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RESEARCH ARTICLE

Hybrid Optimization-Based Efficient Routing Protocol for Energy Consumption Minimization in Mobile Wireless Sensor Network

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Abstract – Mobile Wireless Sensor Network (MWSN) is a dispersed network having autonomous sensor nodes which monitors physical occurrences or environmental variables in real-time. Most MWSNs have limited energy, so energy efficiency is critical. A node's data will be routed by one of two standard methods: single-long-hop or short-multi-hop routing paths. The quantity of energy required to deliver a packet grows directly proportional to the packet's travel distance in MWSN. Single-hop communication in MWSN, on the other hand, is typically relatively energy-intensive. The nodes located nearer to the sink are considerably perform well than the rest of the nodes in MWSN because of the multi-hop connection, resulting in a shorter lifespan for the MWSN. In this paper, Hybrid Optimization-based Efficient Routing Protocol (HOERP) is proposed to minimize the energy consumption in MWSN. HOERP involves grey wolf optimization and particle swarm optimization, where local search is done by grey wolf optimization and the global search optimization is done by particle swarm optimization. Utilizing the nonlinear parameters in HOERP assist in identifying the optimized cum successful route leading to consume less energy. HOERP is evaluated in NS3 using the metrics standardly used in network-oriented researches. Result highlights that HOERP consumes less energy to deliver data packets than the current routing protocols.

Index Terms – Routing, MWSN, Energy, Delay, Hybrid, Optimization, Simulator, Network.

1. INTRODUCTION

In a wireless sensor network, the nodes are either mobile or stationary, and they are used in various contexts, whether known or unfamiliar. Because of their high sensing capacity, it is possible for these sensors to work autonomously and with intelligence and to communicate through a radio link, thus according to predetermined routing procedures [1]. With limited energy, data storage, and computation resources, MWSNs optimize energy restrictions rather than ensuring better service quality, such as bandwidth and transmission latency [2]. If MWSNs have several nodes that perform the same functions in a structured or unstructured operating context, all nodes face a high risk of disconnecting from the network. Data transmission can be hindered by environmental variables or a lack of energy resources [3]. There are instances when human participation is lacking and remedies (such as replacing worn batteries) cannot be provided, and that's not the problem with mobile nodes incorporated into ad hoc networks to fix breakdown concerns. Routers, for example, are a high-level strategy that might help fix faults [4].

MWSNs with a high-density rollout encourage the adoption of multi-hop communication, which involves both low energy usage and consideration of challenges related to signal propagation. MWSN-type applications now require the construction of thousands or millions of sensor nodes to ensure appropriate routing access and the capacity to resolve failures [5]. This is to be expected shortly. The chances of an adjacent node taking over for a non-operational node are consequently relatively high. In other words, the chances of a network breakdown or separation are reduced when nodes randomly placed in a particular environment are spread equally.

It's also possible to deal with communication interference or data duplication issues [6]. MWSN typically consists of sensors that communicate using radio connections. Various channels can be used to distribute information that is generated by environmental stimuli or user requests. The goal is to optimize performance metrics such as resource utilization and service quality to discover the optimum path between a source and a destination [7].

Numerous current protocols follow the following steps: (a) cluster identification, (b) cluster head selection, (c) synchronization, (d) steady-state phase, (e) network architecture (f) route discovery, (g) data aggregation, and (h) data transmission [8]. While each of these processes consumes too much energy where data transmission consumes a negligible amount. Due to the energy constraints of MWSN nodes, these processes require refining to enhance the network's total lifetime. Another constraint on present hardware components is the limited capacity of the packet buffer [9]. The packets of data are buffered in the CHs' network queue and begin to drop when their size surpasses the buffering limit of particular nodes. Nodes are placed across wide regions in a MWSN to acquire interest data. Due to these nodes' low range and battery life, multi-hop communication is required to relay the acquired data to the next node [10].

Clustering is a significant approach. However, it is viewed through the lens of single-hop communication, in which any node may communicate with the target node via intermediary nodes. However, routing, in addition to clustering, is desirable for bigger regions. Failure of any node along the routing path results in data transmission failure. This phenomenon is referred to as the hotspot problem. That's because clustering and routing, while closely related, are studied separately [11]. Optimization is critical in the routing because it helps decrease route overhead [12]–[14].

1.1. Problem Statement

Energy efficiency is critical for the nodes in MWSN to function appropriately and effectively. There must be an effort to minimize the energy spent for routing protocols operating on nodes and managing data and routes. This indicates that the number of data packets delivered and the energy consumed by sensors must be minimized to extend the network lifetime. Certain nodes may fail due to extreme climatic conditions in the deployment location. A MWSN's self-stabilizing characteristic ensures that it can automatically recover in temporary errors, such as when one or more nodes are damaged and no more extended function. More nodes can be added to a network in phases in some circumstances. In such a scenario, the nodes would also be necessary to communicate and function without any human configuration. One or more nodes may move to a new location in the application. Therefore, it would necessitate self-stabilizing algorithms for the nodes to adapt to changes in topology.

1.2. Objective

This research aims to develop a bio-inspired routing protocol called Hybrid Optimization Based Efficient Routing Protocol that will help the MWSN last longer by reducing the energy that each node uses to send data to the next one. Overall, the main goal of the research work is to find and use the best possible connections and the best possible path to the final destination.

1.3. Organization of the Paper

MWSN and routing in MWSN have been introduced in the present Section of the article. Furthermore, the problem statement of the research work and its objectives were examined. Section 2 provides an overview of the relevant literature used in this research. Section 3 proposes a routing protocol known as Hybrid Optimization Based Efficient Routing Protocol to extend the MWSN's life span. Section 4 explains how the simulation was run, including the parameters utilized. Several metrics are used to evaluate the performance of new and current routing protocols. Section 6 focuses on the simulation findings. Section 7 wraps off the piece with a look towards the future.

2. LITERATURE REVIEW

"Depth-based Routing" [15] is proposed for incorporating the model with performance-based metrics, namely delivery probability, end-to-end delay, and energy consumption. The configuration is specified for optimizing the energy consumption and delay of the network. The mobility, deployment, and transmission loss are modelled to avoid delay while finding the route. "Multi-Modal WSN" [16] is proposed to build an energy-efficient and reliable architecture. ContikiOs platform is used for implementing the framework, and the performance is evaluated. Experiments were carried out to generate the results in the multi-hop network by comparing it with traditional networking and low-duty cycling technique. "Butterfly Optimization Algorithm" [17] is proposed for selecting the optimum cluster through a group of nodes in WSN. The cluster head is chosen using available energy neighbor distance, and the route is detected among the base station and cluster head. The foraging behavior of ants is used to measure the proposed performance. **"**Reverse Glowworm Swarm Optimization" [18] is proposed for achieving better energy through a sensor in WSN. The efficiency of the network is improved through movement score, and nodes are positioned using grid points. Simulation results were generated, and the outcome proved to work better by the nodes of the sensor in WSN. **"**Node stability-based routing" [19] is proposed for handling the issue of stability in WSN. The key factors were presented, and the stability of the node is defined using Node Stability-based Routing (NSR) technique. The simulator is used for experimenting, and the performance is compared using different metrics like Expected Transmission count, nearest gateway and Reinforcement learning techniques.

"Fuzzy logic scheme" [20] is proposed to cluster different sensor nodes in WSN. Additional factors were considered for increasing the network lifetime, and the node density is measured by calculating the distance among base stations and nodes. Balanced node consumption is demonstrated through experimental analysis. **"**Block Tri-Diagonal Matrices" [21] is proposed for clustering and compression sensing in WSN.

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The recovery functionality, data prediction, and compression were executed through theoretical study. Simulation outcome is produced using real-world data, and better efficiency is acquired. "Self-Adaptive Neighbor Discovery" [22] protocol is proposed for integrating the sensor-based antenna in WSN. The introduced super frame is used to perform the cycle operations, and the protocol uses the in-network information. The cooperative methodology utilizes the neighbor information, and the message collision is handled. Simulation results are generated to prove its performance over other techniques. **"**Routing-based Cascading Model" [23] is proposed for loading sensor nodes in WSN. The model's vulnerability is evaluated using the routing protocols related with overloaded nodes and congestion-based coefficient through which sink nodes are fixed. The data packets were processed, and the state of congestion was modelled.

"Clustering Wolf Pack Algorithm" [24] is proposed for heterogeneous WSN. Edge degree is used for enhancing the algorithm called DEEC. The common nodes in the cluster are dynamically used to enhance the node transmission after grouping the cluster. Simulation results were presented in the study to improve the network's lifetime and energy usage. **"**Neuro-Fuzzy Cluster Routing Protocol" [25] is proposed to enhance network performance using machine learning methods for WSN. Effective routing is carried out to increase the packet delivery without delay, and experimental study is performed. Better network performance is proved in packet delivery ratio, energy utilization, and network life time, which are portrayed using the simulator. "Cluster Sub-graph Selection based Routing (CSSR) " [26] is proposed to decrease energy consumption and improve routing efficiency. Comparison is performed to measure the network lifetime and energy consumption with conventional algorithms. The sleep-awake procedure is used to enhance the results generated and the routing algorithm is used to enable the routes in the network. Simulation-based results are fetched and the performance is measured. "Energy-efficient Adaptive cum Cooperative Routing (EEACR)" [27] is proposed for managing the QoS and energy consumption in the network of WSN. Reinforcement learning is employed to balance the energy-based routing through which the reliability and delay are managed. Simulation-based results are generated to reduce consumption, and QoS is compared with the state-of-the-art techniques of protocol for routing. Various methodologies [28], [29] were also proposed to detect intrusion in internet based wired and wireless networks.

3. HYBRID OPTIMIZATION-BASED EFFICIENT ROUTING PROTOCOL

3.1. Hunting Behavior

The grey wolf is a top-level predator in animal world. Wolves often live in packs of five to twelve. Each wolf also has a specific function in the pack's social structure

In the first place, the top grey wolf leader, δ, is in charge of decision making and also the hunting habitat. In the second place, the junior leader of the grey wolf, γ, is in charge of assisting superior wolves (i.e., δ), and the activities of other wolves in the pack. In the third place, θ, which is in charge of monitoring the search space boundary and alerting the entire wolves in the pack and it is countable. Taking care of grey wolves that are weak and injured is referred to as π wolves and it is composed entirely of sub missives who must surrender to all other dominant grey wolves. The π wolves may have a little role in the dynamic wolf pack's, but they are critical in keeping the pack's internal dynamicity of check.

Prey capture is greatly influenced by the wolf pack's hierarchy. In the first place, the grey wolves search and pursue their prey. Then, the δ grey wolves lead some other wolves to surround their victim from all sides. Finally, the δ grey wolves guide the γ and θ wolves to attack their victim. If indeed the victim manages to flee, then the other wolves in the pack will pursue the same until the grey wolves capture it.

3.2. Optimization

Predating skills of grey wolves such as search, invasion, hunting and other predation-related behaviors are used to optimize the route-finding strategy in MWSN. The sth wolf's location may be expressed as follows: Given a wolf having the rate of population as T and y exact location: $P_s = \left(P_{s1,}P_{s2,}P_{s3,} \dots, P_{sy}\right)$. Mathematically while simulating the social hierarchy of wolves relies on the alpha (δ) wolf as the best option. As a consequence, the beta (γ) and delta (θ) wolves rank second and third, respectively. Omega (π) wolves are thought to be the last of the viable options. The alpha wolf's position in the protocol is directly related to the location of the prey on the hunt.

Grey wolves' circling behavior may be mathematically described in Eq.(1) and Eq.(2).

$$Y = |U \times P_m(f) - P(f)| \tag{1}$$

$$P(f+1) = P_m(f) - D \times Y \tag{2}$$

where the set f represents the current incarnation, the set $P_m(f)$ defines the position vector of the prey, the set $P(f)$ denotes the position vector of a grey wolf, as well as the set U that represents a control coefficient generated using Eq.(3).

$$U = 2b_1 \tag{3}$$

Stochastic process in the interval [0,1] is the set b_1 and D is the convergence factor.

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$$D = 2db_2 - d \tag{4}$$

$$d = 2\left(1 - \frac{f}{F\,max}\right) \tag{5}$$

Where [0,1] is the range of the stochastic process in the set b_2. The control coefficient d declines linearly from 2 to 0 during the iterations time limit, i.e. $d_{max} = 2, d_{min} = 0$.

Initially, the grey wolves encircle their victim (i.e., prey), led by the leader wolf δ. To capture the prey, the δ wolf leads γ and θ wolves. They can figure out where the prey is by looking and where the δ, γ, and θ wolves are. Eq.(6) to Eq.(12) provides the mathematical details of wolves and victim position.

$$Y_\delta = |U_1 \times P_\delta(f) - P(f)| \tag{6}$$

$$Y_\gamma = |U_2 \times P_\gamma(f) - P(f)| \tag{7}$$

$$Y_\theta = |U_3 \times P_\theta(f) - P(f)| \tag{8}$$

$$P_1 = P_\delta - D_1 \times Y_\delta \tag{9}$$

$$P_2 = P_\gamma - D_2 \times Y_\gamma \tag{10}$$

$$P_3 = P_\theta - D_3 \times Y_\theta \tag{11}$$

$$P(f+1) = \frac{P_1 + P_2 + P_3}{3} \tag{12}$$

Before applying Eq.(12) to detect wolves' movement toward the prey, Eq.(6) to Eq.(11) is used to determine the length between $P(f)$ and the wolves δ, γ, and π.

3.3. Initiation of Chaos

Issues in optimization can be solved using random data which act as a value of starting population (i.e., initialization). However, this might lead to a bad algorithmic outcome and it doesn't preserve the dynamic population. An Optimized Tent Chaotic Map ($OTCM$) is proposed as a core initialization population for this research work. Dynamic chaos is characterized by a (i) periodicity, (ii) regularity, and (iii) mixture of disorder. In function optimization issues, these properties might lead the routing protocol to avoid local optima and so increase its global optima, thereby preserving the dynamicity in the population. There are a variety of types in chaotic maps. In contrast, the search characteristics of various chaotic mappings are distinct. The logistic map (LM) has mostly been used in multiple scholarly research articles until this point in time. In spite of this, the ranges $[0, 0.2]$ & $[0.8, 1]$ are not evenly distributed in terms of values. $OTCM$ outperforms the LM in terms of homogeneous traversal that creates a highly unique initial value between 0 and 1. This helps to speed up the process of identifying the best route in MWSN.

As a result, this research work proposes a novel strategy to initiate the grey wolves using $OTCM$ and the Eq.(13) describes the same.

$$p(f+1) = \begin{cases} \dfrac{p(f)}{o} & 0 \le p(f) < o \\ \dfrac{1-p(f)}{1-o} & o \le p(f) \le 1 \end{cases} \tag{13}$$

In a traditional Tent Map (TM) the value of o is set as 0.5 in default. The sequence has an even distribution and evenly distributed density for various values.

Eq.(14) highlights the operation performed by $OTCM$.

$$p(f+1) = \begin{cases} 2p_f & 0 \le p_f \le \frac{1}{2} \\ 2(1-p_f) & \frac{1}{2} < p_f \le 1 \end{cases} \tag{14}$$

To create a series of $OTCM$, following steps are performed:

Step 1: To prevent fixing of $\{0.25, 0.45, 0.65, 0.85\}$cycles, use the random beginning value p_0. Mark the array with $q(1) = p_0, s = 1$ and $w = 1$.

Step 2: To generate a collection of p sequences, apply Eq.(14) for each iteration.

Step 3: At the count of maximum iterations move to Step 4; otherwise, skip to Step 2. Replace the starting value of the iteration with the equation $p(s) = q(w) + u$,$w = w + 1$; if $p_s = \{0,0.25,0.45,0.65,0.85\}$ or $p_s = p_{s-a}$, $a = \{0,1,2,3,4\}$

Step 4: Save the x sequence data at the end of the operation.

3.4. Non-linearity Parameters

Location selection and the predatory behavior of grey wolves are always critical components of HOERP. Global search (GS) and local exploitation capabilities are balanced by the parameter D and it is according to Eq.(1). Its capacity to do GS broadens the search range to find a better candidate solution when $|D| > 1$. HOERP feature exploit locally when $|D| < 1$, which reduces the range of the search and does an extensive search in the current area. From Eq.(2) it is also

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observed that the variable of D changes continually with the change in the control parameter at every iteration. Eq.(4) depicts how the control limit D declines linearly with the number of iterations. However, the optimization procedure is quite complex but ends with a better result. The algorithm's optimization search process cannot be captured with linear parameters. Nonlinear parameter strategies outperform linear strategy optimization in typical test functions. However, they are still unable to satisfy the algorithm's requirements.

Eq.(15) shows a new set of nonlinear control parameters proposed for performing optimization in selecting the new route in MWSN.

$$d_1(f) = d_{ini} - d_{fin} \times \left(\frac{f}{Fmax}\right)^2 \quad (15)$$

Where the start and end values of the control parameter d are represented by the sets d_{ini} and d_{fin}, respectively. The current iteration is f, and the number of iterations is $Fmax$.

HOERP compare the control parameter d with the linear and nonlinear control parameters to validate its validity, and it is mathematically expressed in Eq.(16) to Eq.(18).

$$d_2(f) = d_{ini} - d_{ini} \times \left(\frac{f}{Fmax}\right) \quad (16)$$

$$d_3(f) = d_{ini} - \left(d_{ini} - d_{fin}\right) \times cot\left(\frac{1}{\omega} \times \frac{f}{Fmax} \times \pi\right) \quad (17)$$

$$d_4(f) = d_{ini} - d_{ini} \times \left(\frac{1}{h-1} \times \left(h^{\frac{f}{Fmax}} - 1\right)\right) \quad (18)$$

Where the set ω is a coefficient that isn't linear.

D's convergence factor formula is mathematically expressed:

$$D = 2d_1 b_2 - d_1 \quad (19)$$

The aggregation factor D is demonstrated to have a low drop rate, which can assist the system in avoiding slipping into a local optimum. For search engine and algorithmic improvement, D falls significantly as time goes on which is a good thing. As a result, the capacity to search and exploit can be improved.

3.5. Hybridization

The wolf optimization algorithm considers the following while updating the locations to share the obtained information: (i) the individual wolves' current locations (ii) the wolf pack's ideal, (iii) the second-best and third-best solutions locations. However, it overlooks the wolf's ability to learn from its own experiences. Because of this, the PSO algorithm was enhanced and made a hybrid with wolf optimization to improve the process of updating the location information.

When employing the PSO approach, the particle's current location is changed based on input from all particles in the network. Equations of location updating can be improved by using the enhanced PSO algorithm in conjunction, which will allow it to keep track of its ideal location. Eq.(20) mathematically expresses the same.

$$P_s(f+1) = u_1 b_1\left(n_1 P_1(f) + n_2 P_2(f) + n_3 P_3(f)\right) + u_2 b_2\left(P_{sbest} - P_s(f)\right) \quad (20)$$

When it comes to cognitive learning, the set u_2 differs from the set u_1. Individual and group ideal values have a significant impact on the results u_1 has a large value, which improves global search capability; u_2 has a large value, which improves local search capability. Because of this, too many particles will be left behind by a large u_1 if it is too huge. Particles will converge to the local optimum early if u_2 is too big. [0, 1] is where the random variables b_1 and b_2 are found. It's clear from the P_{sbest} set that the grey wolves have been in the best possible position. This is a set of inertia weight coefficients, n_1, n_2, n_3. The algorithm's global and local search capabilities can be dynamically adjusted by altering the weight distribution of the δ, γ, θ, wolves.

$$n_1 = \frac{|P_1|}{|P_1 + P_2 + P_3|} \quad (21)$$

$$n_2 = \frac{|P_2|}{|P_1 + P_2 + P_3|} \quad (22)$$

$$n_3 = \frac{|P_3|}{|P_1 + P_2 + P_3|} \quad (23)$$

As a first step, Eq. (20) illustrates the optimal prey position that may be found by using δ, γ, and θ wolves to seek. This increase in lookup interval helps to make the method more global. An Individual's best position impacts the algorithmic search and maintains the node in the best location.

3.6. Flow of HOERP

The following are the stages of HOERP

Step 1: Set the population size to T, the dimension to y, and the D, U, and its values to zero.

Step 2: Using $OTCM$, generate a population of individuals with $\{P_s, s = 1,2,3 \ldots, T\}$

Step 3: Compute the fitness value $\{g_s, s = 1,2,3, \ldots T\}$;

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Step 4: Arrange the function value by size and label the first three δ, γ, and θ fitness values related to the nodes. P_δ, P_γ, and P_θ are the appropriate position codes.

Step 5: Recalculate d and then update D and U using Eq.(2) to get the nonlinear control parameters by applying Eq.(19).

Step 6: Recompute the estimated fitness values and make any necessary updates to variables, γ and , using Eq.(20).

Step 7: If d approaches F_{max}, then the optimum solution is attained. Otherwise, proceed to Step 3.

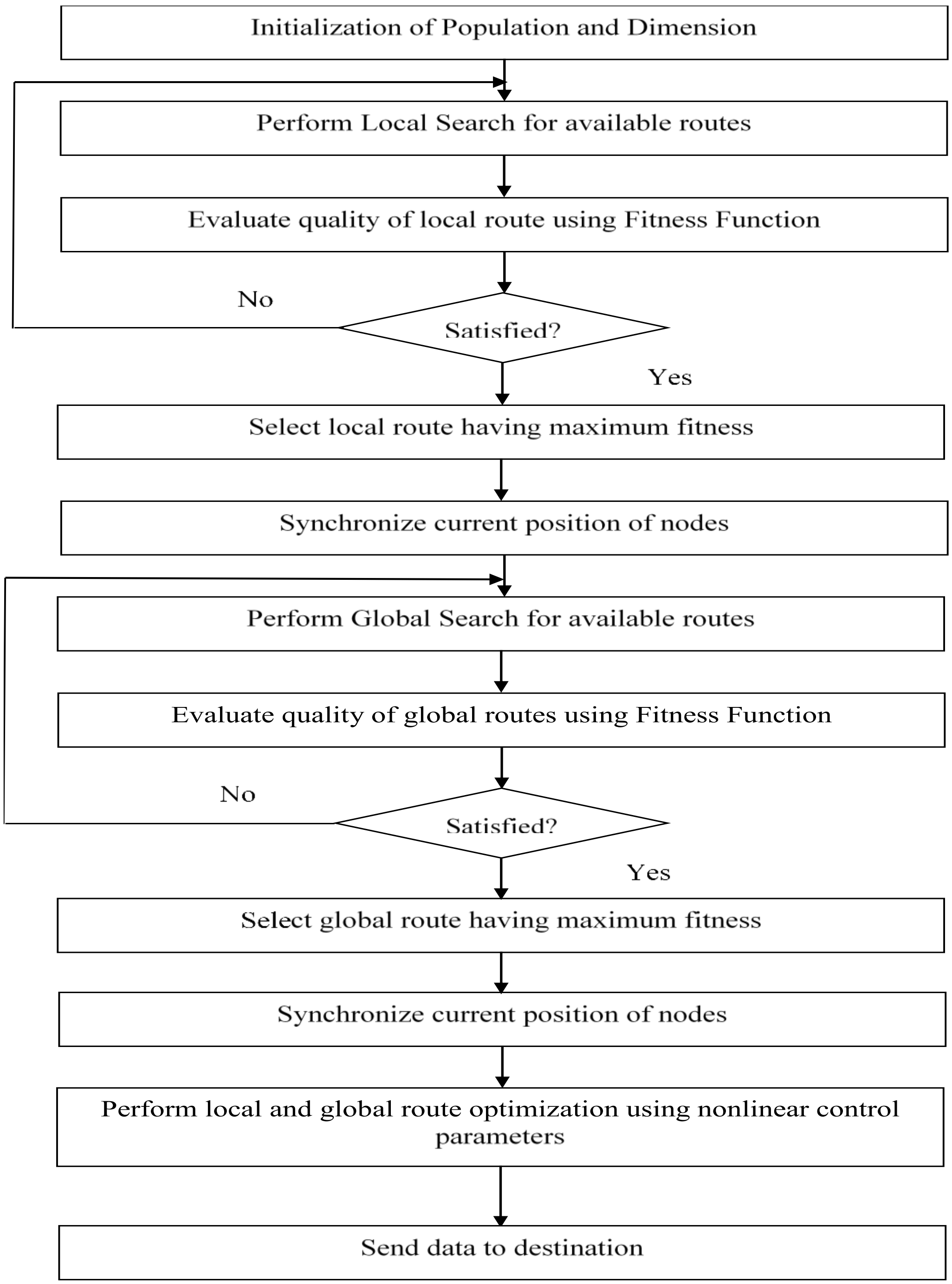

Figure 1 Framework of HOERP

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4. SIMULATION SETTING

Analysis of MWSN routing protocols is done using various simulations. A comparison between HOERP and the current routing protocols is performed using NS3 simulations. HOERP was compared to current routing protocols using the NS3. Researchers have been confounded by the MWSN's protocol modelling and implementation aspects, notably the network's overall performance. The design of HOERP and current routing protocols is examined to determine its strengths and limitations. According to this study, the NS3 simulator performs best with the C++ programming language.

Table 1 Simulation Settings

Bandwidth	100Hz
Initial energy level at nodes	10J
MAC Protocol Version	CW-MAC802.11DCF
Node density	350
Network Boundary Limit	1.5kmx1.5kmx1.5km
Packet size	74bytes
Runtime	300s
Rate of data transmission	10kbps
Sink density	4
Size of packet header	10bytes
Sensor nodes transmission range	≈350m
Transmission power	20W

5. PERFORMANCE METRICS

Delay is the difference in time between the packets that arrive at the destination node from the packets that travel from the source node.

Packet Delivery Ratio measures the ratio between the number of packets received by the receiver-end and the number of packets transmitted from the source end.

Packet Loss Ratio is the number of packets lost in transit against the number of packets sent.

Throughput refers to the amount of data transmitted in a given time.

Energy Consumption measures the amount of energy a packet uses to travel from its source to its destination.

6. RESULTS AND DISCUSSION

6.1. Delay Analysis

The performance of HOERP is analyzed for the delay in Figure 2. HOERP is compared against the NFO and FIS-RGSO. From Figure 2, it is evident that HOERP has a better result than NFO and FIS-RGSO, i.e., HOERP faces a minimum delay than NFO and FIS-RGSO. The core reason for HOERP to face lower delay is that it gives its significance to the quality of the route and the distance, rather than giving preference only to the shorter distance. Due to this reason, HOERP faces lower delays. NFO and FIS-RGSO prioritize the route having a minimum distance ending in route failure multiple times, resulting in delays in finding the alternate route. Table 2 highlights the result values of Figure 2.

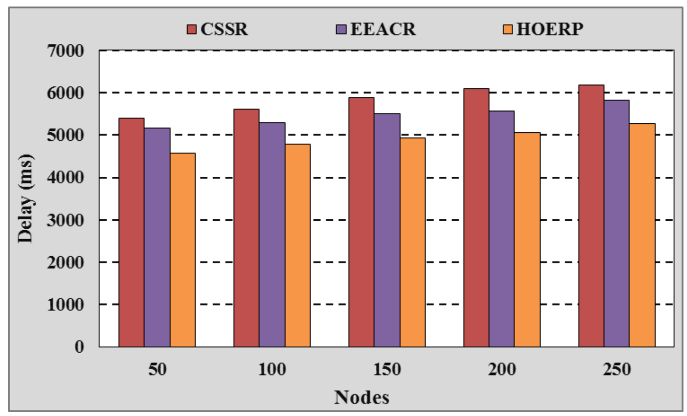

Figure 2 HOERP vs Delay

Table 2 Delay - Result Values

Nodes	CSSR	EEACR	HOERP
50	5399	5176	4582
100	5620	5285	4779
150	5876	5498	4932
200	6091	5577	5063
250	6177	5813	5280

6.2. Packet Delivery and Loss Ratio Analysis

The performance of HOERP is analyzed for the delivery of packets in Figure 3 and Figure 4. In Figure 3 and Figure 4, HOERP is compared against the NFO and FIS-RGSO for packet delivery and loss ratio of packets. Figure 3 compares the delivery ratio of packets, and Figure 4 compares the loss ratio of packets. From Figure 3 and Figure 4, it is evident that

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HOERP has a maximum delivery ratio of packets and a minimum loss ratio of packets. Identification of optimized cum stable routes leads to HOERP attaining better results than NFO and FIS-RGSO. Nonlinear parameters present in HOERP assist in identifying the better routes to the destination than NFO and FIS-RGSO, where they don't prioritize the route quality resulting in route failure and selecting the expired/failed routes. Corresponding result values of Figure 3 and Figure 4 is given in Table 3 and Table 4.

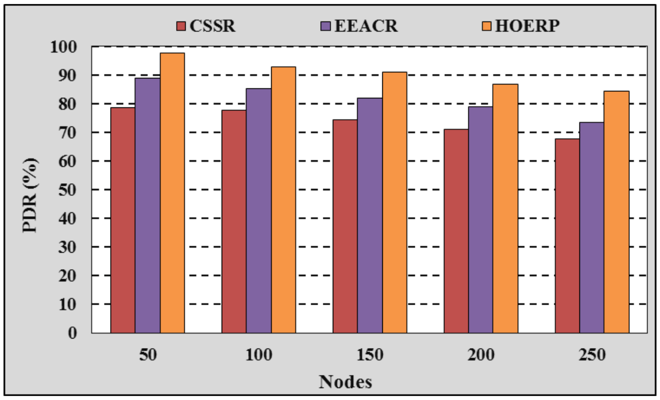

Figure 3 HOERP vs Packet Delivery Ratio

Table 3 Packet Delivery Ratio - Result Values

Nodes	CSSR	EEACR	HOERP
50	78.744	88.802	97.575
100	77.580	85.322	92.758
150	74.326	82.046	91.050
200	71.215	78.891	86.864
250	67.874	73.357	84.279

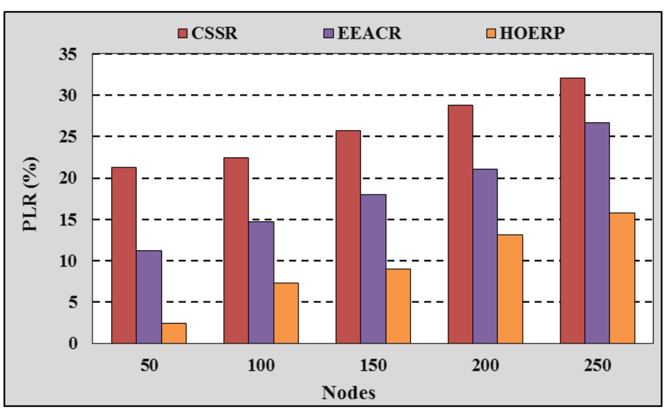

Figure 4 HOERP vs Packet Loss Ratio

Table 4 Packet Loss Ratio - Result Values

Nodes	CSSR	EEACR	HOERP
50	21.256	11.198	2.425
100	22.420	14.678	7.242
150	25.674	17.954	8.950
200	28.785	21.109	13.136
250	32.126	26.643	15.721

6.3. Throughput Analysis

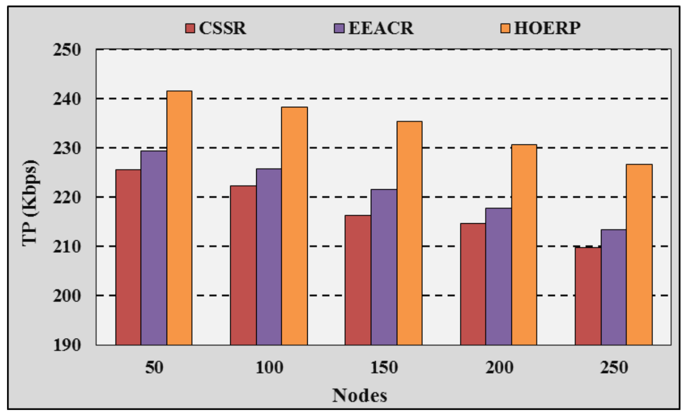

Figure 5 HOERP vs Throughput

Table 5 Throughput - Result Values

Nodes	CSSR	EEACR	HOERP
50	225.644	229.425	241.611
100	222.365	225.761	238.344
150	216.292	221.595	235.437
200	214.586	217.815	230.562
250	209.679	213.329	226.570

Figure 5 highlights the performance of HOERP against NFO and FIS-RGSO in terms of throughput. From Figure 5, it is understood that HOERP provides better throughput than NFO and FIS-RGSO. Chaos strategy present in HOERP assists in achieving better throughput, that is, even though the route gets failed, HOERP identifies the subsequent best route by performing the optimization. NFO and FIS-RGSO do not

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involve any optimization in finding the stable route. Due to unstable routes, NFO and FIS-RGSO cannot provide better throughput. It is also identified that; all protocol's throughput performance degrades when the density of nodes gets increased, and among them, HOERP provides better throughput than NFO and FIS-RGSO. Table 5 highlights the corresponding result values of Figure 5.

6.4. Energy Consumption Analysis

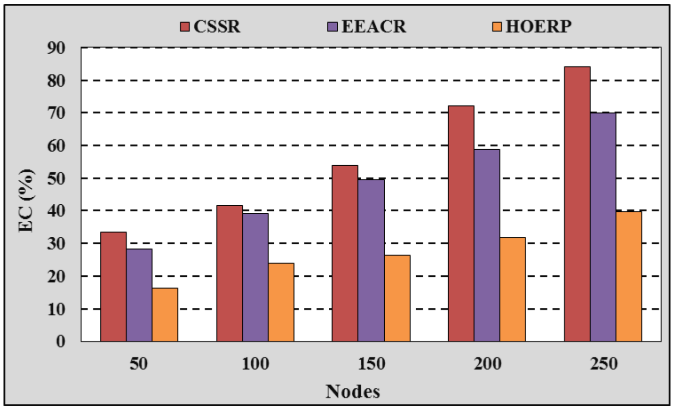

Figure 6 HOERP vs Energy Consumption

Table 6 Energy Consumption - Result Values

Nodes	CSSR	EEACR	HOERP
50	33.543	28.156	16.314
100	41.594	39.196	23.887
150	53.827	49.495	26.348
200	72.034	58.832	31.715
250	84.207	69.932	39.812

Consumption of energy to deliver the packets from source to destination throughout the simulation is analyzed via Figure 6. From Figure 6, it is identified that HOERP consumes low energy than NFO and FIS-RGSO. HOERP's low energy consumption is also an indicator of utilizing the routes that give the success ratio at the maximum. NFO and FIS-RGSO consume exhaustive energy to deliver the packets to the destination because of utilizing the poor-quality routes that fail. When the route fails in NFO and FIS-RGSO, they perform more computation in identifying the alternate route, which is a root cause for consuming more energy. When the node density increases, all protocols consume more energy, but the dual optimization in HOERP assists in consuming less energy than the NFO and FIS-RGSO. Table 6 highlights the corresponding result values of Figure 6.

7. CONCLUSION

A wireless sensor network (MWSN) is a collection of sensors that can detect, collect, and perhaps respond to sounds and vibrations. MWSNs are also known as "data acquisition networks" when they are linked to a larger data distribution network to gather and analyze data. They are used for security monitoring in medical and environmental studies. This paper has proposed a Hybrid Optimization-based Efficient Routing Protocol (HOERP) to reduce energy consumption to deliver the packets in MWSN. HOERP attempts to improve local search as well as global search through the use of Grey Wolf Optimization and Particle Swarm Optimization. HOERP's nonlinear characteristics are applied to discover the most efficient route that consumes less energy. A common set of measures used in network-oriented research is utilized to evaluate HOERP in NS3. The results show that HOERP uses less energy than the present routing techniques to transmit data packets. Future enhancement of this research work can focus on applying machine learning strategies to efficiently classify the routes.

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