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RESEARCH ARTICLE

AFSORP: Adaptive Fish Swarm Optimization-Based Routing Protocol for Mobility Enabled Wireless Sensor Network

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Abstract – Advances in information and communication technology and electronics have led to a surge in interest in mobility-enabled wireless sensor networks (MEWSN). These minuscule sensor nodes collect data, process it, and then transmit it via a radio frequency channel to a central station or sink. Most of the time, MEWSNs are placed in hazardous or difficult-to-access locations. To increase the lifespan of a network, available resources must be utilized as efficiently as possible. The whole network connection collapses if even one node loses power, rendering the deployment's goals moot. Therefore, much MEWSN research has focused on energy efficiency, with energy-efficient routing protocols being a key component. This paper proposes an Adaptive Fish Swarm Optimization-based Routing Protocol (AFSORP) for identifying the best route in MEWSN. AFSORP functions based on the natural characteristics of fish. The two most important steps in AFSORP are chasing and blocking, which respectively seek the optimal route and choose the appropriate route to send data from the source node to the destination node. Standard network performance measurements are used to assess AFSORP with the help of the GNS3 simulator. The results show that AFSORP performs better than the existing routing methods.

Index Terms – Routing, Mobility, WSN, MEWSN, Optimization, Fish, Energy.

1. INTRODUCTION

Communication technology is becoming an imminent progression to wireless from wired networks in the current era. The advances in modern communications for wireless, digital electronics, and embedded communications pave the way for developing autonomous components that lend measurements for physical environments [1]. The nodes connected in the network facilitate the formation of new networks called Mobility Enabled Wireless Sensor Networks (MEWSN). MEWSNs are a group of dedicated sensors accompanied by communication arrangements to track environmental conditions. It is a self-organized network and can hold a considerable number of micro-sensors. Also, the deployment model is random, producing a rich quality of information utilizing wireless communications. The physical measurements are fetched using the small components called sensor nodes [2]. The quality of the data may be evaluated based on how the node is put to use. Base Station (BS) is built to handle the processed data sent collaboratively, and they offer a tremendous amount of storage and processing power. The specified network's many properties also make it possible

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for each node to function autonomously for extended periods [3].

Sensor nodes are often deployed and are vulnerable in a dangerous environment. Failure of nodes usually occurs due to any physical damage or hardware issues. Also, there is always node failure in wireless or wired networks. The protocols deployed in the network should be designed to identify the failures at the right time and robustly handle massive failures while preserving the network functionality [4]. It is also related to routing protocol design and poses its requirement in fault tolerance. The sensor nodes differ in their scale at nodes that range up to thousands. Also, the density of deployment varies. The node's density also reaches the stage where thousands of neighbors are present in the transmission range. The protocols in the sensor network should be scalable, and their performance needs to be scaled [5]. Even though MEWSNs have progressed in many phases, they connect with specified resources: computing power, memory, energy, and communication capability. Among these, energy consumption is gaining more importance than others, which were exaggerated by massive algorithms, protocols, and techniques developed for energy saving, and the network's lifespan will get extended [6]–[8]. Maintenance of Topology is also an important issue to be researched to reduce energy consumption in the network. As known already, most of the challenges for sensor networks are based on insufficient power resources. The node size always limits the battery size. The hardware and software design should consider this issue when designing. For example, energy is reduced when the data is compressed for radio transmission. Some applications can turn the node subsets off to save energy [9].

Sensor networks are a new technology with many illustrations for their success, but they still hold some barriers to working on it. The sensor node device functionality makes network deployment easy, but there is also a place to incorporate malicious attacks. Many sensor nodes act as access points for malicious attackers with issues in their deployment [10]. These networks are designed with short-range and diminutive energy devices and are often inexpensive. Also, periodical toggling of power has been extended on the sensor node to extend the lifetime of their operations, but there may be routing overhead and network latency [11]. In common, the following competing needs are to be handled to solve the issues:

- The sensor nodes with transmitting capability and better battery life are used.
- They should never be inexpensive to operate or purchase.
- Engineers should use the modern tool for diagnostics to ensure its functionality and prove there is no power wasted.

1.1. Problem Statement

Many features set MEWSNs apart from wireless networks without infrastructure, making the design challenge of routing protocols for MEWSNs particularly difficult. There are many different sorts of routing problems that might arise in a wireless sensor network. Following is a list of some of the most pressing problems that need to be addressed are:

- A large number of sensor nodes makes it almost impossible to provide unique IDs to each one. As a result, wireless sensor nodes cannot effectively use standard Internet Protocol (IP) protocols.
- Many different sensors must send their observed data to the same central hub. However, this isn't how standard networks of the communication function.
- In many instances, the generated data flow is very redundant. It's possible for a large number of sensing nodes to provide the same data. It is, therefore, crucial that routing protocols take advantage of this redundancy and make effective use of the available bandwidth and power.
- There are severe constraints on wireless nodes' transmission power, bandwidth, storage capacity, and onboard energy. Because of these variations, many novel routing techniques have been proposed to address the difficulties inherent in wireless sensor networks.

1.2. Objective

The primary objective of this research is to design low-power routing protocols for MEWSNs. This research aims to develop a bio-inspired optimization-based routing strategy for MEWSNs by examining current energy-efficient routing protocols and highlighting their relevance and limitations. To solve the novel issues, present in MEWSN, this research modifies fish swarm optimization to lessen network latency and power consumption, hence extending the lifespan of MEWSN.

1.3. Organization of the Paper

The paper begins with an introduction, providing background on the topic and outlining the research problem. The literature review section then reviews relevant previous studies on the topic. The third section introduces the Adaptive Fish Swarm Optimization based Routing Protocol (AFSORP), a proposed solution to the research problem. The fourth section details the simulation setting and performance metrics used to evaluate AFSORP. Results and discussion are presented in the fifth section, and the paper concludes with a summary of the main findings and future research directions.

2. LITERATURE REVIEW

The current section discusses the literature that faces higher energy consumption and delay.

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“Energy efficient routing algorithm” [12] is proposed as a load-balancing strategy to validate and enhance the network's lifetime. The algorithm could also eradicate the delay in data aggregation and efficiently avoid the loops in routing. The evaluation results show that the network's efficiency was better for handling delays, errors, efficiency, and energy. “Mobile Energy Aware Cluster Based Multi-hop Routing” [13] is designed as an innovative technique for selecting cluster heads in the hierarchically heterogeneous WSN. Here, three levels of nodes in the sensor were considered, and the deployments were made. The technique was tried out with the simulator, and the protocol's effectiveness was compared to show how well it worked [13].

“Hyper Graph Clustering” [14] is proposed as a heuristic hypergraph theory based on clustering to optimize the sensor node’s energy. The evaluation was performed to choose the header for the cluster. The proposed HGC was evaluated for its performance, and the efficiency was tested with other techniques, which were compared in terms of the total number of alive nodes, the consumption rate of the network, and the energy. “Routing-based Model” [15] is proposed as a routing mechanism recovery for WSN. The number of data packets and their load was defined and processed, along with their congestion state.

The parameters for modeling were also explored and evaluated. The simulation results show the state of its vulnerability to WSN, and the implemented recovery mechanism justifies the placement of sink nodes. “Delay Queuing Graphical Evaluation and Review Technique” [16] is proposed as the finest algorithm for handling the delay in the routing. The minimum path was set, and all the candidate paths were selected. The delay evaluation index was evaluated, and the simulation results portray its superiority over the existing algorithm. A wireless sensor network model was designed to protect the Rhino in the Kaziranga National Park against poachers.

“Position Aware Routing And Medium Access” [17] is proposed for estimating the location of each node. A route of loop-free nodes is generated, with sink nodes given priority. Every node was selected with the back-off intervals, and the performance was analyzed. The proposed technique was compared with other network parameters, increasing the network's lifetime. “Novel RSA Algorithm” [18] is proposed to estimate bit error rate values in fragmentation-aware networks. The simulated result of the technique demonstrates its impact on increasing the level of blocking in the adhered connections by increasing the power from the transmitter modules. Based on the algorithm's performance metrics, a histogram was generated to display the active connections and aid those with bandwidth-intensive queries. “Q-based Learning” [19] is proposed for FANET with multi-objective optimization. A routing protocol was recommended for the study. The routing process's underlying connection was re-estimated, and a fresh and inventive technique for capitalizing on multiple routing path discoveries was designed and implemented. Finally, the simulation results demonstrate that compared to the conventional routing approach, the developed strategy results in a greater packet ratio while consuming less energy. “Comparison of Routing Protocols” [20] was carried out for different communication applications based on HTTP, voice protocols, and FTP. Different routing protocols were considered, and with efficient traffic congestion management, energy, and time consumption were reduced, as shown in the study's outcome. “Improved Genetic Algorithm-based Route Optimization Technique” [21] was developed to define the optimal route for communication between the vehicles in VANETs. Using simulations, it is possible to assess the suggested model's outcomes and conclude that they will help with navigation by lowering the number of accidents

“Adaptive Ranking-based Energy-efficient Opportunistic Routing (AREOR)” [22] was developed for detecting the efficient node in the cluster. The energy and its position were used, and ranks were computed. The impact of the routing was investigated, and the reports were evaluated. It demonstrates that energy consumption was reduced during transmission and is carried out using the simulator. “Power Aware Routing Protocol (PARP)” [23] is designed to lessen the burden on the wireless node's power supply during peak traffic times. PARP builds a multicast tree to get messages to their intended recipient efficiently and quickly. PARP uses the idea of multicasting to lessen congestion and energy usage, and it also double-checks the loose ends to ensure a higher standard of service.

In this study, we choose the node in the WSN geographically closest to the forwarding node, which is ideal for conserving energy between two nearby targets in a multicast tree. “Efficient and Reliable Grid-Based Routing by Exploiting the Minimum Hop Count” [24] is developed as a grid-based protocol. The classification was performed with their count nodes, and the packets were forwarded through cell heads. The test was conducted to enhance the network's performance, and the void management approach was also employed to increase the network's dependability. "Depth-Based Routing" [25] is proposed as a model for deriving the metrics of WSN. The insight into the essential settings was configured, and the parameters were optimized with their trade-offs. Energy consumption, end-to-end delay, and delivery probability were considered when determining its performance. “Temporal Differential Privacy” [26] is proposed as a model for packet forwarding with a delayed trace of traffic. The measurement of event privacy was considered, and the reduced jitter for the FCFS was estimated. The simulation results show that the preservation mechanism was close to the traffic information at each node at a given time.

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3. ADAPTIVE FISH SWARM OPTIMIZATION BASED ROUTING PROTOCOL (AFSORP)

The natural characteristics of fishes inspire this proposed routing protocol in this research work. The hunting behavior prototype is considered to progress a new bio-inspired optimization-based routing protocol. The hunting space is defined as the search space, and the individuals are the group of fish. At first, the model is initiated with a group of populations based on the distribution of members. The proposed routing protocol is divided into two categories, namely, chasers and blockers. One fish will adopt the chaser role in every subpopulation, and all others will act as blockers. Based on the classification, every element undergoes a different progression in hunting. The experiments will represent the success of the individual. Five different steps were undergone in the model of hunting and discussed below:

3.1. Initialization

Population called Q of n individuals (fishes) $\{q_1, q_2, .., q_n\}$ were generated randomly and distributed uniformly inside the limits b^{high} andb^{low} of m-dimension search space in which m refers to the size of the population and $q_j \in Q$ where$q_j = \{q_j^1, q_j^2, \ldots, q_j^m\}$. Eq.(1) formulates the initialization step:

$$q_j^i = rand.\left(b_i^{high} - b_i^{low}\right) + b_j^{low}$$
$$i = 1,2,\ldots,n;\ j = 1,2,\ldots,m, \quad (1)$$

Where the random number falls between [0,1] and is defined using $rand$.

Fish school together to hunt more efficiently. Based on the hypothesis mentioned above, we partition the whole population Q into distinct groups, or subpopulations, whose behavior may be modeled separately. The chief aim of this study is to construct the groups in the spatial neighborhood for initiating its search. The population is partitioned into k clusters in which each cluster c_o holds the chaser fish (CF) Φ_r at the centre and the blocker fish (BF) s φ_f swims around it. Following the biotic model, k clusters are generated and remain constant throughout evolution based on the number of elements and their size.

Two significant categories of clustering methods are partitioned and hierarchical, respectively. There are several clustering approaches suggested in the literature. However, the O-means method is used by AFSORP because of its simplicity, ease of implementation, and greater efficiency.

O-mean is a popular and widely used clustering algorithm for segregating the elements consistently. It also groups the data sets into o number of clusters called,$\{c_1, c_2, \ldots, c_o\}$ in which μ_r of each cluster c_r is calculated. The total squared error to the nearest cluster's mean for every data point is minimized. In most cases, the Euclidean metric is utilized to compute the distance between the cluster mean and data points. The fish population Q is considered as the initial data, and the error of mean square between μl and $\{q_1, q_2, \ldots, q_g\}$ data points in the cluster c_r are represented as Eq.(2)

$$e(c_r) = \sum_{q_f \in c_r} \| Q_f - \mu_r \|^2, f = 1,2,\ldots g;$$
$$r = 1,2,\ldots \quad (2)$$

Here, g is defined based on the O-mean algorithm, and its value will differ for each cluster c_r. The algorithm's importance is reducing the objective function with the total squared error on the cluster o, and the same is mathematically expressed in Eq.(3).

$$E(C) = \sum_{r=1}^{o} e(c_r) \quad (3)$$

3.2. Chasing

Chasing is executed by Chaser Fish (CF). Each fish groups have a single CF $\Phi_r \in Q$ for handling the hunting process. This feature is modeled using the Levy flight technique, generating random walks. The CF is selected based on the fitness value. The best fitness value is chosen for every cluster, and the individual particle will act as CF. The prey will escape and hide in the corals and crevices in the hunting process. The CF will immerse into the crevice and search at different cracks to check whether the prey is moved.

The CF will find the crevices in which prey may hide by modifying its position with random walks, and the new location is calculated using Eq.(4).

$$\Phi_r^{s+1} = \Phi_r^s + \alpha \oplus L\acute{e}vy(\beta), 0 < \beta \le 2 \quad (4)$$

The current and new positions of the CF will be $\Phi_r^{s+1}$and Φ_r^s respectively. In this model, the step size will be defined using α where $\alpha = 1$ and entry-wise multiplication is used $\oplus$. The Levy index is represented using β, and the tail controls the distribution probability. The distribution of probability is defined when $\beta = 1$. When $\beta = 2$, the probability distribution will be updated as Gaussian-based distribution.

When the value of β is smaller, the distribution tail is complex, and it attempts to produce jumps in a lengthier manner. When the value of β is more significant, the distribution tail value will be shorter and shorter jumps will be produced. This shows that the value of α and β will normalize the size of the perturbation step. Also, α is used to control the step size and is adopted as a control strategy, and the value is set to 1. In this algorithm, the value for β is increased to 2 from 1.99, and the length of the step is decreased in

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generations which makes the Gaussian distribution exploitation. Based on these criteria, the search space is expanded as the element is nearer to its prey. Sometimes, the hidden place of the prey is also explored. In this case, the value of β is delimited in a shorter range for smaller steps. It is not just the Levy flight that is considered but also the investigation of the CF, as the latter might sometimes lead to more substantial advances. This procedure will mitigate the resulting decrease in the local maximum. Calculation of β value is performed using Eq.(5):

$$\beta = (E(C) \times 0.099) + \frac{0.001s}{s_{max}/10} \quad (5)$$

In which s refers to the current generation and s_{max} refers to the maximum iterations. Also, the Levy flight algorithm devices the random walks by random step generations through the Lévy distribution. As every group ignores, other population elements and the best prey are obtained. This is modeled using Eq.(6)

$$T = \prod \alpha \oplus levy(\beta) \sim \alpha \left(\frac{u}{|v|^{1/\beta}} \right) (\Phi_r^s - \Phi_{best}^s) \quad (6)$$

Where T indicates the randomly proceeded step and the Φ_{best}^s indicates the best-identified CF. The u and v represent the normal distribution, which is calculated using Eq.(7).

$$u \sim M(0, \sigma_u^2)$$
$$v \sim M(0, \sigma_v^2) \quad (7)$$

Where σ_u and σ_v are defined as Gamma function as Γ in Eq.(8):

$$\sigma_u = \prod \left(\frac{\Gamma(1+\beta)\,\mathrm{Tan}\frac{\pi\beta}{2}}{\Gamma\left(\frac{1+\beta}{2}\right)\beta 2^{(\beta-1)/2}} \right), \sigma_v = 1 \quad (8)$$

Based on these assumptions, the CF's new position in Eq.(4) is rewritten as Eq.(9):

$$\Phi_r^{s+1} = \sum \Phi_l^s + T \quad (9)$$

Eq.(9) for each CF called,Φ_s to every cluster c_r is validated except the Φ_{best} (global best). With Eq.(9) as a reference, this research calculates the CF's initial location. As a result, both T = 0 and the top CF's location will stay unaltered. Lastly, Eq.(10) is applied to assess the CF' fitness at the relocated locations.

$$\Phi_{best}^{S+1} = \sum \Phi_{best}^s + \prod T' \quad (10)$$

The value of T' is defined using Eq.(11).

$$T' = \sum_{u=0}^{n} \alpha \left(\frac{u}{|v|^{1/\beta}} \right) \quad (11)$$

3.3. Blocking

Blocking is executed by Blocker Fish (BF). The typical fish will continue to act as BF once the CF is selected for each cluster. The BF hunting strategy is represented as $\varphi_f \in Q$, which is used to block the escape routes rounded in the corals for the prey. This behavior is modeled using a logarithmic spiral for observing the BF movement. They recur differently each time but always follow the BF logarithmic spiral motion, and Eq.(12) expresses the same.

$$\varphi_f^{s+1} = Z_f \cdot e^{b\rho} \cdot cos2\pi\rho + \Phi_r \quad (12)$$

Where ρ denotes the random number in $[d, 1]$ to define the closeness between BF and CF, d is reduced linearly to -2 from -1 when the iteration increase. The unique location of the CF is calculated when $\rho = -2$.

In most cases, the range of generations will be between -2 and 1, and the method of approach will grow by a factor of each passing generation. For this reason, the BF will investigate more thoroughly as a fraction of the total number of iterations.

The spiral's orientation and profile are quantified by the constant b in Eq.(12). Here, b=1, and the parameter Z_f refer to the distance among the BF φ_f^s and CF Φ_r current position in the cluster c_r which is defined Eq.(13):

$$Z_f = \left| l.\Phi_r - \varphi_f^s \right|$$
$$\{\Phi_r, \varphi_f^s\} \in c_r \quad (13)$$

where l is said to be the random number in $[-1,1]$ that interrupt the distance of Z_f. By defining the BF movement, avoiding exploration and diversity are promoted. Many different species exhibit similar features of behavioral patterns in a particular process.

For example, circular movements were developed by moths, fish, or hump whales. These forms are used in different entities, namely mating, preying, or navigating. They use logarithmic models for modeling and are efficiently explored in some search spaces. It is also essential to obtain these similarities in some biological models of different species.

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3.4. Role Exchange

The main aim of the BF is to avoid the prey's escape. When the hunting process starts, the prey will travel to the hunting area, and therefore hunt will be initiated by the nearest BF, which will be changed to CF. In turn, the existing current fish will become BF. This behavior is modeled with the finest fitness value. Here, the BF φ_2 achieves a better value of fitness than other fishes. The BF φ_2 which is moved nearer to its prey will change to CF, and therefore, the roles exchange was carried out in the iteration process, $s + 1$.

Based on the search agent's performance, AFSORP adjusts the chance of switching places. Fish always take on the role of the CF, regardless of how close they are to the prey. Fish fitness is also used to determine the proximity. Additionally, the roles will switch if the BF are healthier than the CF. This function is added after each iteration.

Here, CF always pertains to the memory for reaching their best position, which is not present on the BF side. Even if the roles are exchanged, it is always saved in the memory, which avoids the instability of the algorithm. This is the advantage of using the AFSORP algorithm, as other swarm algorithms will not. It also guides the strategy of searching in all the clusters. The role exchange is executed in every cluster individually, and due to this factor, local search is always considered. The information gained through cluster interaction is disseminated to all active clusters when shifting hunting grounds.

3.5. Modification of Zone

Once the search space is exploited, a new position for finding new prey will be selected. Under these factors, the AFSORP model uses the λ parameter for analyzing overexploitation. Four iterations are used for this, and the subsequent search's position will be modified using Eq.(14).

$$q_f^{s+1} = \frac{\Phi_{best} + q_f^s}{2} \tag{14}$$

The fish's new location may be determined without taking its previous behavior as a CF or BF into account using q_f^{s+1}. The optimum solution in the cluster is Φ_{best}, for CF. Using q_f^s, it is possible to determine where the fish is at this moment in time inside the cluster. The CF is not developed, and the global best position is referred by Φ_{best} .

3.6. Computational Technique

The implemented approach of the proposed technique is a process of iteration where the lists of operations are executed sequentially. For this, the algorithm requires n fish elements, o number of clusters, s_{max} for maximum iteration and T search space. The fish population Q is initiated and distributed uniformly in the search space Tin the predefined limits$b_{high}$and b_{low} for representing the population initially with $Q(s)$. During the first generation, the value of s is set to 1.

After the initialization phase, the fitness of each fish is calculated, and the globally best fish is identified as Φ_{best}. Separating the fish population into O distinct clusters $\{c_1, c_2, \ldots, c_o\}$ is subsequently accomplished with the help of the o-means method. For each cluster c_r, the best value of fitness is identified as the CF Φ_r for the particular cluster and all others will be referred to as BF φ_f.Various operators are applied to the searching component: the predictable hunting process for CF and the BF procedure for BF. Every element will move based on the operators, and the hunting process will modify the CF position by producing random steps. The routine of the BF will change the position using the logarithmic spiral path from one place to another CF.

Each fish's fitness level is quantified. The role transition occurs when the BF in a cluster has a higher fitness value than the current CF, at which point the current CF takes on the function of the BF, and the BF becomes the new CF. If any CF performs best, then it is updated. If the CF does not improve for every iteration, the stagnation will increase until the limit λ predefined is reached. When the value of p increases, then the zone change is made. It means no prey will be hunted in the space for searching its prey in different zones. This process is repetitive till the determined iteration is reached, and the procedure is summarized in Algorithm 1.

Input:

$n, o, s_{max,} T$

Output:

Φ_{best} (i.e., the best route)

Procedure:

1. Set the population for fish $Q = \{q_1, q_2, \ldots, q_n\}$
2. Compute the value of fitness for every particle
3. Categorize the global best Φ_{best}
4. Divide the population Q into $o$clusters $\{c_1, c_2, \ldots, c_o\}$
5. Create cluster for CF Φ_r and the BF φ_f fish
6. Check whether $s < (s_{max} + Threshold\ Value)$
7. For eachclusterc_r
8. Perform CF hunting procedure
9. Perform BF blocking procedure
10. Compute individual fish fitness value

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If $\varphi_f > \Phi_r$
Interchange roles by appending Φ_r
Else
If $\Phi_r > \Phi_{best}$
Update Φ_{best}
Else
If the fitness value of Φ_r has not enhanced
$p \leftarrow p + 1$
End If
If $p > \lambda$
Compute a random procedure for changing the zone
$p \leftarrow 0$
End If
$s \leftarrow s + 1$
End Foreach

Algorithm 1 Pseudo-Code of the AFSORP

4. SIMULATION SETTING AND PERFORMANCE METRICS

The simulation setting for evaluating the proposed routing protocol against the existing routing protocols is provided in Table 1.

Table 1 Simulation Settings

Parameter Name	Value
Simulator name	Graphical Network Simulator − 3
Simulator version	2.2.36
Base protocol routing	ORP
Type of Network	Wireless
Type of Antenna	Omni Antenna
Model of Simulation	Energy model
Type of Interface	Wireless Physical
Type of MAC	IEEE − 802:11
Queue type	Droptail − priority Queue
Simulation Duration	100 seconds
Initial energy of nodes	100 Joules
Node Count	20, 40, 60,80,100
Data rate	4500 bits per seconds
Length of Queue	50 bits
Receiving data packet	0.80 Joules per bit
Transmitting data packet	0.90 Joules per bit
Idle power of the node	0.05 Joules per bit
Sense power of the node	0.01750 Joules per bit

Protocol efficiency is assessed using performance measures. The proposed protocol's performance against existing routing protocols is evaluated using the metrics listed below. The count of nodes is utilized as a parameter.

- Delay: Indicates how long a packet takes from source to destination in a network.
- Packet Delivery Ratio: Source-to-destination packet delivery rate.
- Packet Loss Ratio: Source-to-destination packet drop/failure rate.
- Throughput: Quantity of data successfully sent from source destination to destination in a certain period.
- Energy Consumption: Indicates how much energy the packet uses to travel from source to destination.

5. RESULTS AND DISCUSSION

The current section discusses the performance of the proposed routing protocol against the existing protocols with the parameter “Nodes Count” using five performance metrics.

5.1. Delay Analysis

Figure 1 highlights the delay faced by the proposed routing protocol (i.e., AFSORP) and the existing routing protocols (i.e., PARP and AREOR). On the X-axis, the count of nodes is plotted, and the Y-axis represents the performance metric delay measured in milliseconds. From Figure 1, it is clear to make a better understanding that the proposed routing protocol AFSORP outperforms the existing routing protocols PARP and AREOR. AFSORP performs optimization in selecting the routes to the destination, which results in facing minimum delay. PARP and AREOR do not perform any optimization during the route selection process, which ends in route failure. Alternate route identification during route failure is the primary source for PARP and AREOR to face delay. The success rate of the selected route always reflects the delay. Table 2 reflects Figure 1 result values.

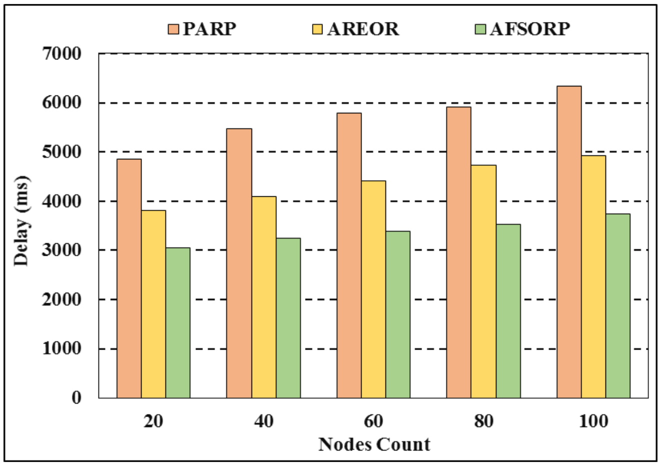

Figure 1 Nodes Count Vs. Delay

Table 2 Nodes Count Vs. Delay

Nodes	PARP	AREOR	AFSORP
20	4844	3818	3046
40	5468	4085	3243
60	5797	4415	3396
80	5912	4730	3527
100	6333	4923	3744

5.2. Packet Delivery Ratio Analysis

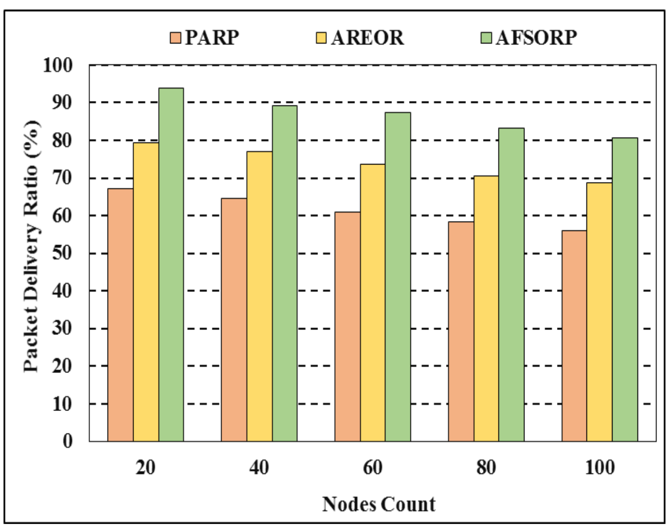

Figure 2 Nodes Count Vs. Packet Delivery Ratio

Figure 2 highlights the packet delivery ratio attained by the proposed routing protocol (i.e., AFSORP) and the existing routing protocols (i.e., PARP and AREOR). On the X-axis, the count of nodes is plotted, and the Y-axis represents the performance metric packet delivery ratio measured in percentage. From Figure 2, it is clear to make a better understanding that the proposed routing protocol AFSORP provides a better packet delivery ratio than the existing routing protocols PARP and AREOR. The selection of stable routes increases the packet delivery ratio in AFSORP, where the existing routing protocols prioritize the distance instead of the stability and quality of the route, which ends in multiple route failures and retransmission. Table 3 reflects Figure 2 result values.

Table 3 Nodes Count Vs. Packet Delivery Ratio

Nodes	PARP	AREOR	AFSORP
20	67.255	79.224	93.995
40	64.583	76.953	89.179
60	60.990	73.698	87.470
80	58.255	70.557	83.285
100	55.982	68.806	80.700

5.3. Packet Loss Ratio

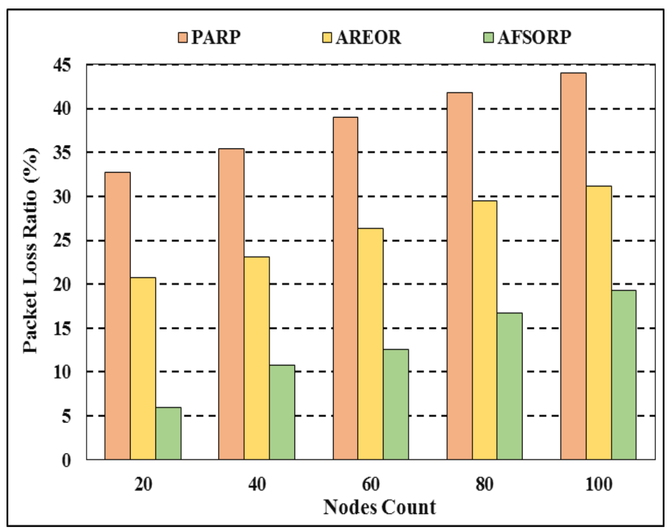

Figure 3 Nodes Count Vs. Packet Drop Ratio

Figure 3 highlights the packet delivery ratio attained by the proposed routing protocol (i.e., AFSORP) and the existing routing protocols (i.e., PARP and AREOR). On the X-axis, the count of nodes is plotted, and the Y-axis represents the performance metric packet delivery ratio measured in percentage. From Figure 3, it is clear to make a better

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understanding that the proposed routing protocol AFSORP has faced a low level of packet drops than the existing routing protocols PARP and AREOR. The selection of stable routes decreases the packet drops in AFSORP, where the existing routing protocols prioritize the distance instead of the stability and quality of the route, which ends in increased packet drops. Table 4 reflects Figure 3 result values.

Table 4 Nodes Count Vs. Packet Drop Ratio

Nodes	PARP	AREOR	AFSORP
20	32.745	20.776	6.005
40	35.417	23.047	10.821
60	39.010	26.302	12.530
80	41.745	29.443	16.715
100	44.018	31.194	19.300

5.4. Throughput Analysis

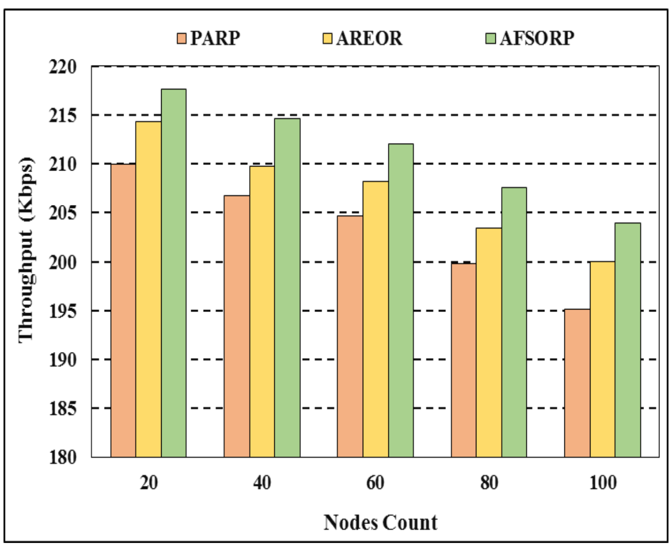

Figure 4 Nodes Count Vs. Throughput

Figure 4 highlights the throughput attained by the proposed routing protocol (i.e., AFSORP) and the existing routing protocols (i.e., PARP and AREOR). On the X-axis, the count of nodes is plotted, and the Y-axis represents the performance metric throughput measured in kbps. From Figure 4, it is clear to make a better understanding that the proposed routing protocol AFSORP has attained better throughput than the existing routing protocols. AFSORP avoids network congestion and balances the network in an optimized manner which leads to attaining increased throughput. In PARP and AREOR, network congestion and unbalanced load lead to a decrease in throughput. Route quality plays a significant role in avoiding network congestion. Table 5 reflects Figure 4 result values.

Table 5 Nodes Count Vs. Throughput

Nodes	PARP	AREOR	AFSORP
20	209.932	214.369	217.621
40	206.783	209.821	214.655
60	204.698	208.162	212.016
80	199.779	203.460	207.589
100	195.173	200.058	203.964

5.5. Energy Consumption Analysis

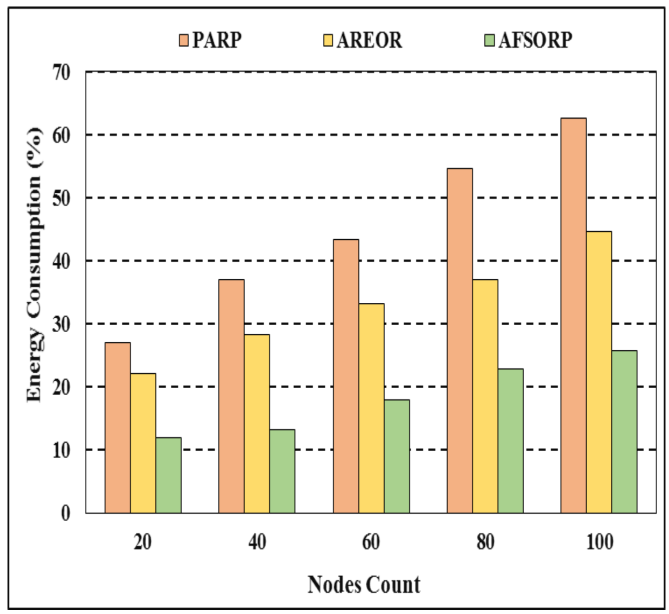

Figure 5 Nodes Count Vs. Energy Consumption

Figure 5 highlights the energy consumption of the proposed routing protocol (i.e., AFSORP) and the existing routing protocols (i.e., PARP and AREOR). On the X-axis, the count of nodes is plotted, and the Y-axis represents the performance metric energy consumption measured in percentage. From Figure 5, it is clear to make a better understanding that the proposed routing protocol AFSORP has consumed minimum energy than the existing routing protocols. Identification of an increased quality route makes AFSORP consume minimum energy. Also, AFSORP faces minimum route failure and retransmission, which consumes low energy to deliver the data packet. PARP and AREOR give priority only to the

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shortest distance route and not the quality of the route, which makes them face multiple route failure cum retransmission, which leads to consuming more energy than AFSORP. Table 6 reflects Figure 5 result values.

Table 6 Nodes Count Vs. Energy Consumption

Nodes	PARP	AREOR	AFSORP
20	27.047	22.103	11.915
40	36.988	28.324	13.228
60	43.377	33.156	17.930
80	54.623	37.042	22.821
100	62.692	44.632	25.709

6. CONCLUSION

Bio-inspired computing is an umbrella term for various research in computer science that has taken place recently. Bio-inspired computer optimization algorithms draw inspiration from the principles and development of nature to build novel and resilient competitive approaches. This research employs a bio-inspired optimization-based routing protocol called Adaptive Fish Swarm Optimization Based Routing Protocol (AFSORP) to reduce power consumption in MEWSN by determining the optimal path following fish behavior. The chaser and blocker phases of AFSORP play a significant role in identifying the best routes in MEWSN. AFSORP provides importance to the distance and quality of the route, which leads to minimizing the energy consumption of MEWSN. AFSORP has been evaluated using NS2 with standard performance metrics. The simulation results represent that AFSORP has superior performance in identifying the best route to the destination that minimizes energy consumption in MEWSN. Future enhancement of this research work can be focused on minimizing the energy consumption even more in MEWSN by utilizing machine learning strategies for classifying the routes more accurately. Security issues in MEWSNs can also be focused on with bio-inspired strategies.

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