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Original Article

A Novel Fuzzy Enhanced Black Widow Spider Optimization for Energy Efficient Cluster Communication by Optimal Cluster Head Selection in WSN

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***Abstract** - Wireless sensor networks' substantial growth and momentous potential have expanded their application in real-world scenarios. However, the energy-constrained characteristics of sensor nodes create various network functioning issues. To deal with such shortcomings, the energy efficient clustering approach is required. The clustering method is the most significant and effective technique for optimising sensor nodes. Although numerous clustering approaches for determining ideal CH in the network area exist, it requires effective solutions to enhance wireless network performance. Therefore, this paper develops a novel Fuzzy Enhanced Black Widow Spider (FEBWS) method that promotes effective Communication between inter and intra clusters by optimal selection of cluster heads. The most-optimal cluster head is selected from the cluster groups by the proposed FEBWS algorithm uses the fuzzy logic system with an improved black widow spider optimisation algorithm considering energy, delay, and distance parameters. The efficiency of the proposed FEBWS algorithm is investigated by relating its performance with the existing techniques. The proposed FEBWS algorithm achieves an enhanced performance rate, especially less energy consumption and high network lifetime, than other state-of-the-art techniques.*

***Keywords** - Cluster head selection, Fuzzy logic system, Improved black widow spider optimisation algorithm, Energy consumption.*

1. Introduction

The technological improvement in the world has led to the development of Wireless Sensor Networks (WSN) in disaster management, tracking systems, and environmental conditions. A better sharing protocol increases the network lifetime and manages energy consumption. The need for energy is minimised by the clustering method while transferring data [1]. The IoT technology in WSN collects real-world data from the combined network. The network sharing of WSN is expanded in IoT, which requires less amount of energy. The spreading of data in a particular network is stopped to conserve the information of the user [2]. A limited number of sensors and low-cost nodes are present in WSN, which contain a battery, Communication, and sensing framework. The sensor nodes are the unique nodes. The battery obtained in the nodes cannot replace, so the nodes can transmit the data until it contains energy [3]. For making the decision, the data from the nodes are transformed into the primary device and its processes to obtain the result. The power is diminished to enhance the network lifetime, which helps to obtain better network performance [27]. The sensor nodes act as a mediator between the WSN and the base station, or they can transfer directly to the Base Station (BS). The overflow of the information is managed by the gateway method, minimises energy overconsumption and improves battery life. The Grey Wolf Optimization (GWO) monitors the sensor nodes for better efficiency and also diminishes the crack present in energy [5].

The energy-efficient of WSN is also suitable in the field of agriculture. The Precision Agriculture (PA) method is applied in the agricultural field to process and command the crop for particular environmental conditions. The WSN obtained in a wide area in agriculture will create traffic congestion in the network. It can be minimised using the Programmable System on Chip Technology (PSoC) [22]. The wireless sensor network is also used in home appliances. The heavy workload in the nodes can reduce the network lifetime. So the nodes are assigned individually for every network by Cluster Head (CH) [7]. If any critical event happens, the sensor nodes can monitor them by ringing an alarm that activates the user to make the decision.

The DDC (Dynamic duty cycle) technique examines the lag that occurs while transmitting data and manages the network lifetime more efficiently [8]. The critical and accessible sensor nodes are connected in the WSN that is applied and processed in various applications. The WSN can also communicate with more than two networks, increasing network lifetime and diminishing the sensor node requirement [23]. The indoor localisation method leads to the introduction of IoT technology. The accuracy of the indoor is measured based on camera, VLC, and infrared based. The WSNs are penetrated in wireless sensor nodes that minimise the total number of nodes and reduce the cost. The distance of the indoor localisation is determined based on the radio signals. The radio signals are joined with the sensor nodes for detecting the locations [10]. This paper develops an energy efficient clustering approach for optimal Communication of data packets from source to destination. The main purpose of this paper is described as follows:

- A novel Fuzzy Enhanced Black Widow Spider (FEBWS) algorithm is proposed to offer energy efficient cluster communication by the optimal choice of cluster head.
- The most-optimal cluster head is chosen from the cluster groups by the proposed FEBWS algorithm by considering energy, delay, and distance parameters.
- The efficiency of the proposed FEBWS algorithm is investigated by relating its performance with the existing techniques.

The rest of this paper is arranged as follows. In section 2, different surveys based on energy efficient WSN are discussed. The system design is described in section 3. In section 4, different proposed methodologies are explained. Section 5 presents the results and discussions. Finally, section 6 is the conclusion of the article.

2. Literature Survey

Ajmi et al. [11] discussed energy efficiency in WSN using a chicken swarm-based genetic algorithm. The major problem obtained in the WSN was it reduced the battery lifetime. The Multi Weight Chicken Swarm improved the battery's power-based Genetic Algorithm (MWCSGA). The developed method was collated with some factors, namely CSOGA and LEACH. As a result, it achieved an accuracy rate. It saved energy efficiency.

Meanwhile, the cluster was discarded and could not process any network protocol. Mohanty et al. [28] developed an energyefficient for WSN using a Recurrent Neural Network with Long Short-Term Memory (RNN-LSTM) method. The main purpose of this paper was to minimise the fusion center overhanging and reduce the transmission data count in Wireless Sensor Networks (WSN). The RNN-LSTM model was introduced in this paper to test the intervals of signals and the numbers of unstable secret nodes. Hence, the developed RNN-LSTM model was attained to optimise the minimal delay of 190ms and decrease the overhanging signals. On the other hand, this model was very difficult to train.

Li et al. [13] elaborated on energy efficient routing protocol in WSN using Ant-colony optimisation-based routing algorithm (ACO-RA). The crucial issue obtained in WSN was it could extend the network lifetime only with the help of energy efficiency. To overcome this issue, ACO-RA was introduced in this paper. ACO-RC accepts a pseudo-random path discovery algorithm for balancing the energy consumption of WSNs. As a result, the evaluation parameters were obtained to achieve superior performance compared to other methods.

Meanwhile, the accurate identification of the solution was delayed. Tabibi et al. [14] established an energy-efficient routing protocol for wireless sensor network (WSN) using Particle Swarm Optimization (PSO) algorithm. The main challenging role is to address the problem of a wireless sensor network with low power consumption. To shortcoming this problem, PSO was introduced to provide the energy consumption uniformly and calculate the weight value of each sensor node. As an experimental result, the PSO algorithm achieved better performance than the weighted rendezvous planning (WRP) algorithm. Meanwhile, this technique

Wang et al. [25] explained Enhanced Power-Efficient Gathering in Sensor Information Systems (EPEGASIS) algorithm with mobile sink support based on Wireless Sensor Networks (WSNs). The optimal communication distance was evaluated to minimise energy consumption. The experimentation result demonstrated that the EPEGASIS algorithm attained higher performance regarding network latency, energy consumption, and lifetime. On the other hand, the sinking trajectory was not properly designed. Rathee et al. [16] discussed QoS aware Energy Balancing Secure Routing (QEBSR) algorithm in Ant Colony Optimization for wireless sensor networks (WSN). The QEBSR algorithm utilised improved designs to calculate the trust factor values. The results were that the QEBSR algorithm achieved higher performance than other approaches. However, the protocols were not applied more broadly. Reddy et al. [17] introduced the selection of energy efficiency of cluster head and routing path Ant Colony optimisation Integrated Glowworm Swarm Optimization (ACI-GSO) algorithm of WSN. The hybrid ACI-GSO algorithm resolved the complications that occurred in selecting the ideal cluster head from the clusters. The ACI-

GSO algorithm achieved a higher percentage of alive nodes in every round compared to the existing methods, but its cost function was complex to evaluate.

3. System Design

The sensors (S) and Base Station (BS) present in the system design comprise equal allocation-based irregular arrangement in the analysis area. The network is improved by filling large sensor nodes used within the location. The WSN network is constant and contains the sensor nodes and base station. Every node contains identical primary energy. The energy obtained in the base station is always high and does not contain restrictions. The chosen Primary Cluster Head (PCH) and the Secondary Cluster Head (SCH) are done infrequently based on the coverage area. The network energy is developed by sensor nodes based on transmission distance. The inclusion of sleep and wake node theory minimises the consumption of energy. The PCH and BS are obtained inside the transmission network. The single jump communication greatly creates problems in energy. To avoid these issues, the n-hop network is applied. Load-balancing clusters diminish energy consumption and increase the accuracy of WSN.

3.1. Energy Design

Two methods of power loss are applied in energy design WSN, namely multipath fading s^4 and free spaces^2. The free space method is obtained as a channel model when the network's distance is lower than the threshold value s_{val}; otherwise, the multipath fading is selected [11]. The use of energy in the data on the distance is expressed as

$$F_{UY}(b,s) = \begin{cases} b \times F_{power} + b \times F_{re} \times s^2, s \leq s_{val} \\ b \times F_{power} + b \times F_{pf} \times s^4, s > s_{val} \end{cases} \quad (1)$$

whileF_{power} is the amount of energy dispersed from the network. The amplifier and transmitter method network is denoted as F_{pf} , and F_{re} the threshold distance is F_{pf}

$$s_{val} = \sqrt{\frac{F_{re}}{F_{pf}}} \quad (2)$$

The application of energy in sink expression is formulated as

$$F_{TM,}(b) = b * F_{power} \quad (3)$$

3.2. Energy Consumption Design

The transfer of node in energy consumption to cluster head is formulated as

$$F_{unC_H} = b * F_{power} + b * F_{re}{s^2}_{c_n - C_H} \quad (4)$$

while $s_{c_n - C_H}$ denotes the child node to the Cluster Head (CH) distance. The consumption of energy from the cluster head is given as

$$F_{C_H} = \left(b\left(\frac{a}{n} - 1\right) * F_{power} + \frac{a}{n} * F_{sta}\right) + F_{TM}(b,s) + F_{UY}\left(b, s_{C_H - B_S}\right) \quad (5)$$

while 'a' denotes the existing node, the cluster present in the network is n, and the energy consumption is given as F_{TM}.

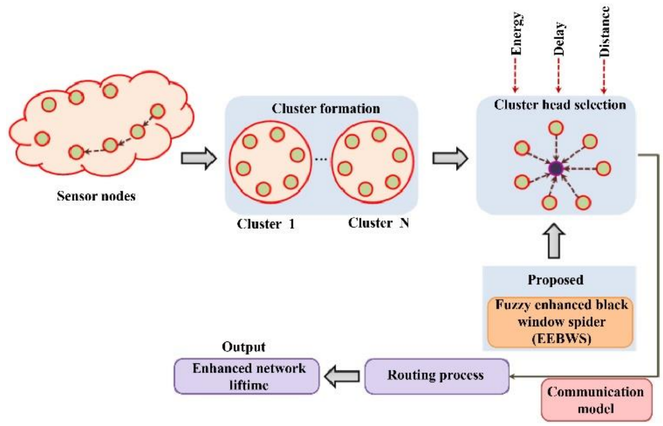

Fig. 1 Structure of proposed energy efficient clustering approach

4. Proposed Methodology

This section describes the energy efficient clustering approach' fuzzy enhanced black widow spider (FEBWS) algorithm' for optimal Communication of data packets from the source to the destination. At first, the wireless network deployed with 'n' sensor nodes is grouped with the neighbouring nodes to form clusters. The increase in network lifetime is essential to transmit data via optimal node and energy-efficient paths. The proposed FEBWS algorithm selects the optimal cluster head between the cluster nodes and transmits data via selected CHs to the base station. It increases both the intra and inter-cluster communication processes by selecting the path of energy efficiency to the base station. In figure 1, the energy efficiency of the clustering approach is mentioned.

4.1. Cluster Formation

Generally, the base station (BS) chooses the nodes which are selected as the cluster heads, and then the hello packets are transmitted to groups to find the cluster heads. The nodes have minimum communication cost as well as the correct location is selected as the cluster head. Lastly, the CHis selected and transmitted the hello packets into nodes for selecting the child nodes (CN).

4.2. Cluster Head Selection

This paper develops a novel FEBWS algorithm that promotes effective Communication between inter and intra-clusters by optimal selection of cluster heads. The detailed description of different techniques is explained as follows.

4.2.1. Fuzzy Logic System

The set of fuzzy logic describes a membership function instead of characteristic functionality. The value of the fuzzy set is either one or zero. The membership function refers to each object's probability in an element set. The membership functions are fallen at the interval of [0, 1]. If the membership functions drop-down at the interval zero, the object does not match the element set. If the membership functions drop down at interval one, the object should match the element set. The sentence with the condition rather than the equation describes the fuzzy logic control method. The interference rule can assess each proposition's validity. The Fuzzy logic control can be classified into three phases such as fuzzification, condition evaluation, and defuzzification [26].

Phase 1: Fuzzification

The formation of fuzzy rules implements every fuzzy logic control system. The fuzzy rules are explained as follows:

Condition 1: If E is $g1$ and F is$h1$, then I is$j1$;

Condition 2: If E is $g2$ and F is$h2$, then $I$is$j2$;

The above conditions denote the conditions' parameters and indicate the reaction parameter, and the fuzzy variables classified by the membership are represented by$g_m, h_m$and j_m, respectively.

Although, the Fuzzy interface procedure has two conditions and a membership function. Take $R_1$and R_2as intervals, and determine the condition parameter of membership function as $\lambda_{g1}(e)$ forcondition1 and$\lambda_{h1}(f)$ condition 2. Therefore, the corresponding fuzzy parameters are matching with the measuring values.

Phase 2: Condition evaluation:

In the condition execution phase, the fuzzy control conditions are satisfied $E = e$and $E = f$can be attached with the below conditions

Condition1: $\lambda_{g1}(e) \wedge \lambda_{h1}(f)$;

Condition 2: $\lambda_{g2}(e) \wedge \lambda_{h2}(f)$;

The above conditions represent the truthfulness degree of conditions 1 and 2, and $\wedge$ the operator denotes the minimum function of condition execution.

Since taken R_3as the interval of the output parameter. The output of the membership function$\lambda_{gm}(I)$ is the addition of every membership function. This scenario is formulated as follows:

$$\lambda_g(I) = \lambda_{a1}(I) * \lambda_{a2}(I), \qquad (6)$$

From the above equation, $*$ the operator denotes the maximum function of condition execution.

Phase 3: Defuzzification

The result of the inference condition is changed into an actual value which acts as an input in the fuzzy logic control system. Although the desired outcome is not a fuzzy result, so the resulting value of the fuzzy logic control system can be obtained$\lambda_{jm}(I)$. In the defuzzification phase, the adoption of a region of gravity (COA) method is described as follows:

$$Y_{coa} = \frac{\int_Y \lambda S(Y)Yey}{\int_Y \lambda S(Y)Ye} \qquad (7)$$

In the above equation, the algebraic integration of every element of the membership function in the subsection of fuzzy output on the domain A is represented by$\int_Y$. The regions on both two sides Y_{coa} are the same.

4.2.2. Improved Black widow (IBW) Spider Optimisation

The IBW optimisation is utilised in the rand function to initialise the population. Gauss chaotic mapping is introduced for initialising the population and improving the algorithm's diversity [19]. The algorithm is enabled to discover the locations with high-quality solutions. Therefore, the algorithm's convergence speed is improved and accelerated. The Gauss mapping is known as classical mappings with one-dimensional mappings, and it is expressed as;

$$a_{y+1} = \begin{cases} 0, a_y = 0 \\ \frac{1}{a_y MO(1)}, a_y \neq 0 \end{cases} \qquad (8)$$

$$\frac{1}{a_y MO(1)} = \frac{1}{a_y} - \left[\frac{1}{a_y}\right] \qquad (9)$$

From the above equation, the residual function is represented by MO; the rounding is indicated by , the chaotic sequence is generated through gauss mapping and denoted as $a_1, a_2, \ldots\ldots, a_y$.

Sine and Cosine Scheme

The nature-like optimisation algorithm is called the sine cosine algorithm (SCA) and randomly creates multiple candidate solutions. The sine and cosine functions transform the amplitudes of cosine and sine functions. The algorithm is utilised to balance the capabilities of local and global exploitation in the search method and identify the optimal global solutions. Then its update is calculated and expressed as;

$$\vec{t}_k(v+1) = \vec{t}(v) + w_1 . \sin w_2 . \left| w_3 . \vec{t} * (v) - \vec{t}(v) \right| \qquad (10)$$

$$\vec{t}_k(v+1) = \vec{t}(v) + w_1.\cos w_2.\left|w_3.\vec{t}*(v) - \vec{t}(v)\right| \quad (11)$$

From the above equation, the individual position after updating is denoted by $\vec{t}_k(v+1)$; the current optimal individual position is represented by $\vec{t}*(v)$, the random numbers in $[0,2\pi]$ are denoted by w_2, the current individual positions are represented by $\vec{t}_k(v)$, If$w_4 < 0.5$, the positions are updated by utilising the below equation, and it is expressed as;

$$w_1 = u.\left(1 - \frac{v}{V}\right) \quad (12)$$

From the above equation, the constant is denoted by$u$, the reduced number of iterations is indicated by$V$, and the number of present iterations represented by v. Mutation probability is computed, and it is expressed as;

$$\beta = EXP\left(1 - \frac{v}{V}\right)^{-20} + 0.35 \quad (13)$$

Elite Opposition-Based Learning

One of the intelligent techniques is opposition-based learning (OBL), utilised for evaluating its opposite and current solutions. It is utilised in a meritocratic way to enhance the search capability and ranges of the algorithm. The result demonstrated that when compared to the opposition-based learning approach, the elite-opposition-based learning method has higher performance. The elite opposition-based learning approach is utilised to enhance population diversity and minimise the approach's probability.

Differential Evolution Algorithm

The Differential Evolution (DE) algorithm is derived from the Genetic Algorithm (GA), and it is expressed as;

$$\vec{t}_k(v) = \vec{t}_{d1}(v) + M.\left(\vec{t}_{d2}(v) - \vec{t}_{d3}(v)\right) \quad (14)$$

From the above equation, the scaling factor is represented by M three individual positions are represented by $\vec{t}_{d1}(v), \vec{t}_{d2}(v), \vec{t}_{d3}(v)$. The new position update is computed, and it is written as;

$$\vec{t}_k(v) = \vec{t}_*(v) + M.\left(\vec{t}_{d1}(v) - \vec{t}_{d2}(v)\right) \quad (15)$$

Time Complexity

The Black widow spider optimisation algorithms time complexity is expressed as $O(N \times \vartheta \times MAX\_IT)$. The population size is represented by N, the dimensionality is represented by ϑ, and the maximal number of iterations is represented by MAX_IT. The chaotic gauss sequence is utilised for initialising the population, and it is calculated as;

$$O(N \times \vartheta \times MAX\_IT + N \times \vartheta) = O(N \times \vartheta \times MAX\_IT) \quad (16)$$

4.2.3. FEBWS Algorithm Based Energy Efficient CH Selection

The fuzzy-enhanced black widow spider (FEBWS) algorithm proposed for identifying the ideal cluster head (CH) from the cluster group is described with its working procedure in figure 2. The proposed FEBWS algorithm integrates the fuzzy logic system with the improved black widow spider optimisation algorithm to effectively resolve the issues accompanied in selecting the ideal CH. The key objective of the CH selection process is to minimise the distance obtained between the chosen Cluster Head (CH) nodes, lower the packet delay in delivering the sensed information to the destination and reduce the energy nodes consume when broadcasting packets continuously to improve network lifetime. The proposed FEBWS technique initialises the black widow population in the search dimension representing the sensor nodes in the network using the gauss chaos mapping process. After initialising population members, the fitness values of each spider are evaluated. The relative significance of the model is defined using the fitness function. The fitness value of the black widow spider is computed by considering the distance obtained among the base station, nodal energy, and member node. This process is numerically described as,

$$fitnessfunction = \sum_k(\omega_k * F_k)\,\forall F_k \in \{\varepsilon, \partial\} \quad (17)$$

The fitness parameters are allotted a random weight function ω_k at the initial iteration. The terms $\varepsilon\partial$ represent energy consumption and packet delay, respectively. Based on the requirement of the application to broadcast sensed information to the destination(BS), the weight functions are updated, which is formulated as,

$$\varepsilon = \sum_{k=1}^{n}\varepsilon(k, CH) + \sum_{k=1}^{n}(n * \Re_Y) + \sum_{k=1}^{n}\varepsilon(k, BS) \quad (18)$$

The terms $\varepsilon(k, CH)$ indicate energy consumed on transferring data from k^{th} the sensor node to CH, energy consumed by the cluster head on transferring the n-bit message from the member node, and energy consumed on transferring data from $k^{th}$the sensor node to the base station. The mathematical expression defining total distance is modelled as,

$$\partial_T = \sum_{k=1}^{n}\partial(k, CH) + \sum_{k=1}^{m}\partial(k, BS) \quad (19)$$

The distance between$k^{th}$the node and the CH is denoted by$\partial(k, CH)$, and the distance amongk^{th} the node and the BS is indicated by$\partial(k, BS)$. After evaluating the fitness function, each spider's movement and location information is updated. Then, the pheromone rate of the black widow spider is optimally computed using a fuzzy logic system. The selection probability of the sensor node with a high fitness value is increased with the fuzzy logic system by effectively

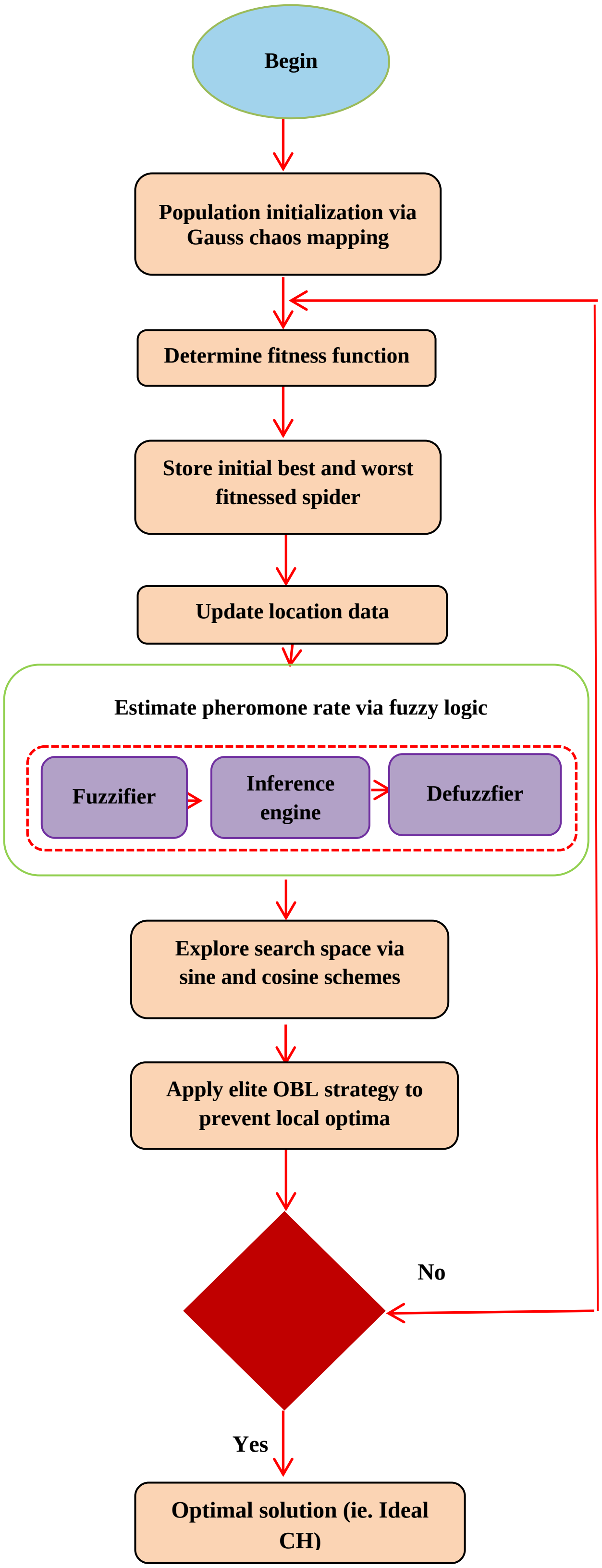

Fig. 2 Flow diagram of FEBWS algorithm

neglecting the worst node as CH. Subsequently, the exploration and exploitation abilities of the generated population are handled and balanced through sine and cosine schemes. The elite Opposition Based Learning (OBL) method is executed, which determines the fitness of the current best solution and its opposite solution. It is considered that the solution opposite to the best solution also obtains higher fitness values. The best fitness solution is compared with the current obtained solution. Thus, the FEBWS algorithm determines the optimal solution (i.e. optimal node which satisfies the objective function) as CH in the search dimension.

4.3. Intra-Cluster Communication

Long-distance Communication is utilised for minimising the network lifetime and consuming enormous energy. The member node is utilised for calculating energy consumption cost with various routing paths for transmitting the data or selecting the optimal relay nodes directly. The energy consumption based on the routing paths is calculated, and it is expressed as [20]

$$E_1(\delta_j, CH_{\delta j}) = \begin{cases} \tau . E_e + \tau . \in_{gt} . e(\delta_j, CH_{\delta j})^2 if e(\delta_j, CH_{\delta j}) < e_0 \\ \tau . E_e + \tau . \in_{nq} . e(\delta_j, CH_{\delta j})^4 if e(\delta_j, CH_{\delta j}) \geq e_0 \end{cases} \quad (20)$$

From the above equation, the distance between CH and the node $k$is represented by $e(\delta_j, CH_{\delta j})$. The total amount of energy consumption is computed, and it is expressed as;

$$\begin{aligned} E_2(\delta_j, \delta_k, CH_{\delta j}) &= E_{\Gamma X}\left(\tau, e(\delta_j, \delta_k)\right) + E_S(\tau) \\ &\quad + S_{\Gamma X}\left(\tau, e(\delta_k, CH_{\delta j})\right) \\ &= 3\tau . E + \in . e^2(\delta_j, \delta_k) + \in . e^2(\delta_k, CH_{\delta j}) \end{aligned} \quad (21)$$

The intracluster Communication is computed, and it is written as;

$$E(\delta_j) = MIN\left(E_1(\delta_j, CH_{\delta j}), E_2(\delta_j, \delta_k, CH_{\delta j})\right) \quad (22)$$

4.4. Inter-Cluster Communication

The greedy algorithm is utilised in inter-cluster Communication to design the chain that removes long-distance Communication. The chain formation process comprises two steps are as follows,

Step 1: The chain formation message is broadcasted by the sink and is obtained to report all cluster head's positions and IDs.

Step 2: When the sink receives information from the cluster head, the nearby CH is selected as the leader. The data packets are directly transmitted to the sink with the help of leader CH.

Step 3: Every cluster head obtained in the greedy algorithm transmits the data packets to relay cluster heads very close to the sink.

5. Experimental Results and Discussions

The fuzzy Enhanced Black Widow Spider (FEBWS) algorithm is proposed in this section for enhancing energy efficiency in WSNs. NS-2 simulator is used as a simulation tool to estimate the proposed FEBWS algorithm's performance by using some performance metrics, namely throughput, packet delivery ratio, network lifetime, and energy efficiency. The simulation parameter details are provided in table 1, and brief explanations about the result are provided in the next subsections.

Table 1. Simulation Parameters

Sl. No	Simulation parameters	Ranges
1	Simulator	NS-2.34
2	Total number of nodes	100
3	Coverage area	1000×1000
4	Initial energy	0.5 J
5	Packet size	4000bits
6	Simulation period	100 ms
7	Cluster head percentage	0.05

5.1. Hyperparameter Configuration

The hyperparameter configuration of the FEBWS algorithm is explained in table 2. The optimal parameter values are predicted through the hyperparameter tuning process, which enhances the performance of the proposed FEBWS algorithm.

Table 2. Hyperparameter configuration

Techniques	Parameters	Parameter ranges
IBW	Total number of population size	30
	Individual sex pheromones rate	<0.3
	u	2
	Number of iterations	500
	Mutation probability	≤0
FLS	Volatilisation coefficient	0.9
	Conditional variables value	1

5.2. Performance Evaluation Metrics

The energy efficiency of the proposed FEBWS algorithm in WSN is evaluated, and the mathematical equations are derived below,

The packet delivery ratio is expressed as,

$$\Gamma_{PDR} = \frac{\Sigma receivedpackets}{\Sigma sentpackets} \tag{23}$$

The operational time of the network to perform the specific task is known as network lifetime. The end-to-end delay network is derived as,

$$\Gamma_{EED} = M * \frac{L}{T} \tag{24}$$

From the above equation M, L and T are represented as the number of links, length of packets, and transmission rate, respectively. Throughput measures the number of packets successfully transmitted within a given time. The mathematical form of throughput is given by,

$$\Gamma_{throughput} = \frac{\Sigma successfullytransmittedpackets}{\Sigma time} \tag{25}$$

5.3. Performance Analysis

The proposed FEBWS algorithm's performance rate is evaluated using different parameters. Table 3 overall performance rate of the proposed FEBWS algorithm is mentioned.

Table 3. Overall performance analysis

Sl. No	Performance metrics	Performance rate
1	End-to-end delay	88 ms
2	Throughput	697 kbps
3	Packet delivery ratio	98.7%
4	Network lifetime	1400 seconds
5	Energy consumption	48%
6	Energy efficiency	92%
7	Packet drop	130 packets

5.4. Comparative Analysis

Figure 3 represents the energy efficiency analysis of nodes by using different methods like ACI-GSO algorithm, MWCSGA, RNN-LSTM model, PSO algorithm, and proposed FEBWS algorithm represented. The experiments are conducted using 100 nodes, and the efficiency is obtained as 92%. The proposed FEBWS algorithm achieved a higher efficiency compared to other existing methods. The energy efficiency rate of 77%, 86%, 70%, and 62% are attained from the ACI-GSO algorithm, MWCSGA, RNN-LSTM model, and PSO algorithm, respectively.

Figure 4 represents the end-to-end delay analysis using the ACI-GSO algorithm, MWCSGA method, RNN-LSTM model, PSO algorithm, and proposed FEBWS algorithm. In the FEBWS algorithm, the end-to-end delay is low. The proposed FEBWS algorithm provided a lower end-to-end delay of 88 ms, improving the energy efficiency in WSN.

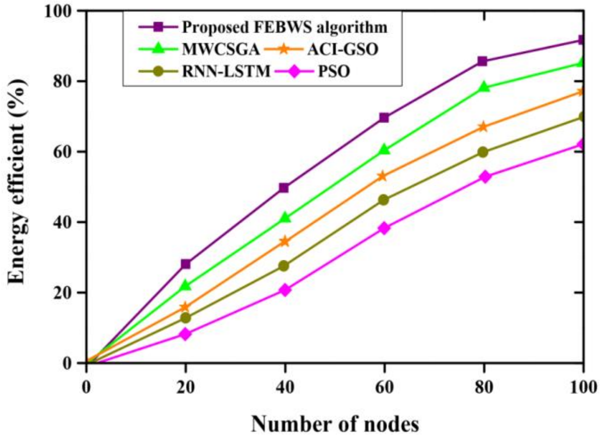

Fig. 3 Comparative evaluation based on energy efficiency

Figure 5 shows the packet drop of various methods, such as the ACI-GSO algorithm, MWCSGA method, RNN-LSTM model, PSO, and FEBWS algorithm. The lower packet drop obtained a better performance, and the proposed FEBWS algorithm attained a low packet drop of 130 packets. The remaining methods, namely the ACI-GSO algorithm, MWCSGA method, RNN-LSTM model, and PSO algorithm, provide the packet drop of 350 packets, 160 packets, 540 packets, and 630 packets, respectively.

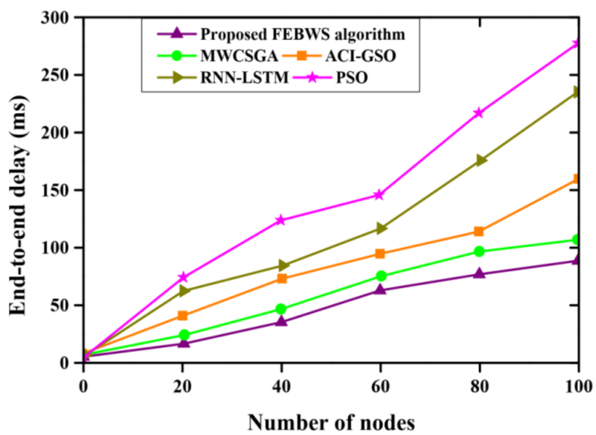

Fig. 4 Comparative evaluation of end-to-end delay

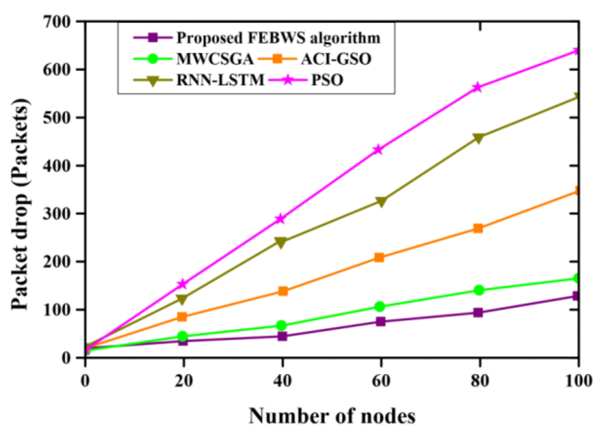

Fig. 5 Comparative evaluation of packet drop

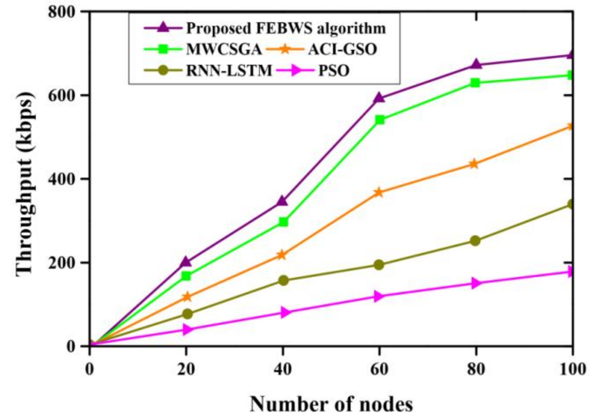

Fig. 6 Comparative evaluation of throughput

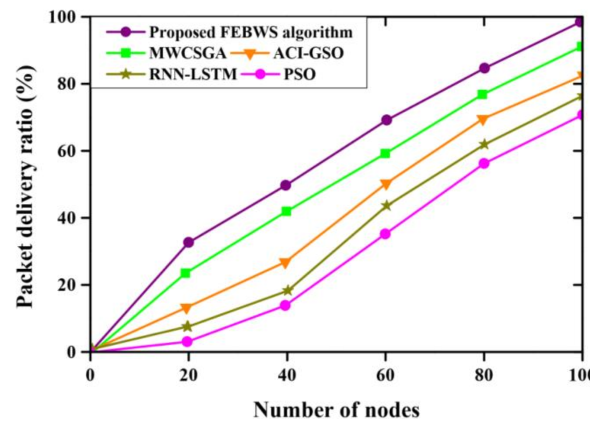

Fig. 7 Comparative evaluation of packet delivery ratio

Figure 6 portrays the throughput analysis of nodes using different methods such as the ACI-GSO algorithm, MWCSGA method, RNN-LSTM model, PSO algorithm, and proposed FEBWS algorithm. The proposed FEBWS algorithm achieved a high throughput of 697 kbps from this comparative analysis. Throughput of 529 kbps, 650 kbps, 360 kbps, and 180 kbps are obtained from the ACI-GSO algorithm, MWCSGA method, RNN-LSTM model, and PSO algorithm, respectively. Packet delivery ratio analysis of various methods such as ACI-GSO algorithm, MWCSGA, RNN-LSTM model, PSO algorithm, and proposed FEBWS algorithm is delineated in figure 7. The proposed FEBWS algorithm achieved a higher packet delivery ratio and is about 98.7%. The PSO algorithm has a lower packet delivery ratio of about 71% compared to other state-of-the-art methods. This higher packet delivery ratio represents better performance related to other methods. The network lifetime of the proposed FEBWS algorithm is compared with other existing methods, namely the ACI-GSO algorithm, MWCSGA, RNN-LSTM model, and PSO algorithm is described in figure 8. The proposed FEBWS algorithm attained a higher network lifetime of 1400 seconds which enhances the energy efficiency in WSN. This graph shows the attained network lifetime of 1130 seconds from the ACI-GSO algorithm, 1185 seconds from MWCSGA, 900 seconds from the RNN-LSTM model, and 820 seconds from the PSO algorithm.

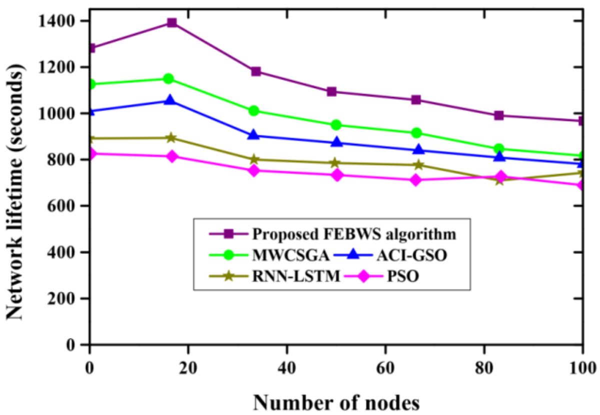

Fig. 8 Comparative evaluation of network lifetime

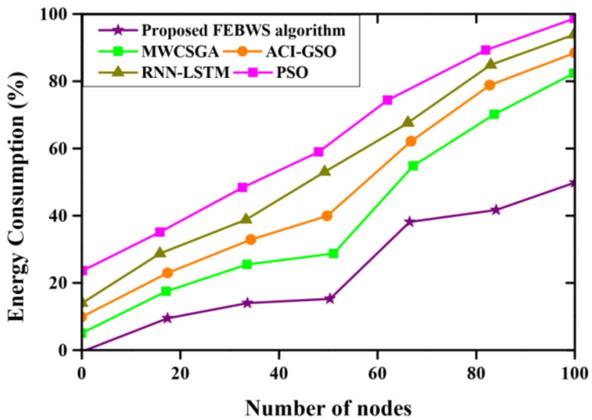

Fig. 9 Comparative analysis of energy consumption

Figure 9 represents the energy consumption of different methods like the ACI-GSO algorithm, MWCSGA, RNN-LSTM model, PSO algorithm, and proposed FEBWS algorithm. The proposed FEBWS algorithm achieved a lower energy consumption of 48%, showing better performance. 88%, 83%, 94%, and 98% of energy consumption are attained from the ACI-GSO algorithm, MWCSGA, RNN-LSTM model, and PSO algorithm, respectively.

6. Conclusion

In this paper, the FEBWS algorithm is proposed to increase the energy efficiency in WSNs. NS-2 simulator is used to estimate the performance of the proposed method. The optimal parameter values are predicted through a hyperparameter tuning process which enhances the performance of the proposed method. Performance metrics are utilised to evaluate the performance, namely end-to-end delay, throughput, packet delivery ratio, network lifetime, energy efficiency, packet drop, and energy consumption. For comparative study, the proposed FEBWS algorithm is compared with other existing methods, namely the ACI-GSO algorithm, MWCSGA, RNN-LSTM model, and PSO algorithm. The proposed FEBWS algorithm achieved an energy efficiency of 92%, end-to-end delay of 88 ms, packet drop of 130 packets, throughput of 697 kbps, packet delivery ratio of 98.7%, network lifetime of 1400 seconds and energy consumption of 48%, respectively. The experimental results revealed that the proposed FEBWS algorithm performs better than other existing methods. In the future, this FEBWS algorithm will be extended to cover the simulation on larger sensor nodes, and node localisation problems can be discussed for particular applications.

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