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Research Article

Improved Butterfly and Fuzzy Logic with Falcon Optimization Algorithm based Routing Protocol in WSN

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ABSTRACT

Introduction: Wireless sensor networks (WSNs) are widely used in real-time applications, but optimizing node energy use and network lifetime are challenging. This issue is solved through clustering and cluster head (CH) selection, and efficient routing protocols enhance performance and decrease energy use.

Objectives: To propose a hybrid optimization approach for minimizing energy consumption and increasing network lifeline. For efficient data transmission, it optimizes the selection of Cluster Head (CH).

Methods: An optimization-based clustering and path selection method for data transmission in WSNs. Cluster heads (CHs) are selected using based on energy, distance, node degree, and centrality. Fuzzy Logic and F-FOA optimize data routing by evaluating node costs and determining the best path using pheromone-based probabilistic selection.

Results: The proposed model exhibits better throughput, lower latency, packet delivery ratio, significantly lower energy consumption and packet loss compared to existing methods (ASFO, GJO and ESO). The results show that it works well to improve WSN.

Conclusions: This study enhances WSN lifetime by reducing energy consumption. CH selection using IBO and routing via FFOA improve efficiency, while IBFFOA minimizes energy use and processing time. Simulations show a 28% reduction in processing time, 26% lower energy consumption, and an 8% increase in clustering accuracy compared to existing models.

Keywords: WSNs, mobility, clustering, F-FOA, and energy efficient.

INTRODUCTION

Many tiny, low-power sensors have been dispersed randomly or in an organized fashion in uncontrolled regions via WSNs (Ali H et al., 2021). These sensors are wirelessly communicating, processing data, and connecting to the cloud, yet suffer from battery life, processing, and mobility (Buddha Singh and Daya Krishan Lobiyal, 2012). Energy consumption is a major issue for WSNs (Danielet al.,2021). Network lifespan and conflicts are enhanced by clustering (Devesh Pratap Singh and R. H. Goudar, 2014). Routing protocols optimize CH selection and data transmission (Dongare, S., & Mangrulkar, R. M, 2016).This study's main contributions are: 1. IBFFOA reduces energy usage and increases network life. 2. For dependable data transmission, CHs are chosen using optimal IBO. 3. F-FOA identifies efficient routing paths.

RELATED WORKS

This section reviews clustering and optimization methods to enhance WSN's lifetime and energy efficiency. Study (Jayaraman, G., & Sarma Dhulipala, V. R, 2022) analyzed algorithms ensuring network reliability, energy efficiency, and security, focusing on routing for data integrity. Authors (Kathiroli, 2021) examined modern routing methods. Researchers (Shivappa N et al., 2019) integrated Black Widow Optimization (BWO) with IoT-enabled CBR protocol to optimize routing, addressing energy but facing high costs and packet loss. Authors (Singh Rathore et al., 2021) proposed a data-centric routing strategy using CCA and RSSI for link validation. Researchers (Zhang B et al., 2020) utilized a Multi-Objective Cluster Head (MCH) with Sailfish optimization for improved routing but encountered performance issues.

2.1 Problem Statement:

WSN energy efficiency depends on an appropriate fitness function. Traditional clustering focuses on remaining energy, while integrating distance and energy improves efficiency. Both large- and small-scale WSNs require energy conservation. High non-CH members and node density affect clustering and routing. Direct CH-to-BS data transfer increases energy use, causing hot spots and packet loss. Unmanaged nodes in hostile environments risk failure, causing instability, while low-energy nodes may discard packets during transmission.

PROPOSED METHOD

An optimization-based clustering and path selection for reliable WSN data transmission is proposed. To reduce energy usages, the CHs are selected by IBO and data transfer is optimized by FFOA. The IBFFOA addresses the issue of enhancing convergence speed, network lifespan, energy efficiency, QoS. Network setup, cluster formation, CH selection using IBO, as well as routing path selection through FFOA constitute parts of the system.

3.1 CH Selection using Improved Butterfly Optimization:

WSN nodes begin with identical energy and processing time. IBO selects CHs based on energy, distance, node degree, and centrality, optimizing selection via stimulus intensity. The following work steps are also included in it: Initialization and depiction of butterflies, butterfly representation and initialization, position improvisation, fitness function computation, residual energy estimation, distance, node degree, and centrality computation. Initially, a random ID in the range of 1,2,.., n determines the position of each butterfly. Here's how the butterfly G_i set is started. Using a first-order radio model, the energy consumption of the transmitter and reception nodes is determined. To get the energy needed to send and receive l-bit packets across a distance$d$, apply equations (1), (2).

$$E_{TX}(1,d) = \begin{cases} 1 \times E_{elec} + 1 \times \varepsilon_{fs} \times d^2 if d \le d_0 \\ 1 \times E_{elec} + 1 \times \varepsilon_{mp} \times d^4 if d > d_0 \end{cases} \quad (1)$$

$$E_{RX}(1,d) = 1 \times E_{elec} \quad (2)$$

$$G_i = \left(G_{i,1}(x), G_{i,2}(x) \dots G_{i,m}(x)\right) \quad (3)$$

Here, d_0 indicates $\sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}}$. In this case, $m$stands for the total number of CHs in the network, and i for the butterfly. After that, the position is changed to $G_{i,k}$ in accordance with $1 \le k \le m$ for the node ID. All butterfly locations are updated in a local or global search space with a range of 0 to 1 after location instantiation. As a consequence, the newly created butterfly group is performed right away, and as the figure illustrates, its motion may be updated in the global search area.

$$s_i^{p+1} = s_i^p + (a^2 \times h^* - s_i^p) \times bf_i \quad (4)$$

In this case, h^* is the current iteration,a^2 is a random number in the interval [0,1],s_i, solution vector of the i-th butterfly and $bf_i$is butterfly's scent. Its local search location is also being updated (eqn 5).

$$s_i^{p+1} = s_i^p + (a^2 \times s_j^p - s_d^p) \times bf_i \quad (5)$$

Where, $s_j^p$and s_d^p are the jthand dthbutterflies. Then, its fragrance $bf$is generated by using the following model. In this case, $b$is power index, L for stimulation intensity, and SM for sensory activity and stimulation intensity. Next, optimal CH selection is determined.

$$fit1 = \sum_{i=1}^{m} \frac{1}{R_E SCH_i} \quad (6)$$

The energy that SCH_i still has is shown here by $R_E CH_i$. As a result, the node's energy level is utilized to calculate the separation between SCH and other sensor nodes, whereas the sole element influencing energy loss is the transmission distance between the source and target nodes.

$$fit2 = \sum_{j=1}^{m}(\sum_{i=1}^{NS_j} dis(sen_i, SCH_j)/NS_j) \tag{7}$$

$$fit3 = \sum_{i=1}^{m} dis(CH_j, basestation) \tag{8}$$

sen_i, for sensors, NS_j, for no. of sensors that belong to CH, and $dis(.)$ for the separation between SCH and sensor nodes. The (eqn 8) is an estimation of the distance between CH and base station. Moreover, the following formulas are used to calculate the node degree and centrality parameters:

$$Nd = \sum_{i=1}^{m} NS_i \tag{9}$$

As the number of sensor nodes in the cluster is denoted by NS_i, and Nd stands for node degree.

$$Nc = \sum_{i=1}^{m} \frac{\sqrt{\sum_{j\in k} dis^2(i,j)/k(i)}}{N_{Di}} \tag{10}$$

The number of sensor nodes in the cluster is denoted by $k(i)$, while the node centrality is defined by Nc. These functions constitute the basis for the formulation of the objective function, as follows:

$$obj = \omega_1 fit1 + \omega_2 fit2 + \omega_3 fit3 + \omega_4 Nd + \omega_5 Nc \tag{11}$$

Among these, weight values $\Omega_{i\epsilon}(0,1)$ refers $\Omega_1, \Omega_2, \Omega_3, \Omega_4, and \Omega_5$. This goal function selects a CH for each group, ensuring dependable and effective data transmission throughout the network.

Algorithm: Ch Selection using IBO

Step 1: Initialize the set of population of butterflies, stimulus intensity L, sensor modality, switching probability, and power exponent;

Step 2: for each j to $M_{itr}//M_{itr}$ Maximum number of iterations;

Step 3: for each BF in population //BF – butterfly

Step 4: Estimate the fragrance

Step 5: end for;

Step 6: Identify the optimal butterfly population;

Step 7: for each BF in population

Step 8: Generate the random number in [0, 1];

Step 9: if $\alpha < p$

Step 10: Estimate the optimal solution

Step 11: else

Step 12: Randomly generate the solution

Step 13: end if;

Step 14: end for;

Step 15: Update the value of b;

Step 16: end for;

Step 17: Based on the optimal solution, select the CH from each cluster;

3.2 Fuzzy Logic and Falcon Optimization Algorithm (F-FOA) based Routing:

Fuzzy systems allow human reasoning to optimize routing. Fuzzy logic selects the best data route, evaluating node cost based on energy use. Convergence node broadcasts the schedule, analyses data, and selects path, while the network controller does route assignment. A logic controller is explicitly computes cost in terms of energy and traffic. Link cost is evaluated by the FLC, FOA [Figure 1] selects the best route, and Falcon finds the shortest path. The sink node then broadcasts the routing configuration for data exchange on optimization. The input output relationship, rule definitions and membership functions give rise to fuzzy set creation. When inputs are not exact rule matches, an approximate reasoning comes into play with an inference engine. Finally, physical system controllers are sent control signals for execution.

3.3 Routing Algorithm:

The routing model [Figure 2] is energy based routing model with distance and traffic awareness. Cost is calculated for fuzzy logic selection of the best node. The input to the fuzzy system is energy and queue flow, and the energy level is classified as low, medium or high (0 to 5). It helps reducing energy consumption and enhances efficiency in WSNs. Nodes are ranked through a first order radio model, some depleting as they transmit on transmission cycles.

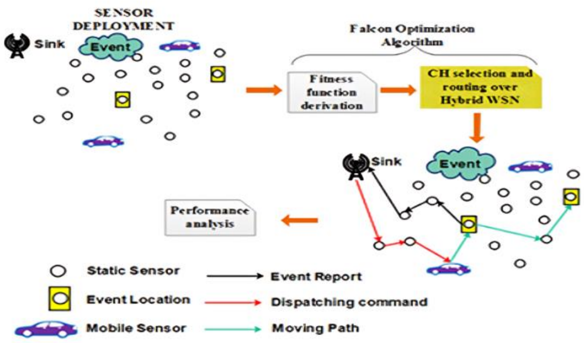

Figure 1: Overview representation of FOA method

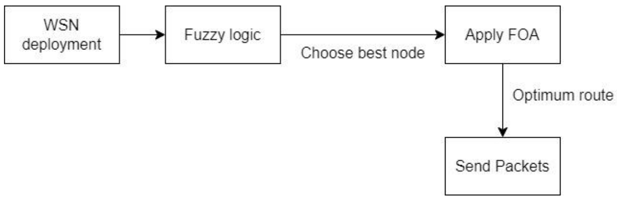

Figure 2: Routing Model

$$E_{TX} = E_{etx} * k + \epsilon_{amp} * d^{a} \quad (12)$$

$$E_{etx} = Vcc * I_{TP} / K_{datarate} \quad (13)$$

Where, k is the data bits transferred, d is a distance between sensor nodes, ϵ_{amp} ensures a low bit

error rate, and E_{etx} is a transceiver energy. $K_{datarate}$ as transmission rate, I_{TP} as the transmission current, and Vcc as operational voltage. (Eqn 8) is the energy required to receive information.

$$E_{RX} = E_{etx} * k \quad (14)$$

Assuming a given distance, the energy consumption is related to the number of data bits. First order radio model energy consumption is dependent on both $E_{TX} and E_{RX}$.The time it takes for a packet to go from the source to destination is determined by the number of packets (k) in the queue. Bits per second (bps) are the maximum allowed, and there are three fuzzy variables: low, medium, and high. Nodes are selected by energy and traffic, with cost values ranging from 0 to 10. The Falcon optimization finds the shortest path, operating in forward and reverse directions. With assist from pheromone traces, node selection is probabilistic and affects future paths.

$$p_{xy}^{k} = \{\frac{\tau_{xy}^{\alpha}}{\sum_{l \epsilon N_x^m} \tau_{xl}^{\alpha}} if x \epsilon N_y^m or\ 0\ otherwise \quad (15)$$

p_{xy}^{k}, a probability of selecting node $y$from x, and $N_x^m$is the neighbor set. The pheromone level is updated in (eqn16). Where, ρ ϵ (0, 1) is a parameter. Pheromone k is added to the arcs after (eqn17) has been applied to each arc. Until the ideal path is discovered, optimization is attained by going through each cycle of movement, pheromone evaporation, and pheromone deposition.

$$\tau_{xy} = \tau_{ij}\Delta_{\tau}^{m} \tag{16}$$

$$\tau_{xy}(1-\rho)\tau xy\colon \forall(x,y) \tag{17}$$

RESULTS AND DISCUSSION

IBFFOA is replicated using the MATLAB with 500 sensor nodes distributed in a 1500 m * 1500 m wireless network from 0 to 20 m/s. IBFFOA employs for 250 seconds using DSR routing and a random waypoint model for mobility. Performance analysis [Table 1] highlights its efficiency. The proposed CORP consumes only 7.53 mJ for 100 nodes, far less than ESO (68 mJ), GJO (58 mJ), and ASFO (48 mJ). IBFFOA achieves 6200 rounds, outperforming ESO (5000), GJO (5200), and ASFO (5700). It also excels in throughput (2 Mbps vs. ESO 0.93, GJO 1.08, ASFO 1.1), lower latency (0.03s vs. ESO 5.28s, GJO 3.98s, ASFO 3.33s), and higher PDR (99.5% vs. ESO 95%, GJO 96%, ASFO 97%). With increased nodes, IBFFOA minimizes packet loss (0.5% vs. ESO 5%, GJO 4%, ASFO 3%), ensuring efficient data recovery.

CONCLUSION

The research implements an intelligent clustering and routing system to extend WSN lifespan by reducing energy consumption, which includes network construction, clustering, CH selection, routing, and data forwarding. CHs are selected using IBO, while routing paths are optimized via FFOA, forming the IBFFOA. Simulations show a 28% reduction in processing time, 26% less energy use, and an 8% increase in clustering accuracy compared to ESO, GJO, and ASFO.

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