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An Energy-Aware Cluster Head Selection and Optimal Route Selection Algorithm for Maximizing Network Lifetime in MANETs

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ABSTRACT

Quality of Service (QoS) is a crucial aspect of Mobile Ad Hoc Networks (MANET) that needs examination to demonstrate optimal performance. The scientific community is increasingly concerned with the challenge of developing an energy-aware clustering method for MANETs. This is owing to the fact that the battery-operated sensor devices that form the backbone of these wireless networks cannot be recharged. The selection of a cluster's leader is a difficult problem in MANET. Additionally, the research focuses on Optimal Route Selection (ORS) within the MANET context, acknowledging the significance of establishing efficient communication paths between cluster heads and member nodes. Through the integration of a reliability pair factor and node energy considerations, the proposed ORS algorithm generates optimal paths based on maximizing energy efficiency while minimizing the sum of hops between nodes. The study suggests a new algorithm based on the way waterwheel plants move and change their places as they explore and exploit new territory in the quest for food. The suggested method is named Binary Waterwheel Plant Algorithm (BWPA). In this method, a novel model is used to represent both the binary search space and the mapping from continuous to discrete spaces. Particularly, mathematical models of the fitness and cost functions used by the algorithm are constructed. Through the use of a reliability pair factor and node energy, the proposed research paper on Optimal Route Selection (ORS) generates the optimal path between the cluster head and member node and establishes the path based on the maximum energy and sum of hops among the nodes. By fusing the reactive power of differential evolution with the exhaustive search efficiency of the BWPA, the proposed method extends the life of networks. The recommended method increases node lifetime by compounding the dynamic capabilities of discrepancy evolution with the high effectiveness of search.

1. INTRODUCTION

A MANET is a network in which no two nodes have the same physical configuration. The routers travel about at will and arrange themselves in a disorganized fashion [1]. MANET has several potential applications, including group communication, emergency response, and even combat. Since MANET has no fixed infrastructure, malicious users can readily exploit its flexibility by connecting and disconnecting nodes at will [2]. Because of how difficult these threats are to identify; it is challenging to create defenses against them. Due to its versatility and speed in network construction, MANET is employed in many different kinds of applications [3].

If every node in the network trusts and collaborates with every other node, the networks will run smoothly. Due to their extremely dynamic nature and multiple communication breaks generated by mobile nodes [4, 5], routing is challenging, and security issues are regularly highlighted. As a result, the routing protocols in a MANET need to incorporate security measures to lessen the impact of potential attacks [5]. The openness, unpredictability, lack of privacy, and lack of authentication that characterize MANETs necessitate a comprehensive security solution [6].

There are two main aspects to MANET security: functional routing security and data broadcast security. In order to avoid tampering with and replaying of routing data transmission, security-based routing systems use a variety of encryption methods [7]. There are a number of different security routing methods [8, 9], including the most fundamental routing. In order for routers in a network to regulate the best path to take between any two points in the system, they need to be able to interconnect and share relevant information [10]. The primary function of a routing system is to determine the most efficient path for sending data from one device to another. Proactive, multicast, and reactive routing methods [11] are the three main types of MANET routing protocols. While there are benefits to using a variety of routing techniques, there are also a number of technical challenges that must be overcome, including issues related to energy [12].

The LEACH protocol has seen extensive application in MANETs as a means of addressing the difficulties associated with energy efficiency in CH selection. By taking turns as CH, LEACH attempts to reduce energy usage at individual nodes and extend the lifespan of the network [13]. However, there may be barriers to obtaining maximum energy efficiency using the standard LEACH method [14]. Optimizing difficulties in many different fields has seen a rise in interest in bio-inspired algorithms in recent years [15]. These algorithms take their cues for solving problems from the workings of biological or natural systems. Bio-inspired procedures can be used to improve MANETs' energy efficiency and performance in the context of CH selection [16].

As a result, this study analyzes the results, advantages, and significance of developing and utilizing a binary WWPA method for cluster head selection. Although the method has not been employed to address the problem since its creation, its performance prompted this binarization. In order to deal with the bounded-continuity character of the issue, we present a binary version of the WWPA.

Here is a list of the important contributions:

·In this research, we describe routing strategies that both prioritize safety and low power usage.

·We present a strategy for selecting cluster heads that balances load efficiently.

·A path-choosing algorithm taking into account trustworthiness, residual energy, and shortest possible hop count is provided.

·The paper recommends a new binary algorithm inspired by the waterwheel plant algorithm (BWPA) for resolving the cluster head problem.

·The effectiveness of the projected BWPA algorithm for node selection is evaluated using a battery of computational analysis measures.

The paper is structured as follows: Section 1 delivers an impression of MANETs; Section 2 contains a literature review on the topic of security in MANETs; Section 3 details the proposed work; Section 4 details the experimental results and evaluation; and Section 5 provides a summary and final thoughts.

2. RELATED WORK

The Differential Evolutionary is presented by Bhatnagar et al. [17] to discourse the issue of energy efficiency in the communication process via the selection of cluster heads. By fusing the reactive power of discrepancy evolution with the exhaustive search efficiency of Sparrow Search, the proposed method extends the useful life of networks. The suggested method extends the life of nodes by combining the dynamic abilities of differential evolution with the high search effectiveness of the method.

A CH election process (CCCH) based on cluster coordinators is presented by Rajathi [18]. The cluster coordinator (CC) is the central figure since they are in control of the operation as a whole. The suggested model consists of three parts: the cluster coordinator (CC), the cluster head (CH), and the cluster members (CM). The Cluster Head (CH) is second only to the Cluster Coordinator (CC) in terms of significance as a serving node inside a cluster. A cluster's nodes all have their own individual values for a variety of characteristics. The combined suggested architecture effectively built dependable routing with the least amount of time and energy utilisation. The assessment measures used to compare the algorithms show that the suggested algorithms perform much better than their competitors in every category.

To augment the presentation of the routing algorithm in MANETs, Deepa and Sridhar [19] designed and implemented a mobility-aware routing protocol (IoT-MARP). By improving the data routing plan, IoT-MARP enables the transfer of messages. Information exchanged across routing protocols improves power efficiency and latency. This study proposes a data routing system for the Internet of Things (IoT) using protocols from WSNs and MANETs. Analyses of the implemented solution reveal that global MANET-IoT systems are capable of achieving optimal energy efficiency. Performance metrics for the proposed method include 93.1% on tests measuring overhead.

A secure and low-power routing system based on group key management is proposed by Saravanan et al. [20]. With the goal of establishing the trust among connected nodes, Particle Swarm Optimisation (PSO) was originally adopted for malicious node detection, with the expectation that all nodes involved would generate and disseminate content that was genuine, accurate, and trustworthy. Asymmetric key cryptography relies on two specialised nodes, the Calculator Key (CK) and the Distribution Key (DK), to generate, validate, and disseminate secret keys across nodes. The suggested technique, known is praised for being a secure routing mechanism that conserves energy throughout the cluster head election process. Three cutting-edge approaches are used to evaluate it. As seen in the simulation results, the proposed OptCH_TAKMP reduces the following: routing overhead by 31.4 percent, end-to-end delay by 23.1 percent, energy efficiency by 78.5 percent, throughput by 94.8 percent, latency by 28.1 percent, malicious detection rate by 91.4 percent, packet delivery ratio by 92.4 percent, lifetime of the network by 85.2 percent, cost of communication by 19.2 percent, and trust computation error by 28.5 percent.

For efficient routing and encrypted data transfer, Jose and Vigila [21] combined the Salp Swarm Algorithm (SSA) with the Replacement Method and the Sine Cosine algorithm (SCA) search (SSARM-SCA). A secure connection is set up using an encryption method based on mutual trust. Throughput, network lifespan, end-to-end latency, packet delivery ratio, energy usage, and routing overhead ratio were some of the performance indicators used to assess the suggested technique. In terms of energy lifespan, our method beats four state-of-the-art strategies with improvements evident for up to 3500 cycles in the simulation results. Our suggested method provides a holistic answer to the problems of energy MANETs, making it useful in fields as diverse as tracking and military settings. We improve network performance and longevity by combining the Fuzzy-based CAPSO procedure with the SSARM-SCA routing protocol to optimise CH selection and routing pathways, correspondingly.

The SOMACA clustering approach, proposed by Salim et al. [22], is based on swarm optimisation and takes mobility into account. Clustering and routing are the two main parts of SOMACA. We use the Sparrow Search algorithm (SSA) to determine which CHs should be used in each cluster by combining mobility measurements and cluster distance during the clustering phase. There are two stages to the routing process: route formation and route maintenance. Establishing an ideal list of connections that are too low, and selecting the best one in each round, is the primary goal of the route creation stage when it comes to constructing a base station (BS). The Upkeep phase also works to keep the connection fresh and running well. The effectiveness of SOMACA is measured in terms of the average cluster lifetime, the broadcast range, and the network grid size through a series of simulated studies.

Here, we present the Emperor Penguin Optimisation Fuzzy Genetic technique (EPO-FGA), a novel energy-efficient procedure established by Hamza and Vigila [23]. The longevity of the mobile node is improved because to the suggested strategy's incorporation of the fuzzy genetic algorithm's adaptability and the high search efficiency of emperor penguin optimisation. The emperor penguin method begins with a very efficient cluster formation that takes into account variables like the mobility, direction, and position of each node. Then, the optimal cluster leader is selected using a method based on a fuzzy genetic procedure and the following three parameters. The NS2 platform is used for the actual implementation. Packet delivery success rate, energy consumption, throughput, and longevity are some of the metrics used to assess the outcomes. The presented technique achieves longer runtimes with less power usage, as seen in simulation results.

Based on the standard BRO method, Mahadevachar and Hosur [24] present a trust based multi-objective battle royale optimisation (T-MOBRO) approach. T-MOBRO is proposed as a revolutionary approach to traditional BRO to overcome the limitations of trust-based energy efficiency routing. By using trust, energy, and distance as its fitness function, the T-MOBRO algorithm achieves both energy efficiency and trust-based routing. The suggested model is supposed to have several objectives, including travel time, power consumption, packet forwarding rate, end-to-end latency, direct trust, and indirect trust. The battle royale genre of video games served as inspiration for the BRO algorithm. Throughput, average energy consumption, packet delivery ratio, and end-to-end delay (EED) are used to assess the effectiveness of the suggested process. T-MOBRO's throughput for a network of 10 nodes is 4032.29 bits/s, its end-to-end latency is just 0.0070 seconds, and its energy usage for a MANET is just 1.7Joules.

The trust aware routing protocol presented by Vatambeti and Mamidisetti [25] provides a safe routing method for WSNs. Based on response portability and energy limitations, the routing protocol is robust in the presence of hostile nodes nursing activity on the routing tiers. We propose a Trust Aware Energy Efficient Routing Protocol (TAE2RP) that uses safe routing data transfer to increase lifespan maximisation in WSN, taking into account energy level-based security. Initially, the packet loss ratio was used to calculate the Resistance Support Factor (RSF) by taking into account the data similarity of route carrying information. Secure Surf-Channel Multicast Routing Protocol (SSCMRP) is then used to study the patterns of behaviour at each layer of the routing hierarchy. The purpose of this TAE2RP study is to assess the impact of trust on data packet transfer rates. The data packets were also encrypted using Redundant Array Shifting Encryption (RASE). Master Node Digital signature authentication was used to strengthen the authentication policy. By managing energy-balancing methods, we were able to reduce the price of security routing while simultaneously enhancing authentication and therefore achieving a greater level of security.

2.1 Problem statement

Existing clustering methods for MANET suffer from a lack of mobility awareness and energy efficiency, both of which are addressed in this study. Inefficient cluster formation and CH selection occur because traditional clustering methods do not take into account the dynamic nature of node mobility. As a result, there is a rise in energy consumption and a decrease in the lifespan of the network. Our goal is to improve MANETs' energy efficiency and network performance, and we provide a novel optimisation approach to do so.

3. PROPOSED WORK

The projected routing scheme is alienated in two stages:

·Originally cluster heads are designated.

·After discovery paths, an optimal route is selected.

This study suggests a novel method that makes use of the BWPA to bring together mobility consciousness and energy conservation. Improved energy efficiency, and overall performance are all goals of the BWPA algorithm, which is designed to optimise CH selection in cluster-based MANETs.

3.1 Mobility concept

The success of routing algorithms and the reliability of clusters in a MANET are both affected by the nodes' capacity to move throughout the network. Poor cluster stability is the outcome of increased mobility, which causes frequent CH re-updates in cluster links. Our method uses mobility data to set up a stable path among less mobile entities, which reduces control overhead and improves stability. Using this strategy, we want to lessen MANETs' sensitivity to node mobility, improve cluster stability, and cut down on control messages that aren't strictly essential.

3.2 Model for energy

The success of a network depends on the routing protocol's ability to do more than merely find the most direct route from one set of nodes to another. With ME routing, the path chosen for packet transmission uses the least amount of energy overall, whereas with max-min routing, the path chosen uses the most energy within the constraints of the nodes. At regular intervals, this energy hub is supplied by:

$$E_{energy}(t_j, \Delta t) = E_{residual}(t_j, l_0) - E_{residual}(t_j, l_1) \qquad (1)$$

The energy node here is characterised by $Eresidual$ at times 0 and 1, correspondingly.

3.3 MANET clustering perfect

The node learned about other nodes by sending out a packet indicating their relative weight. Both the node's degree and its throughput of data contribute to the value of the node. It is the system's mobility and energy that serve as the basic criteria for determining the cluster and CH. Increased CH selection and interface refreshment due to mobility destabilises clusters.

In order to form a cluster, the CHs will broadcast a request for a packet to any collection of sensor nodes within radio range. In the single-node mode, data is transmitted unambiguously to the CH, whereas in the node relays its data to its neighbours. CHs are assigned to rounds in the setup phase in a completely random order. This permits the CH duty to be shared throughout the network's nodes and maintain consistent energy use. Once the CHs have been picked, they announce their function to the surrounding nodes, which subsequently select their own CHs based on the advertised roles. Network scalability is increased, and communication cost is decreased, thanks to this clustering process.

During the steady state, sensor nodes provide data to their associated CHs, which then send the data in bulk to the base station. In order to reduce the quantity of data being transferred and hence the amount of energy being used, the CHs apply data aggregation algorithms. To evenly spread the energy burden and increase the lifespan of the network, CHs are swapped out at the beginning of each new round.

3.4 CH selection

To facilitate communication between nodes in various clusters and supply radio transmitters to the participants, a CH has been set up. At the start of each round, each node chooses whether or not to be a CH with the probability $qs_j(t)$ set so that D is the expected number of CHs. In this light, it follows that if the network has nodes:

$$D = \sum_{j=1}^{N} qs_j(t)^* 1 \tag{2}$$

here, N is the total quantity of network nodes, while $N - l$ represents ordinary nodes.

$$qs_j(t) = \frac{\text{Anticipated number of cluster heads}}{\text{Expected number of nodes are not cluster heads in most recent rounds}} \tag{3}$$

At least one of N-k's nodes will be CH. The likelihood of transformation into a CH is the same for every node in a cluster. This ensures that the energy at each node is about equal after each round. Nodes with more energy tend to cluster more readily than anodes with lower energy. Cluster nodes are expected to number:

$$\begin{gathered} Energy[CH] = D \Longrightarrow (N - D * (rmod\ N\ /\ D)) * \\ N\ /\ D - D * (rmod\ N\ /\ D) \end{gathered} \tag{4}$$

Although key administration approaches facilitate the distribution of keys to cluster nodes, the process becomes inefficient and introduces key overhead if keys must be produced for each node in the cluster. Different nodes are shown in different colours to highlight the many components of the overall structure. Each cluster's CH is the node with the fewest edges.

3.5 Optimum CH selection models

The purpose of the BWPA-based clustering approach is to fortify CHs. For MANET cluster stability to be attained, this is a prerequisite. In networks where CHs are used to relay data between nodes, it is important to remember that this does not guarantee efficient clustering merely by choosing the best possible CHs. This section first describes how to set up WWPA [26], using a model behaviour, and then on to define throughout.

3.5.1 Initialization

In WWPA, several people work together to solve a problem by iteratively searching for the best option. Due to the dispersed nature of the waterwheels throughout the search area, the WWPA population exhibits a wide range of values for the issue variables. Each waterwheel represents a unique vector that may be used to solve the problem graphically. The WWPA population, including all possible waterwheel variants, might be represented using a matrix. Waterwheel placement in the search area is decided randomly as the initial step of a WWPA deployment.

$$P = \begin{bmatrix} P_1 \\ \vdots \\ P_2 \\ \vdots \\ P_3 \end{bmatrix} = \begin{bmatrix} p_{1,1} & \cdots & p_{1,j} & \cdots & p_{1,m} \\ \vdots & \ddots & \vdots & \therefore & \vdots \\ p_{i,1} & \cdots & p_{i,j} & \cdots & p_{i,m} \\ \vdots & \therefore & \vdots & \ddots & \vdots \\ p_{N,1} & \cdots & p_{N,j} & \cdots & p_{N,M} \end{bmatrix} \tag{5}$$

$$\begin{gathered} p_{i,j} = lb_j + r_{i,j}.\left(ub_j - lb_j\right), \\ i = 1,2,\ldots,N, j = 1,2,\ldots,,m \end{gathered} \tag{6}$$

where, N is the total number of waterwheels and m is the total sum of independent variables, $r_{i,j}$ is an independent random variable in the range [0, 1], and Lower and upper bounds for the j^{th} problem variable are denoted by lb_j and ub_j, respectively; P is the populace matrix of waterwheel sites; P_i is the i^{th} waterwheel (a potential solution) and $p_{i,j}$ is the j^{th} issue variable. The goal function for each waterwheel may be calculated separately since they each represent a different way of thinking about the problem. The objective function of the issue may be conveniently written as a vector of values using Eq. (7).

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix} \tag{7}$$

where, F is a vector of all the values of the objective value anticipated for the i^{th} waterwheel. In order to determine which options are the most advantageous, we mostly rely on objective function evaluations. This implies that the solution with the best member) is the optimal one. The poorest solution candidate (or worst member) is represented by the lowest value. Due to the waterwheels' random drive over the search area at each iteration, the current optimum will shift over time.

Phase 1: Position identification and hunting of insects

Because of their superior sense of smell, waterwheels become formidable predators. Any bug that comes into the waterwheel's range will immediately be attacked. Once it has located its victim, it immediately begins attacking and pursuing it. WWPA simulates this waterwheel action as the first step in its population update model. We may be able to enhance WWPA's exploration capabilities in discovering leads to huge fluctuations in the waterwheel's location in the search space. The waterwheel's new position is calculated by using Eq. (8) and a simulation of its approach to the bug. If moving the waterwheel to the location below increases function, the former location will be abandoned.

$$W = r_1.(P(t) + 2K) \quad (8)$$

$$P(t+1) = P(t) + W.(2K + r_2) \quad (9)$$

where, r_1 and r_2 are independent variables that might take on any value between zero and two. K is an exponential variable having values between zero and one, and W is a vector representing the diameter of the search circle in which plant will hunt for sites. If after three repetitions the answer does not change, then the waterwheel's position can be modified using Eq. (10).

$$P(t+1) = Gaussian(\mu_P, \sigma) + r_1\left(\frac{P(t)+2K}{W}\right) \quad (10)$$

Phase 2: Carrying the insect in the suitable tube

A waterwheel draws in phase of WWPA's population update is informed by this simulation of waterwheel operation. The WWPA's power is improved during the local search as a result of tube, which creates small waterwheel in the search space, and already been discovered. By assigning each waterwheel in the population a new random site as an "excellent position for devouring insects", the creators of WWPA mimic the waterwheel population's natural behaviour. If the value of the target function is larger than the initial location, as shown by the subsequent equations, the moves to the new site.

$$W = r_3.(KP_{best}(t) + r_3P(t)) \quad (11)$$

$$P(t+1) = P(t) + KW \quad (12)$$

where, r_3 is a random mutable with values in the variety [0, 2], $P(t)$ is the current key at repetition t, and P_{best} is the finest key.

Similar to the exploration stage, the following mutation is used if the solution does not improve after three rounds in order to prevent getting stuck in a specific local minimum.

$$P(t+1) = (r_1 + K)sin\left(\frac{F}{C}\theta\right) \quad (13)$$

where, [5, 5] is a range for the values of the random variables F and C. Eq. (14) also shows that the value of K falls off exponentially.

$$K = \left(1 + \frac{2*t^2}{T_{max}} + F\right) \quad (14)$$

3.5.2 Search space binarization

The people who make up the BWPA search space are characterised as binary vectors. Each person in the search space is represented by a binary number. The ability to easily identify good and bad qualities is facilitated by this portrayal. First, the populace size dataset dimension D determine how many people will be involved in the search. The WWPA procedure, when practical to the search space, is meant to provide optimum solutions with a novel internal representation.

The whole optimisation process, which is anticipated to take many rounds, will be completed before the results are sent to each ind_i. The selected characteristics should be represented by cells with values of 1 s. For an arbitrary solution ind_i, the dimension of the dataset X, |F|, is generally equal to D. We count the sum of ones in dimension D for each occurrence represented by the variable ind_i in dataset X. When solving feature selection issues, binarization of WWPA might help by formalising the search space. The following is a description of the proposed BWPA strategy and how its parts interact with one another.

3.5.3 Binarization of WWPA

To optimise solutions in a discrete solution space, a new variant of the algorithm was developed by combining the capability of the original WWPA with many additional operators. In the first stage, transformation functions are defined to allow for the continuous to discrete transformation of the solution representation and optimisation process. This is crucial so that the innovative method may address issues associated with feature assortment. The second modelled process for producing the new variant of BWPA is to modify the fitness function. The best solution may be found by calculating the fitness of each choice. We provide the fitness function to account for the details of the current scenario. A schematic of the BWPA's inner workings and an analysis of its algorithmic structure are also provided. By applying the following sigmoid function to the continuous solution returned by the WWPA method, we may obtain a binary representation of the solution.

$$Binary = \begin{cases} 1 & if\ Sigmoid(S_{best}) \geq 0.5 \\ 0 & otherwise \end{cases} \quad (15)$$

$$Sigmoid(S_{best}) = \frac{1}{1+e^{-10(S_{Best}-0.5)}} \quad (16)$$

3.5.4 Fitness and cost functions

A combination of assessing the function was necessary to find the optimal key to the feature selection problem. The subsequent equation illustrates how the solution is evaluated based on its performance using the classifier *clf* when the tuning parameter is applied to a subset of the dataset X[: 1(ind_i)]. When substituted for 1(ind_i) in the notation 1indi returns the total sum of 1s in the array.

$$fit = \Omega * \left(1 - clf(X[:1^{ind_i}])\right) + \left((1-\Omega)\frac{|F|}{D}\right) \quad (17)$$

The cost function is evaluated based on function by deducting the value repaid by fit from 1, as stated in the subsequent equation. The fitness and cost function values are used to visually assess and interpret each optimal key for a certain dataset.

$$cost = 1 - fit \quad (18)$$

3.5.5 Fitness function

The function is used to measure the quality of the solutions fashioned by the suggested algorithm. The amount of characteristics utilised for organisation and the misclassification rate are the two primary factors affecting the fitness function. If a solution reduces the error rate and the sum of features used, it is considered a good solution. The effectiveness of each solution is calculated using the following equation.

$$F = h_1\frac{|s|}{|f|} + h_2Error(D) \quad (19)$$

where, $|f|$ and $|s|$, respectively, stand for the total sum of features and the sum of features that were chosen. $Error(D)$

stands for the classification error. and the parameters h_1 and h_2 are used to control the significance of the chosen features using $h_1 \in[0, 1]$ and h_2=1-h_1.

3.6 The algorithm for optimal path selection

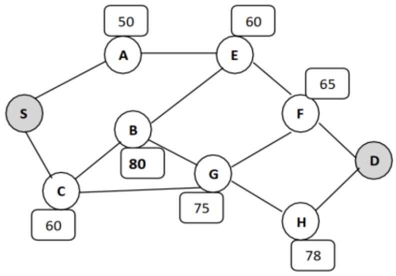

Figure 1. Communiqué path among source and destination

Finding the shortest path between two sites is essential for reaching a destination. This algorithm provides a strategy grounded on the node's greatest energy and the fewest possible hops between nodes.

1. Route RREQ is produced by the basis node.
2. The RREQ header contains the RREQ ID, the terminus address, the arrangement number, the source address, the hop count, and the NmaxE.
3. If a node getting the packet has an advanced energy stays unaffected.
4. Keep checking until the RREQ reaches at its terminus.
5. The multiple RREQ gathered from various routes are used to select the best energy-efficient path.
6. If choose a communiqué route.
7. A RREP is repaid.
8. Data is directed via the afresh stated route.

If the aforementioned methods are applied, it is not required to choose a specific algorithm to select the path. This algorithm may allow us to find multiple paths with the same high energy. The alternate route must be picked if there are any crashes along the route. Thus, computation period can be shortened. Figure 1 is an illustration of finding the node with the most energy along the shortest path.

4. RESULTS AND DISCUSSION

The programme NS2 (Network Simulator version 2) is used to simulate the suggested paradigm for data transport in mobile sink. In the academic world, NS2 is the go-to standard for experimentation because of its event-driven design. NS2 comes with a suite of tools for modelling the operation of wireless and wired networks and their associated protocols. NS2's modularity it a favourite among researchers in the arena of networking.

4.1 Simulation environment

We describe the imitation setup that will be used to test the suggested model. Placement heterogeneity, and the region being monitored is a square with dimensions of 100 x 100 m. These coordinates denote the location of four distinct mobile sinks employed for this study, all situated outside the network. such as (50, -10), (50,110), (-110, The sum of (N_{Adv}) fractions is v=0.1, and sum of (N_{int}) fractions is $v_0 = 0.2$. The portions of E_{adv} is α=2 and E_{int} is β=1. Table 1 specifies the details about the projected imitation situation.

Table 1. Simulation situation of H-WSN

Parameters	Standards
Amplification energy for lesser distance	E_{efs}=10 pJ/bit/m^2
Energy expended during data accumulation	E_{Da}=5 nJ/bit/signal
MMSs site	(50, -10), (50,110), (-10, 50), (-10,50)
3-level heterogeneity	Usual, progressive and midway nodes
The sizes of progressive and middle nodes	v=0.1 and v_0=0.2
Energy fractions	α=2 and β=1
Transmission variety	250 m
Entire system energy	140 J
Packet size	1000byte
Sum of nodes	100
Early energy	0.5 J
Threshold distance	d_0=87 m
Energy vital for receiver, spreader	E_{elc}=50nJ/bit
Strengthening energy for larger coldness	E_{amp}=0.0013 pJ/bit/m4
Size of network	100×100 m^2
Mobile sink	4

4.2 Performances metrics

Utilizing the parameters of network energy remaining, stability retro, and sum of alive nodes, the efficiency of the projected model is examined. The formula for calculating these measures is shown below:

$$Throughput = \frac{Amount\ of\ data\ packet\ transmitted}{time\ taken\ to\ transmit\ the\ data\ packet} \quad (20)$$

$$Stability\ Period = \frac{Number\ of\ rounds\ covered}{First\ node\ depletes\ its\ full\ energy} \quad (21)$$

$$Number\ of\ alive\ nodes = Energy_{rem}^{i}(n) > 0 \quad (22)$$

$$Number\ of\ dead\ nodes = Energy_{rem}^{i}(n) \leq 0 \quad (23)$$

$$Network\ lifetime = \left[\frac{\sum_{i=1} NL_i * Ma_{ij}}{Total\ nodes}\right] \quad (24)$$

where, the protuberance life is signified as $NL_i = \frac{E_0}{EC_i}, 1 \leq i,$ Coverage matrix is represented.

$$Ma_{ij} = \begin{cases} 1 \; if \; SN_i \; monitor \; T \arg et_j \\ 0 \qquad\qquad o.w \end{cases} \tag{25}$$

Network leftover energy is the left over after executing data transfers, while energy efficiency is the measure of how little energy is required to complete a task.

4.3 Network lifetime and stability period analysis

Table 2 characterizes the lifetime and stability retro. In the investigation, the Rat Optimization model attained the Stability period as 3624, and the Network lifespan as 16,522, along with the HND as 7278 correspondingly. Then, the Cat Swarm model achieved the Stability period as 5334, the Network lifespan as 18,926, and the HND as 9817 correspondingly. The Red Deer model attained the Stability period as 4791, the Network lifespan as 20,973, and the HND as 9694 correspondingly. The WWPA model achieved the Stability period as 6515, the Network lifespan as 25,000, and the HND as 13,442 correspondingly. Finally, the BWPA model attained the Stability period as 7184, the Network lifespan as 29,720, and the HND as 15,360 correspondingly.

Table 2. Network lifetime and stability passé

Algorithms	Stability Period (Rounds)	Network Lifespan (Rounds)	HND (Rounds)
Rat Optimization	3624	16,522	7278
Cat Swarm	5334	18,926	9817
Red Deer	4791	20,973	9694
WWPA	6515	25,000	13,442
BWPA	7184	29,720	15,360

4.4 Remaining energy of network analysis

Table 3 provides the network's remaining energy. In the analysis of 5000 rounds, the ROA model determined the network's residual energy to be 60.68, the CSO model determined it to be 80.68, the RDA model determined it to be 85.655, the WWPA model determined it to be 101.37, and the BWPA model determined it to be 119.65, all in the appropriate order. After 10,000 rounds, the ROA model determined that the network's residual energy was, respectively, 11.72, 21.72, 22.41, 61.034, and 80.689. After 15,000 rounds, the ROA model achieved the outstanding energy of the network as 0.68, the CSO model achieved the outstanding energy of the network as 80.68, the RDA model achieved the lingering energy of the network as 1.379, the WWPA model achieved the network's remaining energy as 2.374, and the BWPA model achieved the remaining energy of the network as 48.620, respectively. After 20,000 rounds, the ROA model achieved the network's outstanding energy as 0.04, the CSO model achieved the network's remaining energy as 80.68, the RDA model achieved the network's outstanding energy as 0.14, the WWPA model achieved the network's remaining energy as 0.36, and the BWPA model achieved the network's remaining energy as 8.96. The BWPA model achieved the network's remaining energy as 23.103. After 25,000 rounds, the ROA model, CSO model, RDA model, WWPA model, and BWPA model all achieved an outstanding energy of the network of 0.0, 0.534, and 11.724, respectively. The ROA model also achieved an energy of the network of 0.0, and the residual energy of 80.68, and RDA model, 0.0, respectively. After 30,000 rounds, the network was determined by the ROA model to be 0.0, the CSO model to be 80.68, the RDA model to be 0.0, the WWPA model to be 0.0, and the BWPA model to be 0.3448, respectively.

4.5 Number of alive nodes analysis

The total amount of alive nodes is indicated in Table 4 by the number. In the 5000-round investigation, the ROA model determines that there are 92 alive nodes, the CSO model determines that there are 96 alive nodes, the RDA model determines that there are 99 alive nodes, the WWPA model determines that there are 98 alive nodes, and the BWPA model determines that there are 99 alive nodes. Following the 10,000 rounds, the ROA simulation reaches a node count of 16; the CSO model reaches a node count of 34; the RDA model reaches a node count of 29, the WWPA model reaches a node count of 90; and the BWPA model reaches a node count of 95, respectively. After 15,000 rounds, the ROA model achieves a node count of 2; the CSO model achieves a node count of 6; the CSO model achieves a node count of 8; the RDA model achieves a node count of 29; and the BWPA model achieves a node count of 95, respectively. Then, after 20,000 rounds, the ROA simulation reaches the sum of alive nodes as 0, the CSO model reaches the sum of alive nodes as 0, the RDA model reaches the sum of alive nodes as 10, and the BWPA model reaches the quantity of alive nodes as 29, respectively. After 25,000 rounds, the ROA model, CSO model, RDA model, WWPA model, and BWPA model all reach 0 live nodes, 0 live nodes, and 12 live nodes, respectively. After 30,000 rounds, the ROA model, CSO model, RDA model, WWPA model, and BWPA model all reach 0 live nodes and 3 live nodes, respectively.

Table 3. Remaining energy of network (joules)

No. of Rounds	ROA	CSO	RDA	WWPA	BWPA
5000	60.68	80.68	85.655	101.37	119.65
10,000	11.72	21.72	22.41	61.034	80.689
15,000	0.68	1.379	2.374	27.24	48.620
20,000	0.04	0.14	0.36	8.96	23.103
25,000	0.0	0.0	0.0	0.534	11.724
30,000	0.0	0.0	0.0	0.0	0.3448

Table 4. Sum of alive nodes (rounds)

No. of Rounds	ROA	CSO	RDA	WWPA	BWPA
5000	92	96	99	98	99
10,000	16	34	29	90	95
15,000	2	6	8	29	95
20,000	0	0	0	10	29
25,000	0	0	0	0	12
30,000	0	0	0	0	3

4.6 Throughput analysis

Characterized the Throughput * 105 analysis in Table 5. Following 5000 rounds, the ROA model achieves a throughput of 0.0204, the CSO model achieves a throughput of 0.020, the RDA model achieves a throughput of 3.865, the WWPA model achieves a throughput of 3.559, and the BWPA model achieves a throughput of 3.7840. After 10,000 rounds, the ROA model achieves a throughput of 3.25, the CSO model achieves a throughput of 4.643, the WWPA model achieves a throughput of 6.034, and the WWPA model achieves a throughput of 6.545 and 7.220, respectively. After 15,000 rounds, the ROA model achieves a throughput of 4.377, the CSO model achieves a throughput of 5.665, the RDA model achieves a throughput of 6.299, the WWPA model achieves a throughput of 7.95, and the BWPA model achieves a throughput of 9.138. Then, after 20,000 rounds, the ROA model achieves a throughput of 4.479, the CSO model achieves a throughput of 6.034, the RDA model achieves a throughput of 6.32, the WWPA model achieves a throughput of 8.193, and the BWPA model achieves a throughput of 9.540. After 25,000 rounds, the ROA model achieves a throughput of 4.479, the CSO model achieves a throughput of 6.034, the RDA model achieves a throughput of 8.693, and the BWPA model achieves a throughput of 9.8282, respectively. Following that, after 30,000 rounds, the ROA model achieves a throughput of 4.479, the CSO model achieves a throughput of 6.034, the RDA model achieves a throughput of 6.32, the WWPA model achieves a throughput of 8.693, and the BWPA model achieves a throughput of 9.981 respectively.

Table 5. Throughput *105 (packets)

No. of Rounds	ROA	CSO	RDA	WWPA	BWPA
5000	0.0204	0.020	3.865	3.559	3.7840
10,000	3.25	4.643	6.034	6.545	7.220
15,000	4.377	5.665	6.299	7.95	9.138
20,000	4.479	6.034	6.32	8.193	9.540
25,000	4.479	6.034	6.32	8.693	9.8282
30,000	4.479	6.034	6.32	8.693	9.981

5. CONCLUSIONS

High-speed data transfer is the norm in today's environment. The use of the internet and wireless technology is expanding rapidly. Smartphones, tablets, and other smart gadgets are ubiquitous. Sensitive data is occasionally stored on these sensor nodes. Data traveling through these sensor nodes must be protected from unauthorized access. A route optimization technique is introduced as a consequence of this research into a system for determining the credibility of individual network nodes. Therefore, the plan offers a safe and dependable passage through the whole network. Throughout the data relay phase, the concept of nodes' confidence is used to construct a secure and steady ideal route that is less susceptible to trail failures. The suggested method determines the best way to send data safely through the network. Since MANETs are infrastructure-free, self-organizing networks, this study focuses on how to improve their energy efficiency, network performance, and mobility awareness. These aspects, especially CH selection, may be affected by the changing topology of MANETs. The BWPA is proposed as a solution by the study as a means of improving energy competence in the communication process via better CH selection. The proposed method considerably improves network lifespan, throughput, cluster lifetime, and PDR while reducing energy consumption by combining the dynamic capabilities of DE with the very actual technique. Implementing BWPA in real-world circumstances and completing practical assessments should be the primary emphasis of future research. Investigate the integration of machine learning techniques to improve decision-making processes in cluster head selection and route optimization. Machine learning models could learn from historical data and network dynamics to make more informed decisions, further optimizing energy efficiency.

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