have been employed to boost iteration speed or rather signal concentration therein initial stages of lookup route versatility, because as many periods ants pass, the larger signal concentration as in route, and also this route is much more likely to be targeted by many other ants. Mostly in constrained QoS routing optimization issues, each data transmission path is represented as $p\left(v_1, v_m\right)$. This total count of nodes just on the path is denoted by m, which solves the Eq. (9).

$$m \leq t. \tag{9}$$

Eq. (10) would be employed to describe the population, wherein $y_{N,t}$ is just only one node traveled by the No. n ant while $(y_{n,1}, y_{n,2}, y_{n,3}, \ldots, y_{n,t})$ was a No. n ant's route.

$$\mathbf{Y} = \begin{bmatrix} y_{1,1} & y_{1,2} & \cdots & y_{1,j} & \cdots & y_{1,t} \\ y_{2,1} & y_{2,2} & \cdots & y_{2,j} & \cdots & y_{2,t} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ y_{n,1} & y_{n,2} & \cdots & y_{n,j} & \cdots & y_{n,t} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ y_{N,1} & y_{N,2} & \cdots & y_{N,j} & \cdots & y_{N,t} \end{bmatrix}, \quad n \in [1, N], j \in [1, t]. \tag{10}$$

The routing model coding is used in the ant colony. Its intention seems to be to establish a link between routing difficulties with ACO. As a result, N ants were randomly created as the first ant colony before stimulation. $Y = \{\mathbf{Y}_1, \mathbf{Y}_2, \ldots, \mathbf{Y}_N\}$, describes the starting ant colony, which has N ants. $\mathbf{y} = [y_{k,1}, y_{k,2}, \ldots, y_{k,t}]$, is the formula for the No. k ant.

Every ant has such a fitness value as well as a path-choosing solution. As a consequence, the fitness function (evaluate how close a given solution is to the optimum solution) has a considerable influence on the algorithm's performance. Whenever the multi-condition restricted QoS routing optimization model's latency, connection bandwidth, packet drop, as well as vibration latency criteria, are fulfilled, the fitness value may be dictated by employing Eq. (11);

$$fitness = \min \{LS, p(v_1, v_m)\}. \tag{11}$$

Here LS indicates the quantity of energy utilized by data transfer between nearby nodes. As a consequence, actual routing energy is utilized by every ant there in the population while data transfer may be computed. The route which uses the least amount of energy is the best. As a result, the value of energy consumption is used to evaluate each ant's route. An optimal path would be the one that utilizes the lowest amount of energy.

Every N ant there in the colony always had the following character traits: each ant's choice of a node is governed by the path's energy expenditure as well as pheromone contents. The total number of pheromones within the adjacency link between both two nodes becomes $\tau_{(\mathrm{kl})}$. Additionally, basic search constraints for ants would be as follows: every ant should indeed travel from origin to the endpoint, although it may not be required to visit every node and cannot encounter nodes that have previously been explored. Upon finishing the journey, every ant would leave some certain amount of pheromone on its path. Just at the initial stage, the pheromone concentration all along the route between neighboring locations is just the same. During this point, the No. n ant chooses the very next node, as well as the count of pheromones plus energy usage value evaluates whatever node that ant chooses.

However at point, the No. k ant chooses the next node, and indeed the count of pheromones plus energy usage value dictates whichever node that ant chooses. $P_{(\mathrm{gh})}^{l,l+1}$ symbolizes the potential that ants might pick the upcoming node correlation No. l to No. $l+1$. Both letters g and h were situated nearby to one another. Due to the plausibility of many other nodes, both the quantity of pheromone just on route as well as the energy usage profit may be computed to pick its next routing node. Whenever specific circumstances are achieved, ants would choose routing nodes. The probability P of the No. t generating ant approaching node d from e is estimated by Eq. (12). This roulette method can also be utilized to route nodes down a path that perhaps the ants still have not traversed as in Eq. (12).

$$P_{(\mathrm{gh})}^{l,l+1}(t) = \frac{\tau_{(\mathrm{gh})}^{\alpha}(t)\, u_e^{\beta}(t)}{\sum\limits_{q=1}^{s} \tau_{(\mathrm{g})q}^{\alpha}(t)\, u_{q,l+1}^{\beta}(t)}$$
$$q \in [1,t]\,, e \in [1,t]\,, u_e \in u_{(\mathrm{kl})}, u_{q,l+1} \in u_{(\mathrm{kl})}, \tag{12}$$

$$\mathbf{A} = \begin{bmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,j} & \cdots & a_{1,(t-1)} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,j} & \cdots & a_{2,(t-1)} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{i,1} & a_{i,2} & \cdots & a_{i,j} & \cdots & a_{n,(t-1)} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{N,1} & a_{N,2} & \cdots & a_{N,j} & \cdots & a_{N,(t-1)} \end{bmatrix}, \quad i \in [1,N], j \in [1,t-1], \tag{13}$$

$$u_{(\mathrm{kl})} = \frac{1}{\mathbf{A}_{(\mathrm{kl})}}. \tag{14}$$

The iteration time is given by t in the Eq. (12) $\tau_{(\mathrm{gh})}(t).u_{(\mathrm{kl})}$ symbolizes a reciprocal of such energy usage worth from node No. l to node No. $(l+1)$ which also is described as the energy utilization gain, which would be evaluated mostly by Eq. (14) as well as either the weighted sum of pheromone or even energy usage, that further influences pheromone concentration as well as energy usage, respectively. The likelihood of such ant-picking nodes rises when the value goes up. As the value grows, ants will have a better chance of selecting other nodes based on l nodes. In respect of Eq. (14), The probability of an ant selecting a routing node increases as pheromone concentration and energy efficiency increase.

$\mathbf{A}_{(\mathrm{kl})}$ is the ant's energy consumption value, and it is made up of N equal matrices, which may be expressed as $[a_1, a_2, a_3, \ldots, a_{t-1}]$. $u_{(\mathrm{kl})}$ is an energy consumption fitness matrix that may be calculated using the Eqs. (13) and (14). The pheromone should be computed and updated to find the optimum route. Whenever ants approach every routing node, they transfer pheromone with the No. g node towards the No. h node. Even as the algorithm proceeds to progress, its pheromone concentration would volatilize. After every ant walks from the origin node towards the endpoint node, its pheromone just on the route was updated via ACO. At the $(d, d+1)$ round, the pheromone content on the link (g, h) is modified.

$$\tau_{(\mathrm{gh})}\,(d, d+1) = \rho\tau_{(\mathrm{gh})}\,(d) + \Delta\tau_{(\mathrm{gh})}\,(d, d+1)\,, \tag{15}$$

$$\tau_{(\mathrm{gh})}\,(d, d+1) = \sum_{n=1}^{m} \Delta\tau_{(\mathrm{gh})}^{n}\,(d, d+1). \tag{16}$$

Every ant's pheromone level here on the link (g, h) throughout the round $(d, d+1)$ would be indicated by $\tau_{(\mathrm{gh})}\,(d, d+1)$. This pheromone volatility parameter, which would be utilized to lessen the quantity of pheromone deposited on the link, is indicated. According to Eq. (16), this amount of pheromone left here on the link (g,h) either by No. n ant in during $(d, d+1)$ round would $\Delta\tau^n_{(\mathrm{gh})}\,(d, d+1)$. Eq. (17) represents ACO's ant colony pheromone value update calculation.

$$\Delta\tau^n_{(\mathrm{gh})} = u_h Q. \tag{17}$$

In Eq. (17), Q indicates a constant which describes the pheromone unit level simply left only by ants just on their way to accomplish the search. Energy usage across two nodes does have a profit value of u_h. The ant releases pheromone when it finds the best route in this model.

The algorithm uses a flexible operator and the premier operator in the ACO process, which slows down the methodology during its iterative development phase. One prime objective of such a positive feedback system should be to accelerate the convergence of this same algorithm as well as boost its performance, but it is very easy for the algorithm to become too fast. As a result, an adaptive technique is applied in the flexible operator and the premier operator.

The adaptive operator's goal is to alter the likelihood of choosing different paths during the search process as needed. Throughout multiple loop iterations, every ant colony's evolutionary path can indeed be efficaciously recognized, as well as the pheromone just on the pathway finished either by ants may well be dynamically regulated. It is an amusing strategy for updating data. If indeed the pheromone volatilization component is present, then pheromone concentration just on the pathway which ants pick less or do not choose would be exhausted even as the problem grows more complex.

As a result, ACO's global search capabilities will be affected. If such pheromone contents of many other pathways are significant, the quantity of data in such pathways will grow, enhancing the likelihood of finding these high-content pathways. The past generation of ants' pathway was likely to be chosen either by the upcoming generation of ants, resulting in local optimal search and a decrease in global search performance. As a result, increasing the pheromone volatilization factor can improve ACO's global search capabilities. The flexible operator and the premier operator strategy propose an adaptive technique of pheromone change, and the pheromone update Eq. (18) is written as

$$\begin{cases} \tau_{(\mathrm{gh})}\,(d, d+1) = (1-\rho)^{1+\varphi(w)} \cdot \tau_{(\mathrm{gh})}(d) + \tau_{(\mathrm{gh})}\,(d, d+1)\,, & \tau \geq \tau_{\max}, \\ \tau_{(\mathrm{gh})}\,(d, d+1) = (1-\rho)^{1-\varphi(w)} \cdot \tau_{(\mathrm{gh})}(d) + \tau_{(\mathrm{gh})}\,(d, d+1)\,, & \tau < \tau_{\max}, \end{cases} \tag{18}$$

$$\varphi\,(w) = w/a. \tag{19}$$

Fig. 3 provides the proposed hybrid algorithm flowchart.

As a result, the number of ants taking this path is growing. Then, this output is fed into the DBN model to evaluate the optimum route of the WSN.

3.3 Evaluation of optimum route using deep belief neural network

DBN is a stack of RBMs in the form of a miraculous deep model. The DBN structure having k hidden layers, as well as its layer-wise pre-training approach, are depicted in Fig. 4.

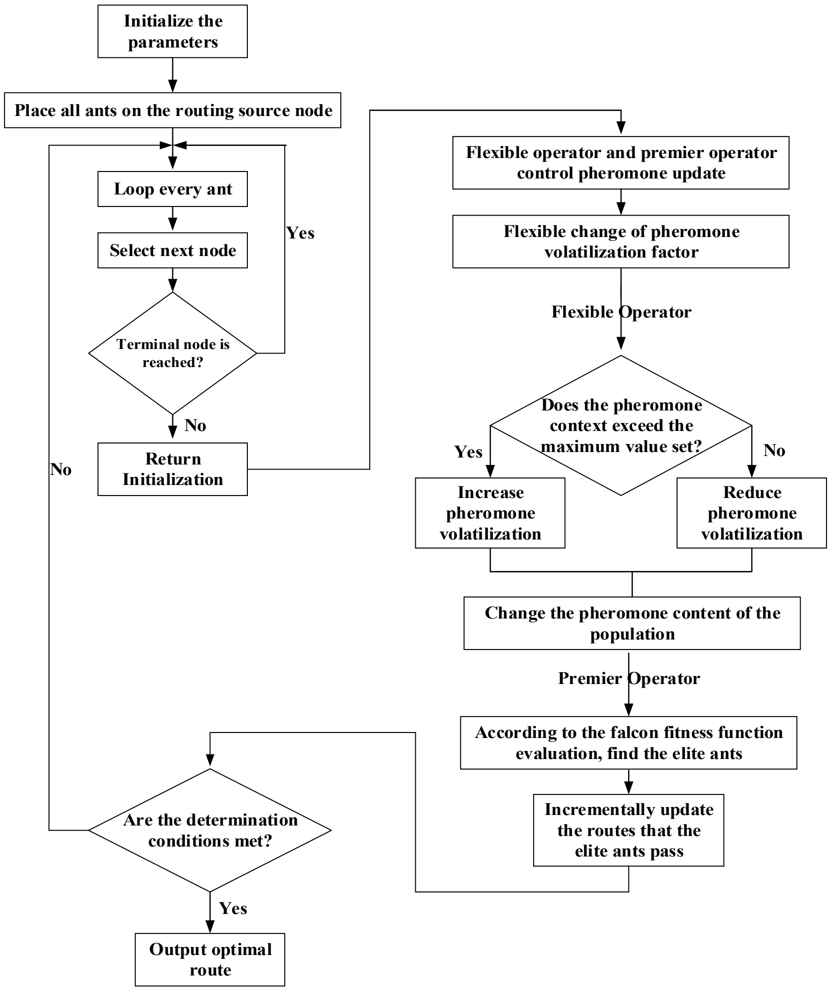

Fig. 3 *Proposed algorithm flowchart.*

Effective activation for a kth hidden layer concerning input sample y might well be computed as follows:

$$C_k(y) = \sigma\left(\sum_{k=1}^{n} w_k y_k + b_k\right), \tag{20}$$

where w_k as well as b_k $(k = 1, 2, \ldots, n)$ are indeed the nth RBM's weighing matrices with concealed bias vectors, correspondingly. Furthermore, σ seems to be the logistic sigmoid function $\sigma(y) = \frac{1}{1+e^{-y}}$. Its DBN optimizes its inter-layer weighing matrix by employing deep architecture as well as layer-wise pre-training for enhancing feature representations. Finally, given favorable input, all ants will focus on the optimum route where the neural network uses a deep belief network to predict the energy and thus the optimal route has been evaluated. To start, assume that

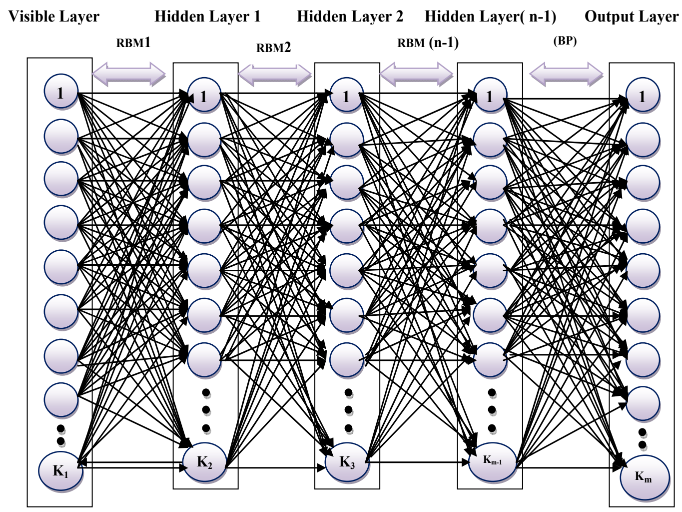

Fig. 4 *Architecture of deep belief network.*

we may have acquired sample data over M continuous days, having T data points received on each day. As seen below, each sampled period series for energy usage information might well be portrayed as a series of 1D vectors.

$$Y = \{\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_M\}, \tag{21}$$

$$\mathbf{y}_1 = [y_1(1), y_1(2), \ldots, y_1(T)]\,, \tag{22}$$

$$\mathbf{y}_M = [y_M(1), y_M(2), \ldots, y_M(T)]\,. \tag{23}$$

T denotes this same count of samples per day. The deep belief network's designing strategy has been outlined below;

Step 1: Retrieve the energy-usage pattern as that of the periodic understanding first from training data.

Step 2: Eliminate any energy-usage pattern first from training data to procure residual data.

Step 3: Utilizing this residual information, train this DBN model.

Step 4: Merge this same DBN system outputs also with periodic knowledge to make the finalized prediction results for such a hybrid model.

As a consequence, this hybrid falcon-improved ACO nature-inspired optimization using a deep learning model gives better routing to the sensor nodes and improves the QoS as well as the energy consumption also less when compared to those other current methodologies, and by doing so prolonging the node's longevity.

4. Result and discussion

This section presents both implementation findings as well as the functionality of our proposed methodology. In addition, comparison findings of existing efforts are shown.

Tool:	MATLAB2018a
OS:	Windows 7 (64 bit)
Processor:	Intel Premium
RAM:	8GB RAM

4.1 Performance evaluation metrics

For performance evaluation, this research utilized MATLAB software. As is shown in Tab. I, there are 200 sensor nodes randomly deployed in a $100 \times 100\,\mathrm{m}^2$, each node with an initial energy 0.5–2.0 J. The transmission range is 75 meters. Each node takes turn to transmit a 500 bits.

- Falcon optimization technique, which employs to select the cluster head, with residual energy, the maximum number of neighbor nodes, inter-cluster distance, intra-cluster distance, and the shortest distance from the base station as constraints in locating cluster head nodes. Falcon in order to catch the best possible cluster heads in the quickest possible time in a viable cluster.
- To reduce energy usage between nodes a new improved ant colony optimization has been proposed.
- Then the neural network which uses deep belief network to predict the energy and thus the optimal route has been evaluated.

Initial energy is the uniform energy source provided to all sensor nodes at the beginning of the simulation. The length of time that the network's sensor nodes are functional determines the network lifetime. Here, the energy consumption is caused by three parts: (1) sending packets, (2) receiving packets, (3) dissipation

Simulation parameters	Values
Network area	$100\times100\ m^2$
Initial energy nodes	0.5–2.0 J
Number of nodes	200
Transmission range	75 m
Path loss	4
Multipath component	0 dB to 10 dB
Standard deviation	0 dB to 12 dB
Energy consumption	50 nJ/bit
Data packet size	500 bits

Tab. I *WSN simulation parameters and values.*

energy consumption for maintaining the node operation. This section describes the performance of our proposed technique whereas; various parameters are used to evaluate the performance of the novel approach.

4.1.1 Number of dead nodes

A node is said to be dead when its energy level drops to zero. The number of dead nodes is calculated and plotted for each cycle of data transmission, as shown in Fig. 5.

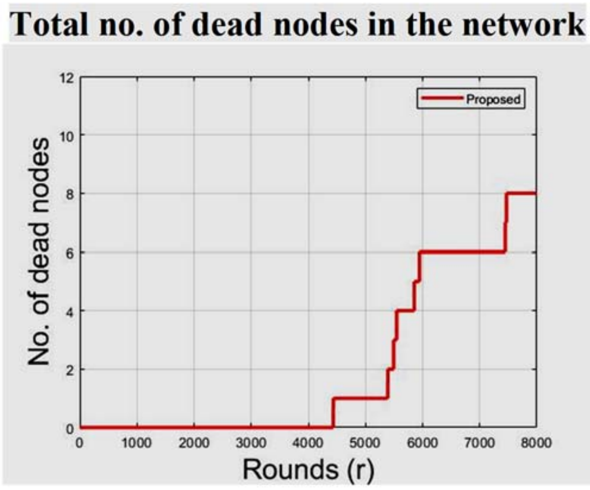

Fig. 5 *Count of nodes that just aren't alive.*

Fig. 5 depicts the number of dead nodes in our protocol wireless sensor networks. Moreover, it illustrates that in our proposed protocol, the first node dies in round 4600, and it maintains up to 7500 rounds. Furthermore, the last node dies in round 7500, it maintains up to 8000 rounds and it is the same throughout the network. A fraction of nodes that seem to be alive grows as such count of rounds rises. For 8000 rounds, the proposed Falcon optimization technique maintains nodes that are connected.

4.1.2 Packets sent to sink node (base station)

Fig. 6 illustrates the proposed model sends out fewer packets to the sink. Regarding routers, the presented falcon optimization strategy makes use of very few cluster heads. Cluster heads became significantly more active with data transfer as well as reception even as the count of packets grows. There is a proposed approach, only packets inside the nodes' coverage areas are sent to the sink. As a consequence of this process, the quantity of duplicate information is decreased.

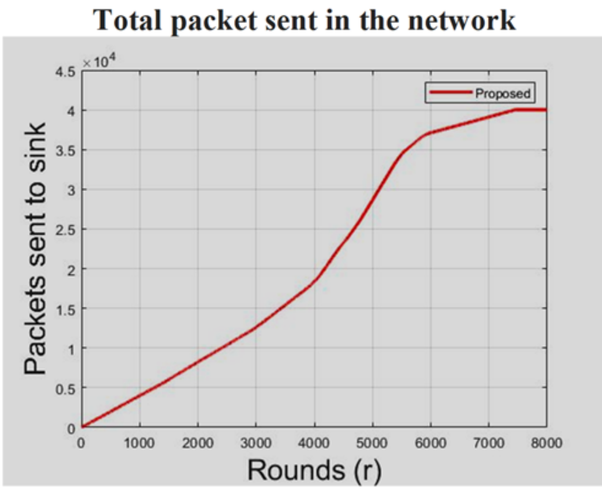

Fig. 6 *Packets sent to sink node (base station).*

4.1.3 Packets dropped

The performance statistic assesses the count of packets lost during transfer. As a result, our proposed technique, packet drop is minimum. The graph is depicted in Fig. 7.

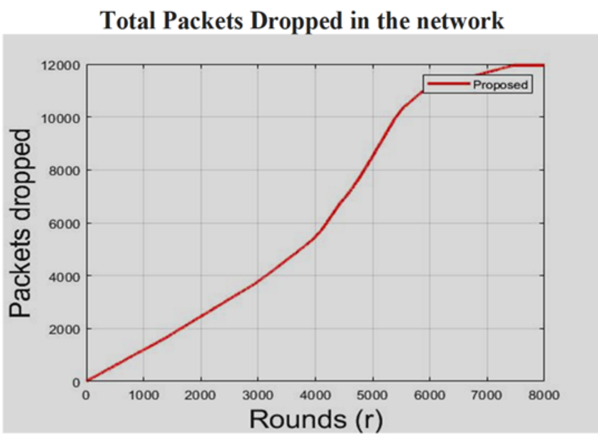

Fig. 7 *Packets dropped.*

Fig. 7 shows the packet loss distribution for various transmits power levels. Packet delivery performance improves dramatically when transmit power is reduced. These simulation findings indicate that the strategy increases network data transfer services significantly. These experimental results show that our proposed falcon optimization technique improves the network traffic stability, reduces packet loss rates, and increases data arrival rates.

4.1.4 Received packets to sink node (base station)

Fig. 8 depicts the total count of packets received just at the sink node. Because of the varying transmission range and unique packet holding time of the nodes, which receive the most packets at the sink node.

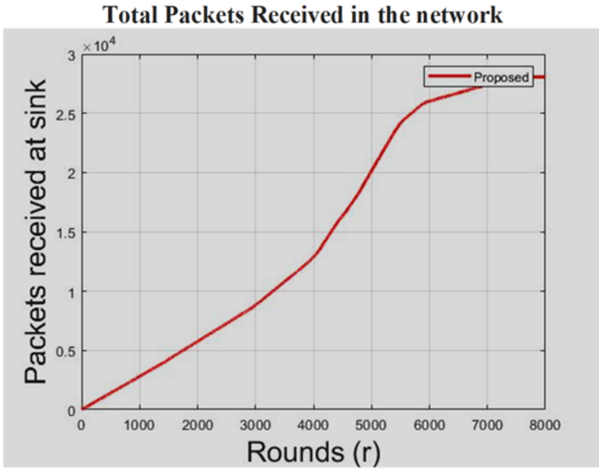

Fig. 8 *Packets received to sink node (base station).*

When a sender node in falcon optimization cannot recognize a neighbor, it extends its transmission range to include one or more forwarder nodes. This improves the possibility of packets reaching the sink node. Moreover, our proposed protocol better in terms of transmitting data.

4.1.5 Residual energy

The methodology quantifies as well as hierarchically aggregates the residual energy of such redundant nodes, letting that cluster head proactively pick redundant nodes for relay nodes that conclude information transfer as well as updated those redundant nodes. Furthermore, every sink node might recluster in a specific layer depending mostly on the residual energy of either the cluster heads.

This deep belief network (DBN) residual energy progressively drops after 5000 cycles, indicating its reliability. Because the energy from our developed model is gradually depleted, the network lifespan is increased to a greater number of rounds.

4.1.6 Path loss

Fig. 10 illustrates a graph showing total route loss vs rounding. This same number of rounds has always been set to 1000 whenever the graph is drawn. This graph demonstrates overall path loss growing linearly until it achieves a peak. After that, overall path loss gradually diminishes before increasing again.

Fig. 10 shows that the path loss is decreases as the number of round increases. In round 3000, obtain path loss is 470 dB, then it gradually decreases upto 5000 rounds, after 7000 rounds it gradually maintains path loss as 4 dB. As a result of

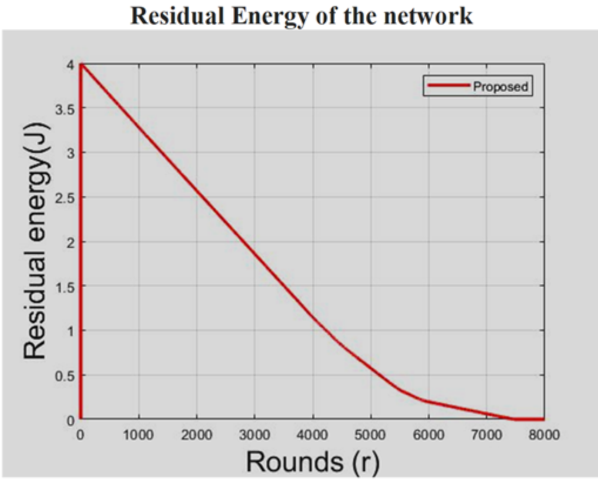

Fig. 9 *Residual energy.*

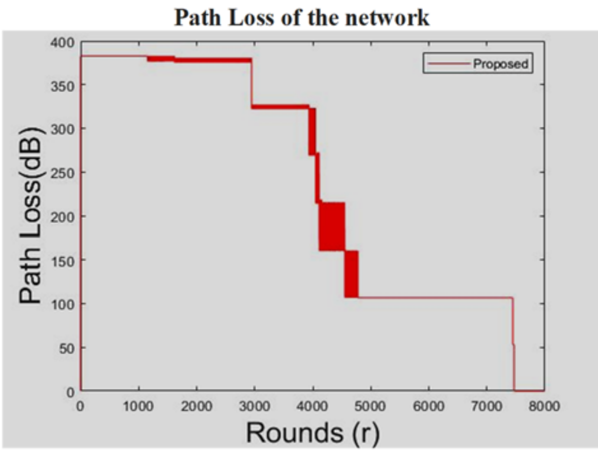

Fig. 10 *Path loss.*

path loss, the received signal power level is several orders of magnitude lower than the transmitted power level. Thus our proposed model shows that transmission power is increased, whereas the path loss reduces.

4.1.7 Delay time

In such a sensor network context, Fig. 11 presents a graph of latency vs. count of attainable rounds. This graph is built having a 1000-meter deployment region in view. This restricted zone forwarder node choosing yields the shortest possible pathways from either a source to a target. Our developed falcon optimization approach reduces overall end-to-end latency. The unit of delay is milliseconds. The maximum delay at 1000 rounds was 0.9×10^{-8} ms, whereas the lowest delay at 8000 rounds was 0.01×10^{-8} ms. Overall, a minimal latency was observed ranging from 7500 to 8000 rounds.

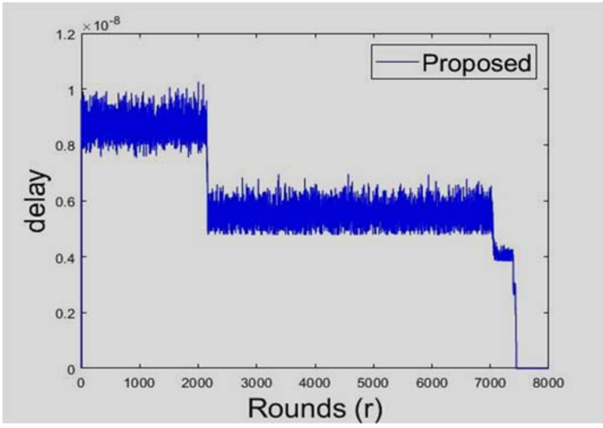

Fig. 11 *Delay time.*

4.1.8 Convergence curve

The landscape of the benchmark function is depicted in Fig. 12(a). Fig. 12(b) illustrates the preliminary search agent's pathway along that x-axis. The units of X and Y axis is number of iterations and average fitness value. These same plots within that graph illustrate that now the search agents encounter large fluctuations regarding their position even during opening rounds of such optimization technique before slowing down as well as converging towards the optimum. It demonstrates how effectively the falcon technique improves fitness to eventually converge toward the optimal. It can be shown that the convergence curve in unimodal functions is constantly improving.

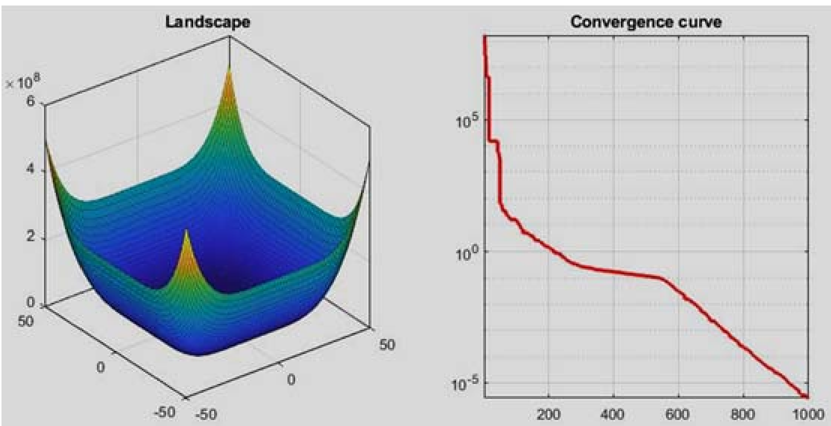

Fig. 12 *Convergence curve.*

4.1.9 Enhanced ant colony optimization

Fig. 13 depicts that such relationship curve of a modified ant colony algorithm diminishes more slowly than that of the standard ant colony algorithm as well as exhibits a consistent decreasing trend even as the count of iterations grows. Now after 150 iterations, this upgraded ant colony algorithm finds its optimum route, which is superior to the outcome of the standard ant colony algorithm, thereby eradicating the difficulty of the standard ant colony algorithm slipping into such a local optimum.

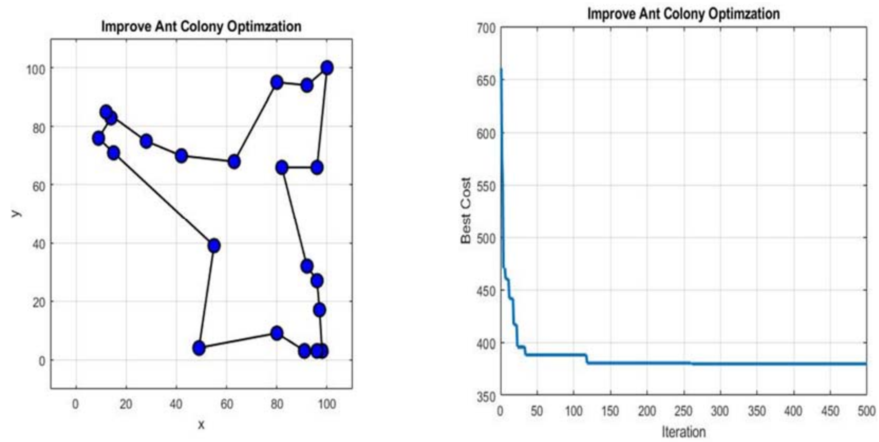

Fig. 13 *Packets sent to sink node (base station).*

Simulation parameters	Values
Number of iterations	10000
Number of ants	50
Quantity of deposit pheromone by the best ant	0.2
Pheromone factor	0.95
Heuristics factor	1
Pheromone weight	2

Tab. II *Simulation of parameters of ACO and its values.*

4.2 Comparison results

This section describes the comparison results of the proposed technique whereas our novel technique is compared with the baseline approach such as genetic algorithm (GA) [47], particle swarm optimization (PSO) [47], and adaptive elite ant colony optimization (AEACO) [47].

This section explores the developed strategy's comparative findings, in which our novel approach is compared to baseline approaches including such genetic algorithm (GA), particle swarm optimization (PSO), as well as adaptive elite ant colony optimization (AEACO).

Algorithm	30 nodes	40 nodes	50 nodes	70 nodes
AEACO	5.5195	3.3449	3.0690	1.8986
PSO	5.7957	4.2094	4.0883	3.1489
GA	6.1329	4.8302	4.6283	3.7012
Proposed	5.2134	2.9756	2.7123	1.6108

Tab. III *Comparison results of energy consumption.*

Fig. 14 illustrates the comparative findings of AEACO, PSO, as well as GA at distinct node scales. Our innovative, enhanced ant colony optimization capacity is still most visible whenever the count of nodes reaches 70, while energy usage is near 1.6108 J between 30 to 70 iterations. Its current values for AEACO, PSO, as well as GA, were 3.7012 J, 3.1489 J, & 1.986 J, correspondingly. Fig. 14 demonstrates that our developed technique beats AEACO, PSO, as well as GA at diverse node sizes.

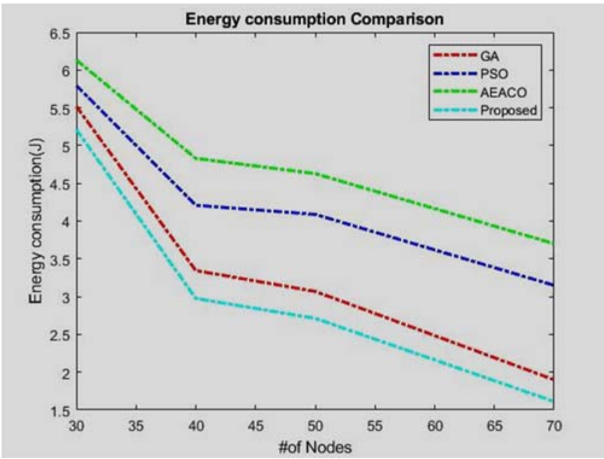

Fig. 14 *Comparison of optimization based energy consumption.*

Algorithm	30 nodes	40 nodes	50 nodes	70 nodes
AEACO	9.63	15.64	19.37	35.49
PSO	14.26	20.53	24.47	48.37
GA	18.95	25.12	28.96	55.83
Proposed	8.21	12.97	16.71	31.61

Tab. IV *Comparison results of convergence time.*

Fig. 15 offer a comparison of convergence durations including AEACO, PSO, as well as GA at distinct node sizes. Our novel, falcon optimization technique performance is most apparent when the number of nodes is 70 whereas the convergence time is close to 31.61 s. 4 s from 30 iterations to 70 iterations. AEACO, PSO, and GA are 21.9 s, 43.6 s, and 53.8 s respectively, Fig. 15 clearly show that our proposed method outperforms AEACO, PSO, and GA at different node sizes.

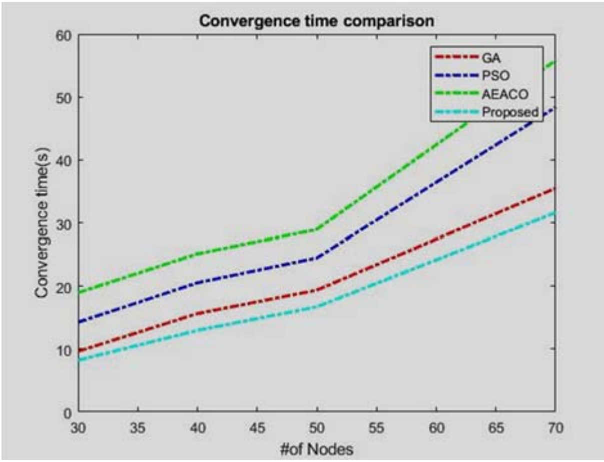

Fig. 15 *Comparison of convergence time.*

Then, our novel technique is compared with the baseline approach such as low energy adaptive clustering hierarchy (LEACH) [46] and enhanced variant of LEACH (ESO-LEACH) [46].

In Fig. 16, the proposed algorithm's nodes lifetime is compared to LEACH and ESO-LEACH in terms of the number of rounds. The proposed approach

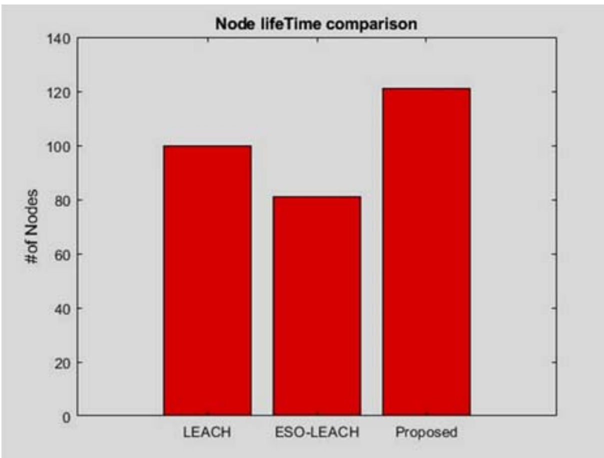

Fig. 16 *Comparison of node lifetime.*

outperforms all existing algorithms, as shown in Fig. 16. The proposed approach improves the number of alive nodes and the residual energy of nodes in the network by using energy-efficient CH selection. Tab. V shows an estimation of the node's lifetime in LEACH [46], ESO-LEACH [46], and the proposed technique during 500 rounds.

Techniques	Number of rounds	Node lifetime
LEACH	500	100
ESO-LEACH	500	81
Proposed	500	121

Tab. V *Comparison of node lifetime.*

In Fig. 17, the proposed algorithm's energy consumption is compared to LEACH and ESO-LEACH in terms of the number of rounds. Tab. VI shows an estimation of energy consumption in LEACH, ESO-LEACH, and the proposed technique during several rounds. The energy consumption of the proposed technique is lower with the baseline approach. Our proposed approach compared with the baseline low energy adaptive clustering hierarchy (LEACH) [46] and enhanced variant of LEACH (ESO-LEACH) [46] whereas the proposed approach outperforms all existing approaches, as shown in Fig. 17.

Techniques	Number of rounds	Energy consumption (J)
LEACH	500	0.061
ESO-LEACH	500	0.048
Proposed	500	0.041

Tab. VI *Comparison of standard energy consumption.*

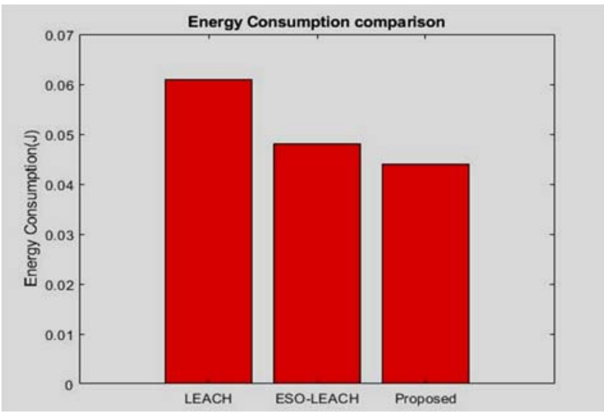

Fig. 17 *Comparison of standard energy consumption.*

5. Conclusion

Energy conservation is the main factor in increasing the network's life. In dynamic environments, hierarchical routing can select an inefficient path, resulting in high energy consumption and a reduction in throughput. This may result in a rapid loss of energy reserves, reducing the network's lifespan. To overcome this our research proposed a hybrid falcon-improved ACO nature-inspired optimization using deep learning model to obtain the final prediction results. Initially, the falcon optimization technique selects the cluster head. As part of the route being constructed, this system utilizes residual energy as a constraint in selecting cluster head nodes. Thus, an enhanced ant colony optimization has been developed to improve route choosing by incorporating the merits of conventional ant colony optimization, adaptive approach, as well as elite strategy. Finally, given favorable input, all ants will focus on the optimum route where the neural network uses a deep belief network to predict the energy and thus the optimal route has been evaluated. The findings reveal that the developed hybrid model does have a fast convergence period and therefore can discover the shortest route only with the fewest amount of energy usage. The comparison results show the effectiveness of the proposed hybrid approach. In the future, we can use some other metaheuristic optimization to discover the routing path where we can extend for an uninterrupted mobile wireless sensor network, such as avoiding handover. Future secure routing may be performed through novel hybrid machine learning approaches.

Furthermore, for routing, leverage hybrid machine learning methodologies as well as security-based optimizations.

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