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Original paper

Energy efficient congestion control scheme for wireless sensor networks using adaptive neuro fuzzy inference system with black widow optimization

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Abstract

Network congestion is one of the major issues in wireless sensor networks (WSNs) that result in packet loss, reduced network lifetime, low throughput and energy waste. Determining a better path to mitigate the congestion is a better approach to improve the performance of WSNs. In this paper, an adaptive neuro-fuzzy inference system (ANFIS) based path determination approach is proposed to mitigate the congestion with black widow optimization (BWO) algorithm. The proposed approach first develops a framework to mitigate the congestion in WSNs. Then it forecast the buffer occupancy with the exponential smoothing technique. Finally, ANFIS is applied in the proposed approach for determining the path with appropriate weights by considering the remaining energy, hop count and buffer occupancy. Here, the hop count, buffer occupancy and remaining energy are considered as the input factors for the ANFIS. The simulation results of the proposed method show better quality of service, high energy, low delay, high packet delivery ratio with number of increasing alive nodes when compared to existing methods.

Keywords: Wireless sensor networks, energy efficient, congestion, ANFIS, BWO, packet delivery ratio.

1 Introduction

Nowadays communication environment is becoming more and more complicated with the number of sensing based devices connected to the Internet of Things (IoT). Thus, the sensor-based network is facing congestion issues due to the overwhelming amount of data. WSNs are the trending area in various applications of IoT such as environmental monitoring, intrusion detection, healthcare and target tracking. WSNs consist of a network tool to fetch data from sensed area through wireless links. The main key function of WSNs is monitoring the environmental conditions like target detection, earthquakes, ood or re expulsion and so on [20]. For this purpose, it comprises a huge number of minimized power multi-functional sensor nodes to sense and send information from the environment [16]. Though, it also has its own limitation in terms of memory, computing, battery life and transmission capacity [17]. Hence, the sensed as well as transmitted signals should be carefully maintained and used.

In WSNs, congestion is one of the main challenging issues. When the nodes traffic load goes beyond its available capacity limited resources of sensor nodes cause congestion. It mainly occurs due to node buffer overflow, packet collision, contention of transmission channel, information transmission from many-to-one, etc [22]. Serious problems such as low throughput, high energy consumption and packet loss, may be caused by congestion that is enormously harmful impact on the WSN's performance [5]. Therefore, an effective approach for congestion mitigation is required in WSNs. In this paper, a congestion prediction approach is proposed with adaptive neuro fuzzy inference system (ANFIS) to determine the adaptive paths. The input parameters of membership function [2], [24] of ANFIS are optimized with BWO algorithm by considering the remaining energy, hop count and buffer occupancy.

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The main contributions of this paper are as follows.

1. Introduce architecture to mitigate the congestion in WSNs.
2. Predict the buffer occupancy with the exponential smoothing technique.
3. Apply ANFIS for determining the path with appropriate weights by considering the remaining energy, hop count and buffer occupancy.
4. Tune the input parameters of ANFIS membership function with BWO algorithm.

The remaining sections of this paper are structured in the following manner. Related works are reviewed in Section 2. Section 3 describes the preliminaries of the methods, Section 4 explains the network model of WSNs and assumptions considered in the proposed methodology. Section 5 describes the proposed optimized ANFIS congestion control system for path determination. Section 6 details the experimental analysis. Section 7 examines the simulation results evaluated for the proposed strategy. Finally, the paper is concluded under Section 8.

2 Related work

In [18] suggested a hybrid congestion control algorithm in WSNs. The major reason behind the occurrence of congestion is the service time which is more prominent than the inter-arrival time of packets. The rate of congestion can be controlled by considering the priority of packets with hybrid congestion control algorithm. [9] proposed a congestion control protocol named Reliable Efficient, fair and interference-aware congestion control protocol (REFIACC). REFIACC avoids interference, guarantee an increased fairness of bandwidth utilized between the sensor nodes by scheduled transmission. Congestion during intra and inter path hotspots are reduced based on the difference between link capacities at the time of process planning.

In general, congestion occurs due to heavy traffic flow rate from high density sensors [11]. [16] designed a fast congestion control method on routing with hybrid optimization algorithm. [4] established a synchronization scheme to control congestion in underwater wireless sensor networks. [3] recommended control of sensor queues protocol. It works on the basis of capturing the level of single-hop nearby nodes and analyzing the length of the queue. [23] implemented fairness congestion control for distrustful wireless sensor network using fuzzy logic (FCCTF). It is an improved combination of fairness congestion control where decision making algorithm based on threshold trust value is used to analyze the traffic ratio. [8] estimated congestion in WSNs by fuzzy based adaptive congestion control.

In [13] suggested congestion detection protocol based on ANFIS. Using fuzzy logic, a priority-based congestion control mechanism for WSNs is invented by [7]. This strategy makes an effort to differentiate among the neighborhood information. The transmission of data is done on need-based system following novel queueing model. [21] presented fuzzy logic-based congestion control technique with the benefits of buffer occupancies.

In [12] suggested an improved bat algorithm mainly depends on echolocation of bats to control congestion in transport layer of wireless sensor networks. Ant colony optimization (ACO) based learning is examined by [20]. [15] utilized firefly calculation to prepare an adaptive neuro-fuzzy inference systems boundary. It is mainly used in stock exchange with period arrangement structure.

In [19] proposed a novel Fuzzy Temporal Rule-Based Cluster-Based Routing Algorithm (FTR-ODA) for outlier identification and trust analysis model for monitoring the participating nodes in data transmission mechanism. The creators of the suggested secured routing algorithm have discriminated between trustworthy and malicious nodes using FTR-ODA. By making effective routing and authentication decisions, they also separated the rogue nodes. In terms of data backup, communication dependability, end-to-end latency reduction, packet delivery ratio, and energy use reduction, the suggested FTR-ODA has shown better service quality. The negatives of this strategy are that it encourages more malevolent individuals since when data is lost, it cannot be recovered because there is no data backup.

In [10] came up with a creative plan to reduce overall energy use. The recommended strategy states that the optimal CH was selected using a Butterfly Optimization Algorithm (BOA) and based on factors such as residual energy, distance to neighbours, distance to base station, node degree, and node centrality. In order to select the optimum course of action for achieving these goals, ACO was utilized. The performance of the proposed model was demonstrated to be significantly superior to that of the leading-edge models in terms of received data packets, dead nodes, energy consumption, and living nodes. However, this technique had more packet drops, which resulted in data loss.

The Exponential Moving Average (EMA) based Replica Detection (EMABRD) technique was created by [1] to identify replica nodes based on threshold energy usage. By utilizing Secured Ant Colony Optimization and Fingerprint based Zero Knowledge Authentication, the detection likelihood, storage, and communication overheads of EMABRD tend to be reduced. But this method has drawbacks, including increased computing costs, high communication costs, more overhead, and shorter life span.

Various authors implemented different techniques in WSNs to detect and control congestion. But there have some drawbacks like time delay, loss of packets etc. In this paper, an adaptive neuro fuzzy inference system using fuzzy logic system (FLS) is proposed for detecting congestion level in WSNs. ANFIS utilize gradient-based methods to examine the weights and variables. Black widow optimization algorithm is utilized to enhance the execution of ANFIS by tuning the input parameters of the membership function.

3 Preliminary

3.1 Adaptive neuro-fuzzy inference system (ANFIS)

The Takagi-Sugeno Fuzzy System, also known as adaptive neuro-fuzzy inference systems, was created in 1993 by J.S. Roger Jang and is commonly recognized as a universal estimator. The Takagi-Sugeno Fuzzy Model is a Type 3 Fuzzy Inference System, where the final output is the weighted average of the outputs of all the rules, and the rule outputs are a linear combination of the input variables and a constant.

The IF-THEN rules for a 3-input Takagi-Sugeno system are described as follows.

- Rule 1: If a is X_1, b is Y_1, c is Z_1, Then $mf_1 = u_1a + v_1b + w_1c + s_1$.
- Rule 2: If a is X_2, b is Y_2, c is Z_2, Then $mf_2 = u_1a + v_2b + w_2c + s_2$.
- Rule 3: If a is X_3, b is Y_3, c is Z_3, Then $mf_3 = u_3a + v_3b + w_3c + s_3$.

Here, a, b, c are the crisp group input, X_i, Y_i, Z_i are the labels of linguistic, u_i, v_i, w_i are the consequent attributes and mf_1, mf_2, mf_3 are the fuzzy membership function output. The standard ANFIS framework is illustrated in Figure 1.

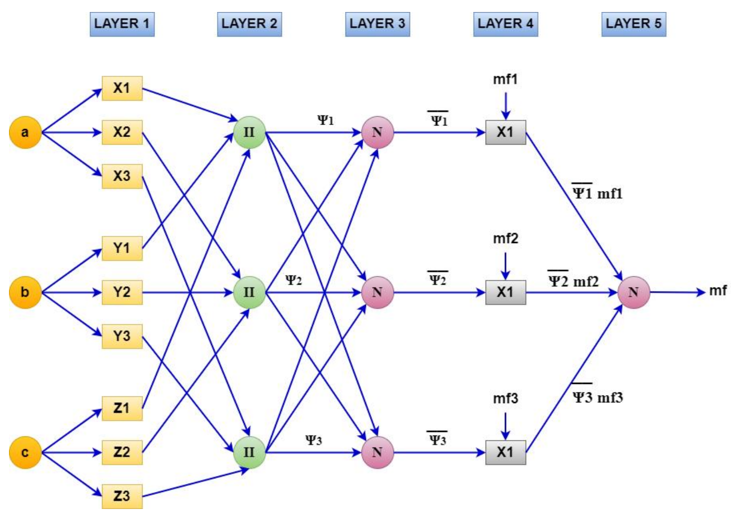

Figure 1: Standard structure of ANFIS

3.2 Black widow optimization (BWO)

Due to their simplicity and flexibility, a novel metaheuristic optimization method based on the black widow spider's mating behaviour was initially suggested by V. Hayyolalam and A. Pourhaji Kazem in 2020. This approach has been utilised to tackle several technical and scientific challenges. The distinctive mating habits of black widow spiders served as the basis for the Black Widow Optimization (BWO) Algorithm. Cannibalism is a unique step in this process. This stage results in early convergence because species with the wrong fitness are excluded from the circle. To assess the BWO algorithm's effectiveness in finding the best solutions for the challenges, 51 different benchmark functions and three actual engineering optimization problems are used. The BWO algorithm differs from other approaches in a number of key ways. The BWO algorithm gives quick convergence speed and prevents local optima problems while performing well in the exploitation and exploration stages. Also worth mentioning is BWO's capacity to maintain a balance between exploitation and exploration.

4 Models and assumptions

The network model, required messages and energy models are discussed in this section.

4.1 Network models

In this network, only one sink node is present at the end of the network. The source node sends the data to the sink node through the non-uniform deployments or neighboring nodes. The Sensor nodes (SNs) are arranged randomly with equal initial energy. There is no explicit information of location and no mobility is involved after the deployment of SNs. Similar communication range is considered for each SN. These assumptions are considered in this paper. An example of the proposed network model with source, sink and other SNs are shown in Figure 2.

From each SN to its neighboring node (NN), the communication connectivity and its range are represented by the dashed line. The broadcast message determines the arrow head. Based on the hop counts the network will be generally separated into layers. The data will send by the source node to the sink node, once the path has been defined.

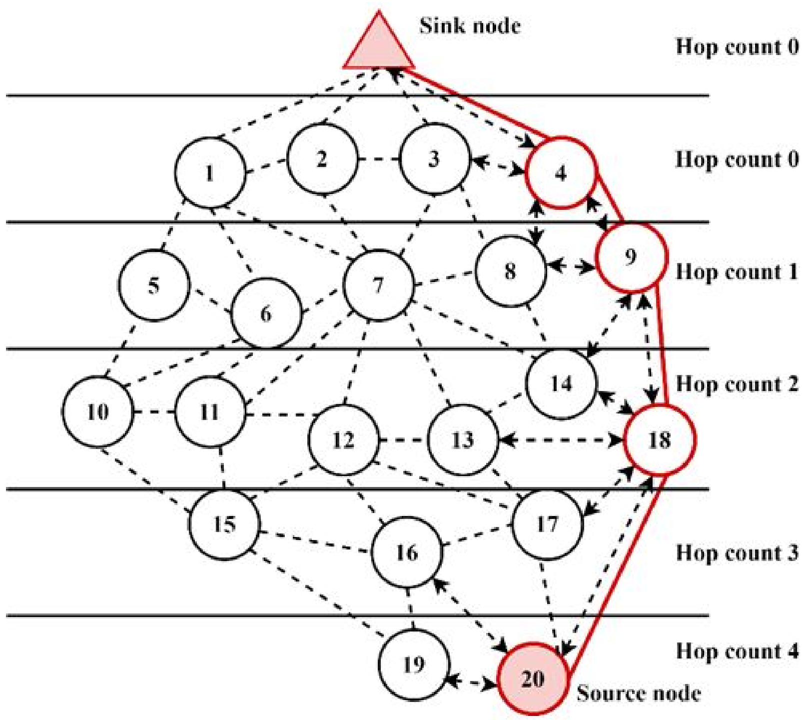

Figure 2: Network model

4.2 Energy models

The energy model for WSN is shown in Equation (1). The i_{th} bit transmission energy E_{Tx} is introduced underneath.

$$E_{Tx}(i,d) = i * E_{elec} + i * E_{tran} * d^2. \tag{1}$$

Where distance is represented by d in the free space propagation model E_{elec} express the energy of information processing and E_{tran} express the energy for one bit transmission at distance d. Similarly, i_{th} bit receiving energy E_{Rx} is given in Equation (2).

$$E_{Rx}(i) = i * E_{Reci}. \tag{2}$$

Where E_{Reci} express the energy for 1 bit receiving.

4.3 Messages of system

Both the unicast and broadcast of the proposed architecture have eight types of messages.

1. Route-Update-Message. To the neighbors this message is broadcasted if enough energy is not possessed by a node for performing an operation. This includes the identifier of node.
2. Route-Request-Message. This message is broadcasted to neighbors, to generate a route query. This includes the hop count and identifier of node.
3. Route-Reply-Message. This message is broadcasted by neighbors, once it receives Route-Request-Msg. This includes the hop count and identifier of node.
4. Route-End-Message. This message is broadcasted by specific node, when no Route-Reply-Message is sent back within a particular time-out. The end of the hop tree is indicated by this message.
5. Request-Stage-Message. For the weight inquiry, this message is broadcasted to the neighbors of SNs.
6. Data-Sent-Message. After the determination of the final path, this unicast message is utilized for the transmission of data.
7. Reply-Stage-Message. Each SN will broadcast this message, after Request-Stage-Message has been received.
8. Data-Ack-Message. This message is utilized for the confirmation of transmission of data.

5 Proposed BWO optimized ANFIS (BWO-ANFIS)

Network congestion is considered as a main problem in resource-constrained networks. This is due to the availability of finite number of bandwidths to transfer huge content of data. The proposed method makes use of ANFIS that belongs to a family of hybrid neuro-fuzzy with neural networks and fuzzy logic. ANFIS is enhanced by a meta-heuristic algorithm called black widow optimization. The architecture BWO-ANFIS is shown in figure 3. It consists of four main components.

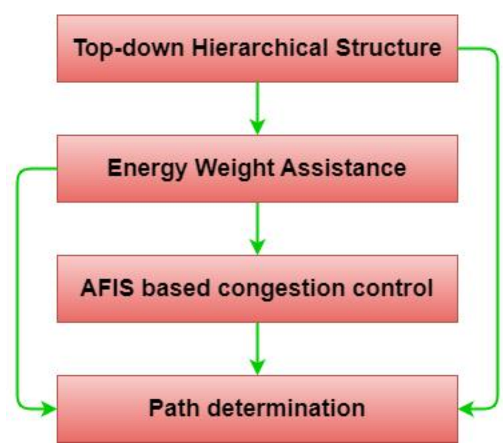

Figure 3: Proposed BWO-ANFIS

5.1 Structure of top-down approach

This approach is utilized at first with hop count as the main metric for the generation of layer-based architecture. A many-to-one-structure is generated by the non-infrastructure less network called AODV from SNs to the sink node. Route create and route update are the two main steps used.

5.1.1 Route create phase

The sink node is recognized as root node of the tree. After the root, an extra layer is crossed in a top-down method until reach the source node. At hop count is zero, the Route-Request Message is broadcasted by the sink node to the neighbor nodes. This information is stored in the neighbor table and hop count is increased by 1 once all neighboring node get this message. Then Route-Reply-Message is send by the neighbor node for the confirmation of its receipt. This process is repeated until there are no extra neighbor nodes. At the end node, the Route-end-Message is send back to the former node. This process is repeated until reach the sink node. This message is employed for the determination of each paths maximum hop count. Six possible paths to the sink node from the SN=20 are shown in Figure 4.

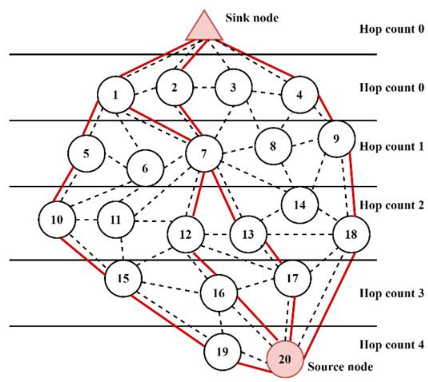

Figure 4: Route Create-Example of possible path selection

5.1.2 Route update phase

The Route Update Phase is employed for switching the route to avoid the disconnectivity. The lack of energy creates the disconnectivity. Hence, energy threshold is applied for all the SNs. If the energy level becomes low behind the threshold, a Route-Update-Message is send by the SN to its nearby nodes for the table updation. An example of route update phase is shown in figure 4. From the possible paths, the final determined path is shown in figure 5(a). The 18th SN will send the Route-Update Message and update the table when the energy is low as shown in Figure 5(b). The final determined path is shown in Figure 5(c).

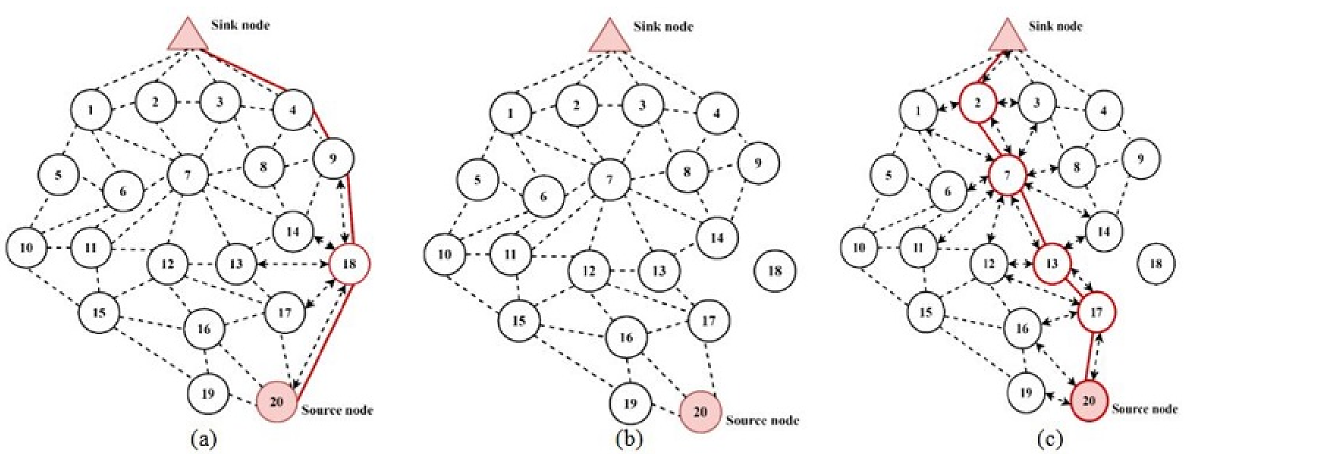

Figure 5: Route Update Phase example

Table 1: ANFIS if-then rule

IF			THEN
Hop Count	Energy	Buffer occupancy	Weight
Lw	Lw	Lw	Vry Hgh
Lw	Lw	Mdm	Lw
Lw	Lw	Hgh	Lw
Lw	Mdm	Lw	Vry Hgh
Lw	Mdm	Mdm	Lw
Lw	Mdm	Hgh	Lw
Lw	Hgh	Lw	Vry Hgh
Lw	Hgh	Mdm	Mdm
Lw	Hgh	Hgh	Mdm
Mdm	Lw	Lw	High
Mdm	Lw	Mdm	Lw
Mdm	Lw	Hgh	Lw
Mdm	Mdm	Lw	Hgh
Mdm	Mdm	Mdm	Mdm
Mdm	Mdm	High	Mdm
Mdm	Hgh	Lw	Vry Hgh
Mdm	Hgh	Mdm	Hgh
Mdm	Hgh	Hgh	Hgh
Hgh	Lw	Lw	Mdm
Hgh	Lw	Mdm	Mdm
Hgh	Lw	Hgh	Mdm
Hgh	Mdm	Lw	Mdm
Hgh	Mdm	Mdm	Hgh
Hgh	Mdm	Hgh	Hgh
Hgh	Hgh	Lw	Hgh
Hgh	Hgh	Mdm	Vry Hgh
Hgh	Hgh	Hgh	Vry Hgh

5.2 Energy assisted route weight

The component is utilized for the weight generation with ANFIS. Remaining energy, hop count and buffer occupancy [6], [14] are considered as the ANFIS input. The final weight is determined by the ANFIS based on the membership function.

5.2.1 Adaptive nuero fuzzy inference system

ANFIS is a feed-forward multi-layer classifier formed from the combination of neural network with the addition of fuzzy logic idea. The membership function of ANFIS represents the output and input. Network architecture of ANFIS consists of five-layered adaptive network where the principal layer is a membership function of an info variable for fuzzification.

It is used to normalize the input between o and 1. To determine the crossing points of each function, the input is mapped. The Gaussian function is used as the membership function. The second layer is a rule based layer which determines firing strength of every rule followed by a normalizer layer. Based on the membership function, the input to output mapping is generated by this layer. Table 1 shows the ANFIS rules for the three input parameters with a combination of low (lw), medium (mdm), high (hgh) and very high (vry hgh). Using an aggregation method, output is derived with the fuzzy rule based system. The final output is computed by the defuzzifier.

The energy assisted routing weight is the output of this system. The membership function for three inputs is shown in Figure 6. Membership function is a function that specifies the degree to which a given input belongs to a set. The output of a membership function is reffered as degree of membership, this value is always limited to between 0 and 1. Also known as a membership value or membership grade. Membership functions are used in the fuzzification and defuzzification steps of a FLS, to map the non-fuzzy input values to fuzzy linguistic terms and vice versa.

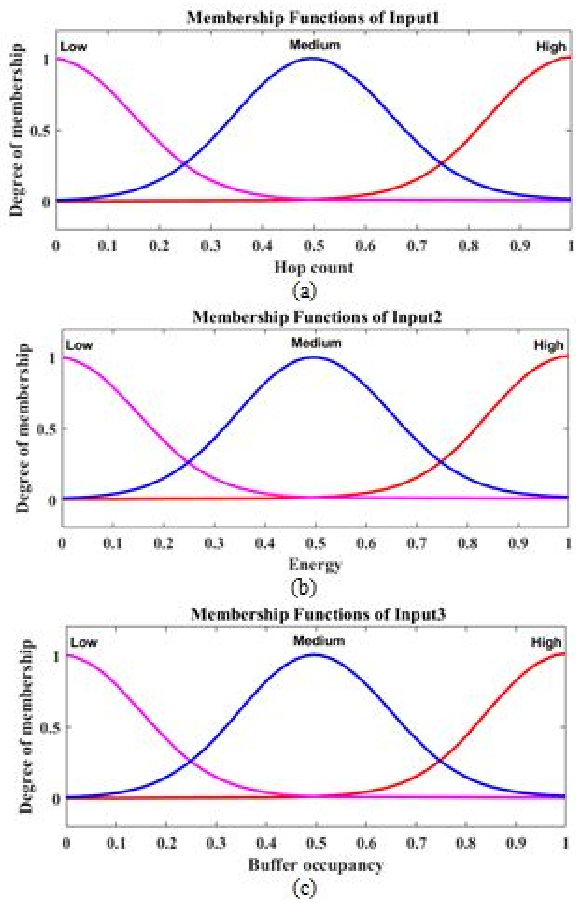

Figure 6: Membership function of ANFIS inputs (a) Input 1 (Hop count) (b) Input 2 (Remaining Energy) (c) Input 3 (Buffer Occupancy)

A membership function curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. The input space is sometimes referred to as the universe of discourse.

The Figure 7 shows the example for EW ANFIS with 27 rules. There are two normalized inputs, i.e., hop count and remaining energy, here with 0.5 as examples. With these inputs, each fuzzy set is considered with AND operation; i.e., the minimum among the twos will be selected to cross over the weight, resulting in output. Next, the aggregation method is applied over the 27 rules before applying the defuzzifier in the next component.

5.2.2 Input parameters of membership function tuning using BWO

In this work, BWO is utilized to tune the input parameters of membership function (MF) of ANFIS. At first the input parameters of membership function are initialized as the population.

The fitness value of the parameters is evaluated to select the best parameters for procreation. The root mean square error (RMSE) is used as the objective function to find the fitness value that should be minimized. The RMSE can be calculated using the Equations (3-4).

$$y_1 = \alpha \times x_1 + (1 - \alpha) \times x_2, \tag{3}$$

$$y_2 = \alpha \times x_2 + (1 - \alpha) \times x_1. \tag{4}$$

Where, y_1 and y_2 represents the offspring, α is a smoothing factor and x_1 and x_2 represents the parents. Then Cannibalism is carried out to omit inappropriate solutions.

Remaining solutions are added with the population. For the mutation process, the parameters are randomly selected from the population. The generated new solution from mutation process is saved in the population.

5.3 Path determination

This component is employed after weight derivation to determine the final path towards the sink node. The path is selected from the 3 classes based on requirements of user.

- Case I: Top-Down approach. Hop counts from the sink node is determined by all SNs after the Route Create phase. The parent is selected by SN with lowest hop count to send the packet upward.
- Case II: Routing Weight based on Assistance of Energy. With the maximum EW, the parent can be selected by the particular SN with an additional process to determine the weight.
- Case III: Prediction and Control of Congestion. Link score (LS) is defined as the path selection measure over EW as derived in Equation (5).

$$LS = EW * \gamma. \tag{5}$$

Here, the weighted constant is represented by γ that determine a relationship between these two factors. The range of this constant is lies between 0 and 1. With the maximum LS, a specific SN can choose the parent after the determination of LS. Where target data is represented by t and function of input data is represented by y. The error function value to be minimized is represented by e and EW represents the energy-assisted routing weight.

The probability of selection is increasing as the lower of the fitness value. After the selection process the selected parameters are procreated for reproduction using Equations (6-8).

$$RMSE = \sqrt{Mean(e_2)}. \tag{6}$$

$$Objective function = min(RMSE). \tag{7}$$

$$e = t - y. \tag{8}$$

6 Experimental setup

The NS2.34 simulator network is used to generate the input parameters and AWK script is used for parameter extraction. The ANFIS is simulated using MATLAB software. The Simulation parameters of the proposed network structure are given in Table2. The simulation is carried out for two cases: case 1: the sink node is presented in the top centre and case 2: the sink node is situated in the top edge. Figure 8 (a, b) demonstrates the deployment of nodes in the network area 100x100. In Figure 7(a) the sink node is placed in the center of the network and its performance is evaluated and next in Figure 7 (b) the sink node is placed at the top edge of the network and its performance is evaluated.

Table 2: Network setup

Parameter	Value
Area	100x100
Number of sensor node	20-300
Number of sink node	1
Initial energy	10 Joules
Packet size	128 bytes
mobility	No
Transmission range	50 meters
Sensing range	100 meters

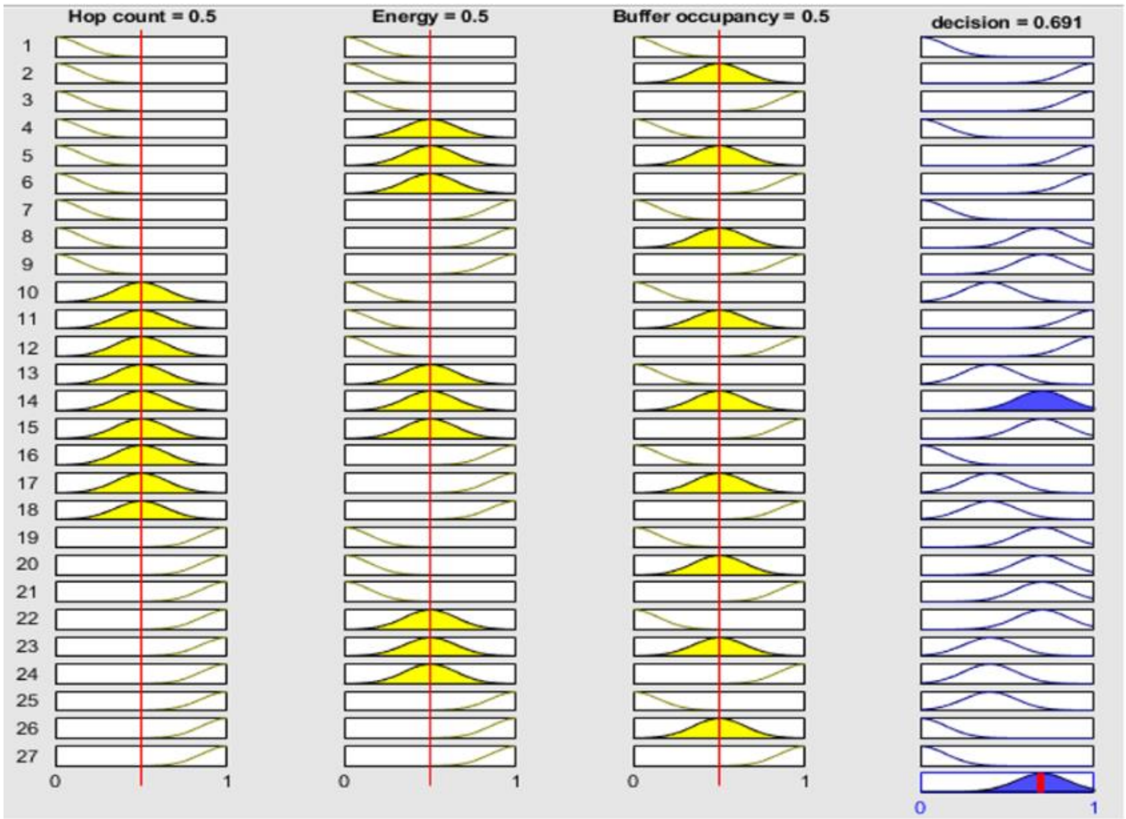

Figure 7: Trained EW ANFIS

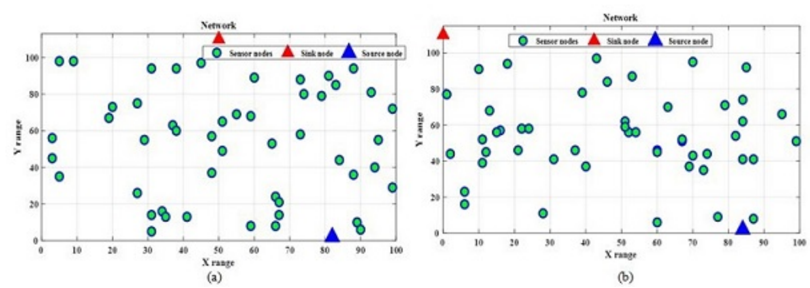

Figure 8: Network setup (a) Sink node located at top centre (b) Sink node located at top edge

7 Simulation result and analysis

This section shows the simulation outcomes of proposed ANFIS-BWO based congestion control scheme. The results of proposed approach are compared with other existing congestion control algorithms such as hybrid Fuzzy with Grey Wolf Optimization (F-GWO) approach, Swarm Intelligence with Adaptive Neuro-Fuzzy Inference System based Routing (SI-ANFISR), fuzzy and LEACH in terms of end-end delay, packet delivery rate, the number of remaining alive nodes, the energy consumption of nodes, throughput and routing overhead.

7.1 Energy consumption

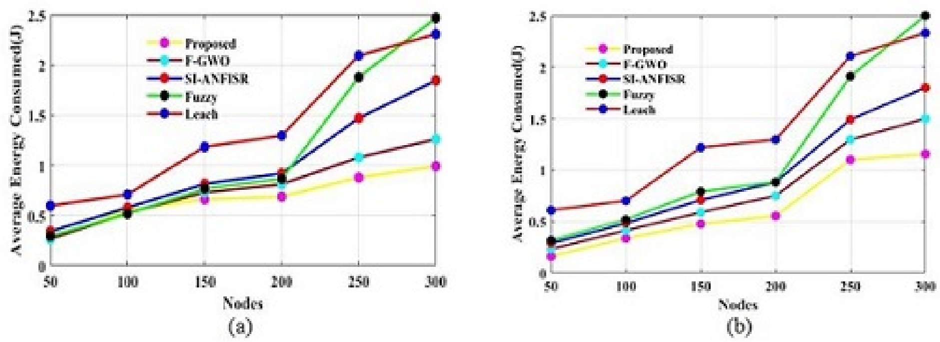

Figure 9: Average energy consumption comparison by varying number of nodes

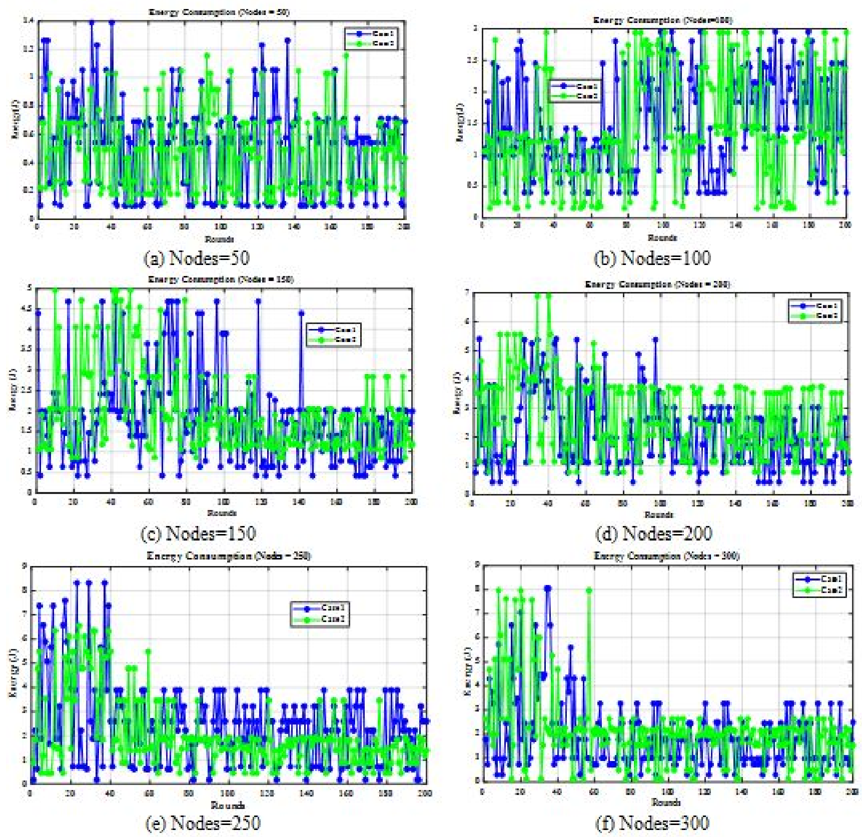

Figure 10: Energy consumed by nodes per round

The quantity of energy used to send and receive data packets over the network is referred as energy consumption. The average energy consumption of proposed approach by varying the number of nodes is compared with other existing approaches such as fuzzy and leach for the two cases (case 1: sink is located at the top center of the sensing field, case 2: sink is located at the top edge of the sensing field) as shown in Figure 9(a-b). From the results it can be known that the proposed approach consumes less energy compared to others due to its effective selection of intermediate nodes for routing. The proposed approach balances both the congestion control and energy consumption of the nodes. The for proposed approach than the existing approaches.low energy consumption for the proposed ANFIS-BWO protocol is achieved due to the prominent selection of relay nodes. Figure 10 (a-f) shows the energy consumption of nodes during each round of proposed approach. From the results it can be known that the variation in energy consumption is based on the location of sink node (case 1) and source node (case 2). Moreover, the comparison results show that, the energy consumption is increasing as the increase in the node count.

7.2 Alive nodes

In a network, the term "alive nodes" refers to the number of nodes that have sufficient energy to finish their cycle. When the network has a higher percentage of living nodes, the network's existence is improved. The number of remaining alive nodes comparison for the two cases (case 1: sink is located at the top center of the sensing field, case 2: sink is located at the top edge of the sensing field) is shown in Figure 11 (a-b). If the energy of any node is lost then it will die and get out of the network topology. Energy of majority of intermediate nodes will lose, because the data transmitted through only one path from a downstream node to an upstream. On analyzing Figure 11 (a and b) it is found that the proposed ANFIS-BWO protocol attains greater number of alive nodes when compared to existing approaches. The equalized energy utilization of the node gets achieved by selecting shortest way between nodes and sink node.

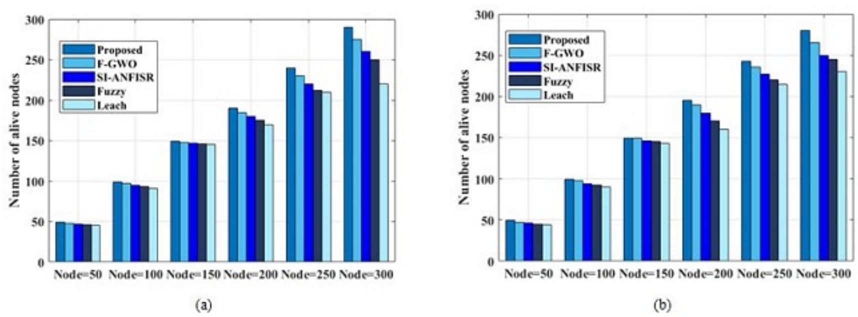

Figure 11: Alive sensor nodes comparison by varying number of nodes

7.3 End-end delay

The time taken for a transmitted packet to be received at the destination is defined as delay. The figures 12 (a-b) show the end-end delay comparison for two cases, case 1: sink is located at the top center of the sensing field, case 2: sink is located at the top edge of the sensing field. From the results it can be known end-end delay for that proposed approach is less due to traffic free packet transmission to the base station by proposed framework. The end-to-end delay of the proposed ANFIS-BWO approach is less when compared to the F-GWO, SI-ANFISR, Fuzzy, and LEACH. The THFCMR approach's lower EED is mostly due to the absence of rerouting necessary in the event of node failure.

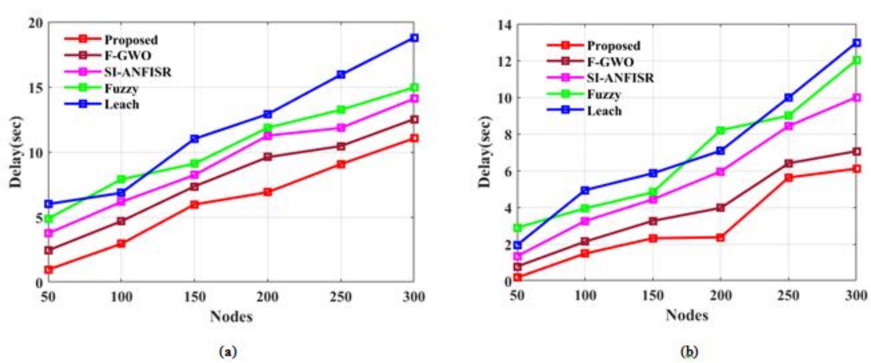

Figure 12: End-End Delay Comparison by varying number of nodes

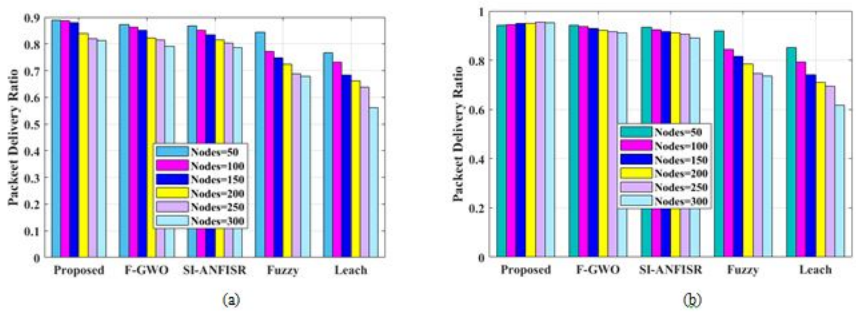

Figure 13: Packet delivery rate comparison by varying number of nodes

7.4 Packet delivery rate

Generally, any node failure in the network during data transmission causes packet drop. The ratio between the total numbers of packets transmitted by the transmitter to number of successfully received packets by the receiver at the destination. The comparison of packet delivery rate for the two cases (case 1: sink is located at the top center of the sensing field, case 2: sink is located at the top edge of the sensing field) is shown in Figure 13 (a-b). The proposed ANFIS protocol selects the best node for transmission. From the comparison graph it can be known that the packet delivery rate of proposed ANFIS is higher than other approaches due to the selection of proper relay nodes with high probability. In the Figure 13 (a-b) the number of nodes is changed from 50 to 300 to examine the ability of proposed ANFIS-BWO approach, when the number of nodes increases the delivery rate of the packet decreases. Finally it is found that the delivery rate of the proposed ANFIS-BWO is highly comparative to existing algorithms due to the selection of optimal path with high probability and higher data transfer rate.

7.5 Throughput

The quantity of data units a framework can measure in a specific amount of time, as shown in Equation (9), is known as throughput.

$$\text{Throughput} = \frac{\text{Number of packets received by the SN}}{\text{Simulation time}}. \tag{9}$$

Table 3: Throughput

Number of nodes	Proposed ANFIS-BWO	F-GWO	SI-ANFISR	Fuzzy	LEACH
52	1.83	1.74	1.68	1.63	1.59
100	1.87	1.81	1.77	1.72	1.64
150	1.92	1.88	1.82	1.78	1.68
200	1.96	1.92	1.87	1.85	1.73
250	2.04	1.96	1.91	1.89	1.78
300	2.08	1.99	1.95	1.92	1.87

Table 3 shows how the proposed ANFIS- BWO throughput varies when compared to F-GWO, SI-ANFISR, Fuzzy, and LEACH while operating with different numbers of nodes. It is amply demonstrated that the suggested ANFIS-BWO approach has a greater throughput rate than the currently used methods. This is due to the fact that ANFIS-BWO selects the most effective method for data transmission to the sink node. The quickest path and highest energy value relative to alternative routes to the sink are taken into consideration while choosing the routes. Thus, using this approach will result in very minimal packet losses. As a result, the suggested approach sends more data bits by choosing the optimum path for data transfer than existing techniques. Mbps are used to describe throughput.

7.6 Routing overhead

The extra control packets that must be sent in order for data packets to be successfully delivered cause routing overhead. It is the proportion of data packets received at the destination node to the total number of routing control packets delivered by all nodes. The routing overhead is computed by Equation (10).

$$\text{Routing Overhead} = \frac{\text{Total number of control packets sent}}{\text{Total number of successfully delivered datapackets}}. \tag{10}$$

Table 4: Routing Overhead

Number of nodes	Proposed ANFIS-BWO	F-GWO	SI-ANFISR	Fuzzy	LEACH
50	0.05	0.12	0.17	0.23	0.28
100	0.11	0.16	0.22	0.27	0.34
150	0.16	0.22	0.28	0.33	0.41
200	0.21	0.27	0.34	0.39	0.45
250	0.27	0.32	0.40	0.44	0.51
300	0.32	0.37	0.45	0.49	0.56

The routing protocol overhead used to distribute the packets specifies how many control packets (or bytes) are needed for route maintenance and discovery. This statistic is used to evaluate the performance of the internal algorithm of the routing protocol. Resources are spent more when a protocol has a higher routing overhead (measured in packets or bytes) (bandwidth). As a result, the routing overhead of a protocol must be taken into account while evaluating its efficacy. In comparison to the current F-GWO, SI-ANFISR, Fuzzy, and LEACH techniques, the suggested ANFIS-BWO strategy results in less routing overhead, according to an analysis of Table 4.

8 Conclusion

In this paper, the WSN architecture for path determination is considered with Optimized ANFIS congestion control scheme. BWO algorithm tunes the input parameters of membership function to optimize the ANFIS weight. The hop count, buffer occupancy and remaining energy are considered as the input for ANFIS. Finally, a comparative analysis for ANFIS-BWO with existing methods is carried out to show the effective performance of the proposed approach. The comparison are done in terms of end-end delay, packet delivery rate, the number of remaining alive nodes, the energy consumption of nodes, throughput and routing overhead with the proposed ANFIS-BWO approach and other existing approaches like hybrid Fuzzy with Grey Wolf Optimization (F-GWO) approach, Swarm Intelligence with Adaptive Neuro-Fuzzy Inference System based Routing (SI-ANFISR), fuzzy and LEACH. From the experimental outcomes it is found that the proposed approach gives better congestion free routing by optimal path determination. Moreover, in future it should be thoroughly examined with large number of nodes for IoT applications.

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I confirm that all authors listed on the title page have contributed significantly to the work, have read the manuscript, attest to the validity and legitimacy of the data and its interpretation, and agree to its submission.

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