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

D. Jayaraj
Department of Computer Science and Engineering, Annamalai University, Cuddalore, Tamil Nadu, India.
jayarajvnr@gmail.com

J. Ramkumar
Department of Computer Science, Dr. N.G.P. Arts and Science College, Coimbatore, Tamil Nadu, India.
jramkumar1986@gmail.com

M. Lingaraj
Department of Computer Science and Applications, Sankara College of Science and Commerce, Coimbatore, Tamil Nadu, India.
maillinga123@gmail.com

B. Sureshkumar
Department of Computer and Information Science, Annamalai University, Cuddalore, Tamil Nadu, India.
sureshaucis@gmail.com

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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
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.
“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 VANET 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.
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 $b^{high}$ and $b^{low}$ of $m$-dimension search space in which $m$ refers to the size of the population and $q_i \in Q$ where $q_i = \{q_{i1}, q_{i2}, ..., q_{im}\}$. Eq.(1) formulates the initialization step:

$$q_i^j = \text{rand}. (b^{high}_j - b^{low}_j) + b^{low}_j \quad i = 1, 2, ..., n; \quad j = 1, 2, ..., m,$$

(1)

Where the random number falls between [0,1] and is defined using \textit{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 $c_r$ holds the chaser fish ($CF$) $\Phi_r$ at the centre and the blocker fish ($BF$) $q_{fr}$ 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 AFORSOP 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, $\{c_1, c_2, ..., c_o\}$ in which $\mu_r$ 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 $\mu_l$ and $\{q_1, q_2, ..., q_g\}$ data points in the cluster $c_r$ are represented as Eq.(2):

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

(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).

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

(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).

$$\Phi_r^{t+1} = \Phi_r^t + \alpha \odot \text{Levy}(\beta), 0 < \beta \leq 2$$

(4)

The current and new positions of the $CF$ will be $\Phi_r^{t+1}$ and $\Phi_r^t$ respectively. In this model, the step size will be defined using $\alpha$ where $\alpha = 1$ and entry-wise multiplication is used $\odot$. The Levy index is represented using $\beta$, 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 $\beta$ is smaller, the distribution tail is complex, and it attempts to produce jumps in a lengthier manner. When the value of $\beta$ is more significant, the distribution tail value will be shorter and shorter jumps will be produced. This shows that the value of $\alpha$ and $\beta$ will normalize the size of the perturbation step. Also, $\alpha$ 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 $\beta$ is increased to 2 from 1.99, and the length of the step is decreased in
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 $\beta$ is delimited in a smaller 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 $\beta$ value is performed using Eq.(5):

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

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

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

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

$$u \sim \mathcal{N}(0, \sigma_u^2) \quad v \sim \mathcal{N}(0, \sigma_v^2) \quad (7)$$

Where $\sigma_u$ and $\sigma_v$ are defined as Gamma function as $\Gamma$ in Eq.(8):

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

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

$$\Phi^s_{r \text{best}} = \sum \Phi^s_i + T \quad (9)$$

Eq.(9) for each $CF$ called,$\Phi_s$ to every cluster $c_r$ is validated except the $\Phi^{s \text{best}}$ (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 $CF$’s fitness at the relocated locations.

$$\Phi^{s+1}_i = \sum \Phi^s_i + T' \quad (10)$$

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 $q_r \in Q$, 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.

$$\phi^{s+1}_f = Z_f \cdot e^{w \cdot \cos 2\pi p} + \Phi_r \quad (12)$$

Where $p$ 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 $p = -2$.

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 $Z_f$ refers to the distance among the $BF$ $\phi^s_f$ and $CF$ $\Phi_r$ current position in the cluster $c_r$ which is defined Eq.(13):

$$Z_f = |l, \Phi_r - \phi^s_f| \quad (13)$$

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.
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 $q_2$ achieves a better value of fitness than other fishes. The BF $q_2$ 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).

$$ q_i^{s+1} = \Phi_{best} + q_i^s $$

(14)

The fish’s new location may be determined without taking its previous behavior as a CF or BF into account using $q_i^{s+1}$. The optimum solution in the cluster is $Φ_{best}$, for CF. Using $q_i^s$, 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 T. In 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 $\{c_1, c_2, ..., c_o\}$ 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 $CF \Phi_r$ for the particular cluster and all others will be referred to as $BF \Phi_i$. 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 $Q = \{q_1, q_2, ..., q_n\}$
2. Compute the value of fitness for every particle
3. Categorize the global best $Φ_{best}$
4. Divide the population $Q$ into $o$ clusters $\{c_1, c_2, ..., c_o\}$
5. Create cluster for $CF \Phi_r$ and the $BF \Phi_f$ fish
6. Check whether $s < (s_{max} + \text{Threshold Value})$
7. For each cluster $c_r$
8. Perform $CF$ hunting procedure
9. Perform $BF$ blocking procedure
10. Compute individual fish fitness value
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>
<thead>
<tr>
<th>Parameter Name</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simulator name</td>
<td>Graphical Network</td>
</tr>
<tr>
<td></td>
<td>Simulator – 3</td>
</tr>
<tr>
<td>Simulator version</td>
<td>2.2.36</td>
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<tr>
<td>Base protocol routing</td>
<td>ORP</td>
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<tr>
<td>Type of Network</td>
<td>Wireless</td>
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<tr>
<td>Type of Antenna</td>
<td>Omni Antenna</td>
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<tr>
<td>Model of Simulation</td>
<td>Energy model</td>
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<tr>
<td>Type of Interface</td>
<td>Wireless Physical</td>
</tr>
<tr>
<td>Type of MAC</td>
<td>IEEE – 802: 11</td>
</tr>
<tr>
<td>Queue type</td>
<td>Droptail – priority Queue</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Nodes</th>
<th>PARP</th>
<th>AREOR</th>
<th>AFSORP</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>4844</td>
<td>3818</td>
<td>3046</td>
</tr>
<tr>
<td>40</td>
<td>5468</td>
<td>4085</td>
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<tr>
<td>100</td>
<td>6333</td>
<td>4923</td>
<td>3744</td>
</tr>
</tbody>
</table>

5.2. Packet Delivery Ratio Analysis

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

<table>
<thead>
<tr>
<th>Nodes</th>
<th>PARP</th>
<th>AREOR</th>
<th>AFSORP</th>
</tr>
</thead>
<tbody>
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<td>79.224</td>
<td>93.995</td>
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<td>64.583</td>
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<td>89.179</td>
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<tr>
<td>60</td>
<td>60.990</td>
<td>73.698</td>
<td>87.470</td>
</tr>
<tr>
<td>80</td>
<td>58.255</td>
<td>70.557</td>
<td>83.285</td>
</tr>
<tr>
<td>100</td>
<td>55.982</td>
<td>68.806</td>
<td>80.700</td>
</tr>
</tbody>
</table>

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
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

<table>
<thead>
<tr>
<th>Nodes</th>
<th>PARP</th>
<th>AREOR</th>
<th>AFSORP</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>32.745</td>
<td>20.776</td>
<td>6.005</td>
</tr>
<tr>
<td>40</td>
<td>35.417</td>
<td>23.047</td>
<td>10.821</td>
</tr>
<tr>
<td>60</td>
<td>39.010</td>
<td>26.302</td>
<td>12.530</td>
</tr>
<tr>
<td>80</td>
<td>41.745</td>
<td>29.443</td>
<td>16.715</td>
</tr>
<tr>
<td>100</td>
<td>44.018</td>
<td>31.194</td>
<td>19.300</td>
</tr>
</tbody>
</table>

5.4. Throughput Analysis

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

<table>
<thead>
<tr>
<th>Nodes</th>
<th>PARP</th>
<th>AREOR</th>
<th>AFSORP</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>209.932</td>
<td>214.369</td>
<td>217.621</td>
</tr>
<tr>
<td>40</td>
<td>206.783</td>
<td>209.821</td>
<td>214.655</td>
</tr>
<tr>
<td>60</td>
<td>204.698</td>
<td>208.162</td>
<td>212.016</td>
</tr>
<tr>
<td>80</td>
<td>199.779</td>
<td>203.460</td>
<td>207.589</td>
</tr>
<tr>
<td>100</td>
<td>195.173</td>
<td>200.058</td>
<td>203.964</td>
</tr>
</tbody>
</table>

5.5. Energy Consumption Analysis

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
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

<table>
<thead>
<tr>
<th>Nodes</th>
<th>PARP</th>
<th>AREOR</th>
<th>AFSORP</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>27.047</td>
<td>22.103</td>
<td>11.915</td>
</tr>
<tr>
<td>40</td>
<td>36.988</td>
<td>28.324</td>
<td>13.228</td>
</tr>
<tr>
<td>60</td>
<td>43.377</td>
<td>33.156</td>
<td>17.930</td>
</tr>
<tr>
<td>80</td>
<td>54.623</td>
<td>37.042</td>
<td>22.821</td>
</tr>
<tr>
<td>100</td>
<td>62.692</td>
<td>44.632</td>
<td>25.709</td>
</tr>
</tbody>
</table>

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.

REFERENCES


Dr. J. Ramkumar working as Assistant Professor in Post Graduate and Research Department of Computer Science at Dr. N.G.P. Arts and Science College, Coimbatore, Tamilnadu, India. He obtained his PhD degree from Bharathiar University. He has published more than 38 research papers in International Journals and Conferences which includes SCOPUS and SCIE publications. His area of interest includes ad-hoc networks, route optimization, decision support systems and Internet of Things. He acted as Technical Committee Member, Scientific Committee Member, Advisory Board Member and Reviewer in more than 413 International Conferences and 42 Refereed Journals.

Dr. M. Lingaraj is currently working as Head of the Department & Assistant Professor, Department of Computer Science and Applications, Sankara College of Science and Commerce, Coimbatore, Tamil Nadu. He received his Ph.D. in Computer Science at Bharathiar University, Coimbatore, Tamil Nadu. He has published articles in the SCI journals. His research thrust mainly focuses on Wireless Sensor Network, Network Security and Cloud Technologies. He has guided 18 research scholars so far.

B. Suresh Kumar working as Assistant Professor in the Department of Computer and Information Science, Annamalai university, Chidambaram, Tamilnadu. Currently, he is pursuing PhD in the same university. He completed his M.C.A. in Madras University and M.Phil Degree in Annamalai University. His research interest lies in the area of Deep learning, Image processing, Decision Making. He has published 9 research articles in International Journals and Conferences. He is a life member of Computer Society of India.