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HDOMLM: Hybrid Dual Optimized Machine Learning Model for Cluster Head Selection in MANET

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Abstract: The selection of cluster heads with efficient energy awareness is a crucial concern in mobile ad hoc networks (MANETs). MANETs' energy efficiency is enhanced when a suitable cluster head (CH) is selected. Clusters are established in Mobile Ad hoc Networks (MANETs) to enhance communication among nodes. Efficient clustering is necessary to provide the rapid and precise transmission of information in the middle of nodes. In this work, we proposed a hybrid dual optimization of the machine learning model (HDOMLM). In this protocol, we are performing two different optimizations for clustering. Initial clustering is performed using Particle Swarm Optimization (PSO) based on node location and mobility as objection function cost. Once the initial cluster is formed, the selection metric is evaluated from the available network topology for the execution period. Delta difference, average distance, related energy, related mobility, and transmission delay are the five selection metrics used as features in the Optimized Machine Learning Model (O-MLM). By using O-MLM, we can classify that the node belongs to a normal node or cluster head node. To evaluate the effectiveness of our proposed HDOMLM, we are performing the simulation in MATLAB tool. Different performance metrics such as Alive nodes, Residual energy, Energy Tax, Average End-to-End Delay, Number of Successful packets received as BS, and Total processing time. The objective of network lifetime improvement is achieved in the proposed HDOMLM by 200 rounds and residual energy of 56% increased than earlier works.

Keywords: MANET, Clustering, Network Lifetime, Energy Efficiency, Transmission Cost, PSO Optimization, Machine Learning, Cluster Head Selection.

1. Introduction

Mobile Ad Hoc Network (MANET) is a trustable area of applications for nascent computing practices. The decentralization and the dynamic nature of the environment differ this protocol from the conventional distributed systems. Currently, cluster-based routing protocols are well-recognized strategies for prolonging the lifespan of Mobile Ad hoc Networks (MANETs) [1, 2]. Clustering has been addressed using several methods, including hierarchical clustering, partitioning clustering, fuzzy clustering, density-based clustering, and topology-based clustering [3]. In the hierarchical clustering protocol, the information is structured in the manner of hierarchical order object relationship, with the reference of this structure the root node is the primary entity of the cluster whereas the leaf node is the point of reference [3]. Organizing an ad-hoc network presents several obstacles, including constraints on battery power and bandwidth, the need for multi-hop routing, variable topology, and security concerns. However, the primary concern in MANET is the use of energy because the nodes are in movement also these nodes depend on battery power. At the time of power down in a mobile node, the entire system performance is degraded and it also affects the entire usefulness [4]. To improve the lifetime of the entire network there is a requirement of ad-hoc routing protocols. These protocols are designed with an intact focus on energy consumption. Implementing efficient lowest energy routing strategies can significantly decrease energy usage and prolong the lifespan of the network [5]. Various routing protocols are specifically created for Mobile Ad hoc Networks (MANETs) to address the aforementioned difficulties. However, they fail to take into account the energy-efficient routing.

The clustering technique is employed to reduce the congestion in the dispersed Mobile Ad hoc Network (MANET). The head selection from the cluster is a crucial step in the clustering method. The Cluster Head selection is conventionally achieved with the reference to two algorithms namely connectivity-based and identity-based [6]. The primary objective of the Head node is to register and maintain the member's information. The information takes account of the total cluster member's (nodes) details and the alleyway details of each member from the head node [7]. CH is accountable for transmitting information to all nodes within its group. Nevertheless, the Cluster Head (CH) must establish direct communication with the nodes belonging to different groups. This can be achieved by either communicating with the appropriate CHs or utilizing gates. When determining the optimal CH node, various criteria can be considered [8].

Wireless connections will consistently maintain a notably lower capacity compared to their wired equivalents. Furthermore, the actual data transfer rate of wireless communications, taking into consideration factors such as multiple access, fading, noise, and interference situations, is generally far lower than the maximum transmission rate of a radio [9]. One consequence of the relatively low to moderate link capacities is that congestion is usually the rule rather than the exception. In other words, the total demand from applications will often come close to or beyond the capacity of the network. The problem of selecting routes based on throughput in ad-hoc networks remains challenging due to various constraints, including the lack of central control, changeable network architecture, and the self-centered behavior of nodes [10]. An optimal outcome can be achieved by a routing technique that gives priority to wireless links based on their quality and takes into account high-quality and efficient connectivity when selecting a path [10].

Selected nodes for the leader of the cluster task are essential to minimize overhead and improve overall efficiency. As a result, a number of methods have been put forth to help choose and upgrade the cluster head more effectively. In our work, we proposed a novel clustering algorithm for Hybrid Dual Optimized Machine Learning Model (HDOMLM). In this proposed method, we are using PSO for initial clustering and Optimized MLM for further rounds of clustering with the help of feature extraction from the network topology information. The features of nodes extracted as selection metrics are named, delta difference, mean distance, related energy, and related mobility. The main contributions of the proposed are as follows:

- We are merging the dual optimization of the PSO and Machine Learning Model in order to maintain the fairness of node selection and minimize selfishness in the network.
- To utilize multiple factors of the network such as energy, mobility, and delay, five different selection metrics are calculated and used as features for machine learning.
- To prolong the network lifetime by making a more energy-efficient scheme.
- Measure the performance of the proposed work with multiple evaluation metrics of Alive nodes, energy, and delay

The remaining paper is organized as section II discusses the related literature works of routing in MANET. Section III describes completely for our proposed algorithm and system model of implementation. Section IV provides the evaluation results and analysis of metrics. The conclusion is available in section V of the paper.

2. Related Works

In this work [10], the novelist has derived energy efficient cluster head selection procedure with the protocol of HybridPSO-GA. This work supports minimizing the consumption of energy issues in MANET. To achieve this the author [7] primarily used the soft k-means clustering method it's cumulating the distance of the node, node position, and finally the mobility speed for efficient cluster formation. In the secondary phase, the HybridPSO-GA procedure have been used for the selection process of clusters from all the cluster members (nodes). Regarding experimental results, the researcher [11] shows the outperformed key performance index (KPI) of energy efficiency, network lifetime, throughput, and end-to-end delay parameter values.

In this study the researcher suggested the emerging method named as genetic particle swarm optimization algorithm (GPSO) [12]. This method is the key solution to multi-cast routing optimization problems. It enhances the algorithm's running performance by optimizing the mutation process into a genetic process by incorporating the concept of PSO. The suggested method utilizes performance measures such as packet delivery ratio, packet loss ratio, BER, energy usage, end-to-end delay, network lifetime, and throughput. The optimization enactment of the GPSO algorithm surpasses that of the Genetic and PSO algorithms.

In proposes an innovative procedure RANCE, This protocol is designed to randomly centralize and cluster nodes in mobile ad hoc networks [13]. Its goal is to extend the duration of nodes' clustering period to facilitate collaboration between nodes, while still being energy efficient. RANCE develops a randomly centralized CH selection method that allows every node in the local wireless network to participate in the selection process. This enables the optimization of head selection by leveraging the self-organizing properties of mobile ad hoc nodes. Furthermore, in order to address the unpredictable changes in wireless connectivity due to factors such as topology, obstructions, and signal strength, the maintenance of precise cluster relationships is ensured through the use of multilayer aliveness and adaptive bidirectional heartbeat packets. In addition, RANCE operates in an event-driven and on-demand fashion rather than following a time-triggered approach like LEACH-type protocols. This is done to minimize the disruption to continuous services that might occur due to frequent handovers of Cluster Heads (CH) among all nodes. The simulation results demonstrate that RANCE offers extended periods of clustered time, with over 99% of nodes' lifetime in networks containing more than 100 nodes. Additionally, RANCE exhibits excellent scalability in terms of clustering, maintaining high consistency while minimizing energy consumption. These findings suggest that RANCE has significant potential in mobile wireless environments that lack infrastructure or have limited resources for continuous missions.

The QoS-aware Multipath Routing (QMR) technique has established multiple optimal routes between sources and destinations of WSN network nodes topology. In this algorithm, clustering and CH selection for coordinated transmission, and integration of two optimization methods are merged as a hybrid named Cuckoo Search Particle Swarm Optimization(CSPSO). It performs transmission via several channels and provides exceptional management of network traffic [14-16]. Then, a new Eagle Based Density Clustering (EBDC) technique is implemented to forecast the link failure and increased the lifetime of the nodes [17].

3. Proposed Manet Clustering and Cluster Head Selection Using Hdomlm

3.1 System Model

In a Mobile Ad-hoc network, a messaging linkage may be styled with the representation of T = (S, R), where a set of nodes is S with corresponding links set in R. The link in the middle of the starting point node **a** and endpoint node **z** stands for (**a, z**) i.e.,$\boldsymbol{a}, \boldsymbol{z} \in \boldsymbol{S}$. If node **a** and node **z** are adjacent, they know how to in a straight line communicate with one other. In the centralized grid, the responsibility of maintaining the network architecture details lies with a network regulator. In a regionalized grid, the node and its neighbors share information to preserve network topology. The suggested routing strategy is designed for regionalized MANET, where whole movable nodes (MN) function like both mediators and routers to establish the network infrastructure for other nodes. The coordination between each node in the network is considered in the main process of path prediction and communication by interchanging the node's configuration. The MANET topology undergoes continual and unanticipated alterations due to the dynamic mobility of nodes. The routing method is employed for relay nodes by the nodes when they are not in the straight link for transmission. Relay nodes are responsible only for propagating the data. The HDOMLM routing strategy incorporates several crucial elements, including energy consumption, latency, distance, and mobility.

3.2 Energy Model Assumptions

The vitality ingesting of nodes is a crucial factor in determining the choice of reliable and competent intermediate nodes that work together to enhance the complete performance of the network. In MANET, MN is powered by batteries with inadequate vitality capacity. Hence, it is crucial to consider the battery life of the nodes while choosing a group of intermediary nodes to build a route to an endpoint. Additionally, the MN functions for the following stages: Transmit, Idle, Receive, and sleep. The amount of power usage during periods of inactivity and sleep is minimal.

In this method, we used the energy model of Coulomb counting (CC) [18] to linearly discharge the energy of each node based on its current load. Counting is performed at the beginning of the ejection cycle. The difference between the initial battery capacity to the current value is defined as residual energy. The conventional radio energy model [19] is used to evaluate the energy of $E^i_{Initial}(t)$, $E^i_{Residual}(t)$, $E^i_{Consumption}(t)$, $E^i_{operation}(t)$. Every transmission in MANET depends on energy consumed and time of processing.$E^i_{Initial}(t)$ is the initial energy of i-th node at t-th time slot which used to evaluate the residual energy $E^i_{Residual}(t+\tau)$of the same node for a duration τ and is given as,

$$E^i_{Residual}(t+\tau) = E^i_{Initial}(t) - E^i_{Consumption}(t+\tau) \quad (1)$$

where $E^i_{Consumption}(t+\tau)$ declares the amount of energy used by node i for the duration of τ, which includes the energy used for internal node operation and broadcasting, receiving, and exchanging control packets including routing information. In order to develop a protocol in an energy-proficient manner, it is important to ascertain the energy consumption of each node during packet processing. Furthermore, the MN must allocate energy resources to actively monitor the arrival of a packet or to passively await an incoming event. The energy usage at node i on connection for processing a packet is determined by,

$$E^i_c = E^i_l + E^i_{tx} + E^i_{rx} + E^i_{sl} = \left(t^i_l I_l + (I_{tx} + I_{rx})\frac{L}{R} + t^i_{sl} I_{sl}\right) U \quad (2)$$

where $E^i_l, E^i_{tx}, E^i_{rx}, E^i_{sl}$ are the energy expended in the course of the epochs of listening, transmitting, receiving, and sleeping, respectively. $I_{sl}, I_{rx}, I_{tx}, I_{sl}$ denotes the drained current at the time of Sleep, Receive, Transmit, and Listen correspondingly. $t^i_l, t^i_{tx}, t^i_{rx}, t^i_{sl}$ are the time for sleeping and listening, respectively. U is the battery voltage of the nodes, L (bits) is the packet length and R (Kbps) is the data rate in the MANET.

The settings of the Beacon Duration (BD) and the Super-frame Time (ST) are defined below using the

IEEE 802.15.4 super-frame structure for the beacon-enabled mode [20],

$$BD = FS_D \times 2^{B^o} Symbols \quad (3)$$

$$ST = FS_D \times 2^{S^o} Symbols \quad (4)$$

where FS_D is base super frame duration which is equal to 960 symbols. Each symbol has a duration of16 X 10^{-6} sec as per the CSMA-CA method of PHY layer frequency of 2.4GHz [20]. S^o & B^o represent an order of superframe and Beacon as per the superframe structure of IEEE 802.15.4 and these are lies between 0 and 14. The expression of t_{sl}^i, t_l^i are given by,

$$t_{sl}^i = BD - ST = FS_D \times \left(2^{B^o} - 2^{S^o}\right) Symbols \quad (5)$$

$$t_l^i = BD - \left(t_{tx}^i + t_{rx}^i + t_{sl}^i\right) \quad (6)$$

where t_{tx}^i, t_{rx}^i are the time slots of transmit and receive. Each communication deals with L number of packets as bits with an R data rate of Kbps. If either i-th nodes are destination or source, the null (E_{tx}^i, t_{tx}^i) and (E_{rx}^i, t_{rx}^i) will be attained respectively. Thus remodeling of equ (2) is denoted by,

$$E_c^i = \begin{cases} \left(t_l^i I_l + I_{tx}\frac{L}{R} + t_{sl}^i I_{sl}\right) U \text{ if } i \text{ is a source} \\ \left(t_l^i I_l + I_{rx}\frac{L}{R} + t_{sl}^i I_{sl}\right) U \text{ if } i \text{ is a sink} \end{cases} \quad (7)$$

The remaining energy is represented as,

$$E_r^i = E_0^i - E_c^i + E_h^i \quad (8)$$

where E_0^i and E_h^i are the preliminary and the garnered energy of nodes individually. The recommended strategy calculates energy usage by considering the power consumption of the circuitry, the time taken at each mode, and the transmitted data packets. Therefore, the energy depletion during the broadcast phase of MN i, when transferring a total of n packets, may be computed using the following formula:

$$E_{Trasmission}^i(t+\tau) = n \times P_{Transmission}^i(t+\tau) \quad (9)$$

whereas $P_{Transmission}^i(t+\tau)$ denotes the power ingesting during the broadcast of n information packets and the altercation of moving info of switch packets with adjacent nodes over a duration of τ is measured in W/s. By the same perfunctory, the energy dissipation of the node i in the mode of receiving with the configuration of m packets of data communication which is added with switch packet in the time duration slot of τ is intended by,

$$E_{Receive}^i(t+\tau) = m \times P_{Receive}^i(t+\tau) \quad (10)$$

where $P_{Receive}^i(t+\tau)$ is the amount of power that node i used to send and receive exchange control messages while receiving m packets at once τ. In addition, whole nodes expend energy while carrying out inside operations like administering, connecting, updating the Node table, and reserving through the τ duration, as indicated by $E_{operation}^i(t+\tau)$. Hence, the aggregate energy usage of node i over a time period τ, encompassing all transmission, operation, and reception modes can be computed below:

$$E_{Consumption}^i(t+\tau) = E_{Transmission}^i(t+\tau) + E_{Receive}^i(t+\tau) + E_{operation}^i(t+\tau) \quad (11)$$

As a final point, the remaining energy is rationalized at τ is given by,

$$E_{Residual}^i = E_{Initial}^i - \{E_{Transmission}^i(t+\tau) + E_{Receive}^i(t+\tau) + E_{operation}^i(t+\tau)\} \quad (12)$$

The HDOMLM clustering method prioritizes nodes with low energy consumption when the communication between nodes is established in the network. In summary, the HDOMLM strategy optimizes the duration of MANET operation by reducing the likelihood of connection failure inside the network.

3.3 Random Waypoint Mobility Model

Randomized mobility models involve the unrestricted and random movement of mobile nodes. More precisely, the destination, speed, and direction are all selected in a random and liberated manner from other nodes. This particular model is employed in numerous simulation experiments. The Random Waypoint Model was initially introduced by Johnson and Maltz [21]. Due to its simplicity and widespread availability, the mobility model quickly became a standard for evaluating MANET routing technologies.

Mobile nodes in MANETs exhibit dynamic changes in their site, rapidity, and path. We calculated the Euclidean distance in the middle of two adjacent nodes to ascertain if the nodes were approaching or receding from each other. Assume the presence of two mobile nodes, $n1$ and $n2$, each having a transmission range of r, as depicted in Figure 1. Nodes $n1$ and $n2$ are each traveling at velocities V_{n1} and V_{n2}, respectively.

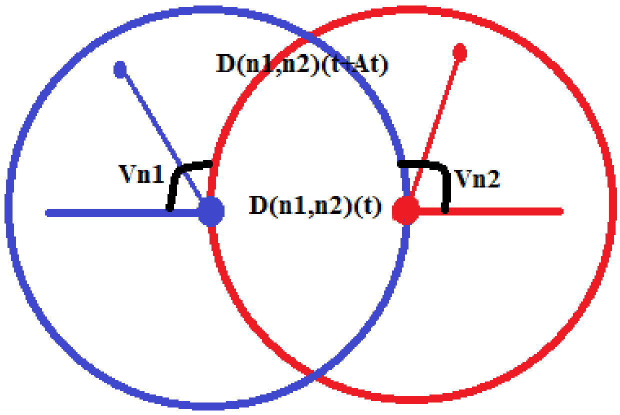

Figure 1. Mobility of nodes

The distance between n1 and n2 at t time is denoted as D (n1, n2) (t),

$$D(n1,n2)(t) = \sqrt{\left(X_{n2(t)} - X_{n1(t)}\right)^2 + \left(Y_{n2(t)} - Y_{n1(t)}\right)^2} \quad (13)$$

where ("X" _n1(t) ,"Y" _n1(t)) and 〖"(X" 〗_n2(t) ,Y_n2(t)) are the x-axis and y-axis positions of nodes n1 and n2 correspondingly. The distance between the nodes n1 and n2 after Δt time is premeditated as,

$$D(n1,n2)(t+\Delta t) = \sqrt{}(("X"\_n2(t+\Delta t) - "X"\_n1(t+\Delta t))^2 + ("Y"\_n2(t+\Delta t) - "Y"\_n1(t+\Delta t))^2) \quad (14)$$

where ("X" _n1(t+Δt) ,"Y" _n1(t+Δt)) and 〖"(X" 〗_n2(t+Δt) ,Y_n2(t+Δt)) are moved positions of nodes n1 and n2 separately. By way of [22], movement refers to the mean variation in distance between all nodes within a specific time interval. The relationship between speed and movement pattern determines this function. The velocity at t time for a node can be determined using the following formula:

$$V_{(t,t+\Delta t)} = \frac{|(X_2 - X_1) + (Y_2 - Y_1)|}{(t+\Delta t) - t} \quad (15)$$

When the distance of nodes n1, and n2 at time t is greater than the distance of nodes at (t + Δt), it denotes both the nodes come closer after a certain velocity. Likewise, when it is less, the nodes are moving apart and it will become detached.

One possible concept that might be used is the average speed of the nodes. Assuming T_p=0 and V_m is evenly and randomly selected from the range [0,V_m], we may determine that the average nodal speed is 0.5×V_m. Nevertheless, it is important to acknowledge that the pause duration parameter should not be disregarded in most cases. Furthermore, the link in the middle of two nodes is determined by the relative velocity of the nodes, more willingly than their velocities. Therefore, it appears that the average speed of nodes is not a suitable measure to accurately reflect the concept of nodal speed. The measure of relative speed [23] in the middle of node n1 and n2 at time t is,

$$S_R(n1,n2,t) = |V_{n1}(t) - V_{n2}(t)| \quad (16)$$

The Mobility metric(S)¯ is computed by averaging the relative speed between all pairs of nodes and complete time periods as below,

$$\bar{S} = \frac{1}{|n1,n2|} \sum_{n1=1}^{N} \sum_{n2=n1+1}^{N} \frac{1}{T} \int_0^T S_R(n1,n2,t)\, dt \quad (17)$$

3.4 Initial Clustering using PSO

The position of Cluster Members is epitomized by N={n_1,n_2,n_3,…..,n_m }in MANET, and these Cluster Members are congregated into K sets K={k_1,k_2,…..,k_k} . The establishment of Clustering in MANET is denoted by,

$$G(N,D,S) = \sum_{s=1}^{i} \sum_{q=1}^{m} d_{sq} \left\| n_q - \gamma_s \right\|^2 \quad (18)$$

Where the speed in the middle of nodes (Cluster Member) is signified by S(γ_s;s=1,…,i)and the distance between nodes is exemplified by D(d_sq;s=1,…,i ;q=1,…,M). The q^th membership degree to the S^th cluster is represented by,

$$\gamma_s = \frac{\sum_{q=1}^{h} d_{sq} n_q}{\sum_{q=1}^{h} d_{sq}} \quad (19)$$

Appropriate Clustering is achieved by reducing the value of a certain variable [24], and this reduction procedure must adhere to the following three requirements:

a The Cluster Member within the MANET is allocated a membership degree ranging from zero to one.

b The sum of all membership degrees for a single Cluster Member must equal one.

c At least one node in the cluster with the node of non-zero membership.

After satisfying these conditions, the centers of clusters are assessed by equation,

$$d_{sq} = \frac{e^{-\alpha \left\| n_q - \gamma_s \right\|^2}}{\sum_{b=1}^{i} e^{-\alpha \left\| n_q - \gamma_s \right\|^2}} \quad (20)$$

where α represents the degree value of each node The main objective of the suggested technique is to enhance the longevity of MANETby developing an energy-aware cluster head (CH) selection process. Therefore, we are presenting a Hybrid Particle Swarm Optimization and optimized machine learning (O-MLM) method to choose the CH. The first selection of CH (Cluster Head) is performed using Particle Swarm Optimization (PSO). From the second round onwards, an optimal CH selection based on MLM is applied using the cluster formation and CH routing table information obtained from PSO.

The engendered Clusters are denoted by Ax, which is poignant inside the Y dimension search area, and mobile nodes are appropriate to N={n_1,n_2,n_3,…..,n_m }. Each node Ni is active to appraise the fitness function. The fitness function is calculated by summing the node mobility characteristic [25]. The site of every single node in the search space is symbolized by "N" _(i,y) and the velocity of each node is represented by "V" _(i,y). The process ongoing selected node is denoted by I_sn, and the neighboring node is represented by "N" _b. Each node of MANET updates its velocity, mobility, energy, and degree values. This process is described in Equation (21) and Equation (22).

$$V_{i,y}(\rho+1) = \varepsilon \times V_{i,y}(\rho) + \alpha \times r_{an1} \times \left(NI_{sn,i,y} - N_{i,y}(\rho)\right) + m_0 \times r_{an2} \times \left(N_{b,n,y} - N_{i,y}(\rho)\right) \quad (21)$$

$$N_{i,y}(\rho+1) = N_{i,y}(\rho) + V_{i,y}(\rho) \quad (22)$$

Where the energy of the node is represented by ε, mobility of the node is denoted by m_0. The random numbers in the middle of zero and one are signified by r_an1and r_an2. The flowchart of CH selection using PSO is given in Figure 2. During the initial phase, the velocity and position of each node are assigned, followed by the calculation of the fitness function for each node [26]. The ongoing process selected node"C" _snand adjoining nodes are initialized. Additionally, the velocity and location of the nodes are updated in relation to each repetition of n. However, the process of determining the fitness value of the nodes is being performed.

3.5 Proposed HDOMLM algorithm based CH selection

To our knowledge, for the first time Machine learning algorithm is used in the CH selection algorithm in MANET in our proposed work. In this section, the proposed O-MLM based CH selection is performed using different selection metrics dealing with related energy, delay, mobility, delta difference of idle degree to the movement, and average distances. These metrics evaluated from the current environment of MANET are used as features for the O-MLM.

3.5.1. Selection Metrics as Features of O-MLM

3.5.1.1 Delta Differences

The delta difference is employed as a criterion for load balancing. While all clusters can have an equal number of nodes in some instances, achieving this in real-world scenarios is challenging owing to factors like as the changing positions of sensor nodes and other external impacts [27]. Subsequently, in receipt of the initial clusters with the CH node and their member nodes, the delta dissimilarity is valued for each CH with member nodes degree. Delta difference ∆_d is utilized to quantify the deviation from an optimal degree to the displacement of a node from its neighboring nodes it is deliberate as;

$$\Delta_d = \frac{|D_i - D_n|}{360} \tag{23}$$

where D_i is the comparative degree of each node in the network and D_n is a degree of the stimulated member node of analogous CH. The node degree of comparative value in this work is set as 45° and the ongoing node mobility direction angle is measured for the individual member node degree.

3.5.1.2 Distance Average

Distance average A_d is the metric to evaluate the mean distance of respective CH to the neighbor nodes of CH.

$$A_d = \frac{\sum_{m=1}^{M} D_m}{M} \tag{24}$$

where, M is the aggregate count of neighboring nodes inside the respective cluster and D_m is the distance in the middle of the neighbor node and the CH node of the same cluster.

3.5.1.3 Related Energy

The energy consumed by the CH as a result of the activities taking place within the clusters is referred to as associated energy. The term "energy utilization ratio" refers to the ratio of energy used between member nodes and cluster heads (CH) inside each cluster, compared to the energy used between two member nodes. It is epitomized by,

$$E_R = \frac{Q_{energy}}{P_{energy}} \tag{25}$$

$$Q_{energy} = \sum_{j=1}^{K} \Phi_{E,j} \tag{26}$$

$$\Phi_{E,j} = \sum_{i=1}^{M} (1 - [E_i - E_{C,j}]) \tag{27}$$

$$P_{energy} = K * \max_{i=1:M} E_i * \max_{j=1:K} E_{c,j} \tag{28}$$

where K represents the number of clusters in the network, whereas M represents the number of cluster members in each cluster, E_i is the energy of i-th member node in the j-th cluster and $E_{C,j}$ is the energy of the CH node in the j-th cluster.

3.5.1.4 Related Mobility

Related mobility is defined as the distance ratio of distance dissimilarity in the middle of member nodes to CH and surrounded by from CH towards the BS and finally added the two member nodes distance and it is given as,

$$M_R = \frac{Q_{mobility}}{P_{mobility}} \tag{29}$$

$$Q_{mobility} = \sum_{i=1}^{M} \sum_{j=1}^{K} \|DCH_{j,i}\| + \|CHB_j\| \tag{30}$$

$$P_{mobility} = \sum_{i=1}^{M} \sum_{j=1}^{K} \|d_{i,j}\| \tag{31}$$

The variable $DCH_{j,i}$ represents the distance between the i-th member node and the j-th cluster head and CHB_j is the distance in the middle of j-th CH node to BS. $d_{i,j}$ is the distance between to member nodes in each cluster.

3.5.1.5 Transmission Delay

The data transmission delay of nodes is defined in Equation (32), where the delay value must be within the range of [0, 1]. When the number of nodes in a cluster decreases, the latency is significantly reduced. In equation (32), CH represents the component of the numerator value, while the total node count in the cluster represents the denominator value.

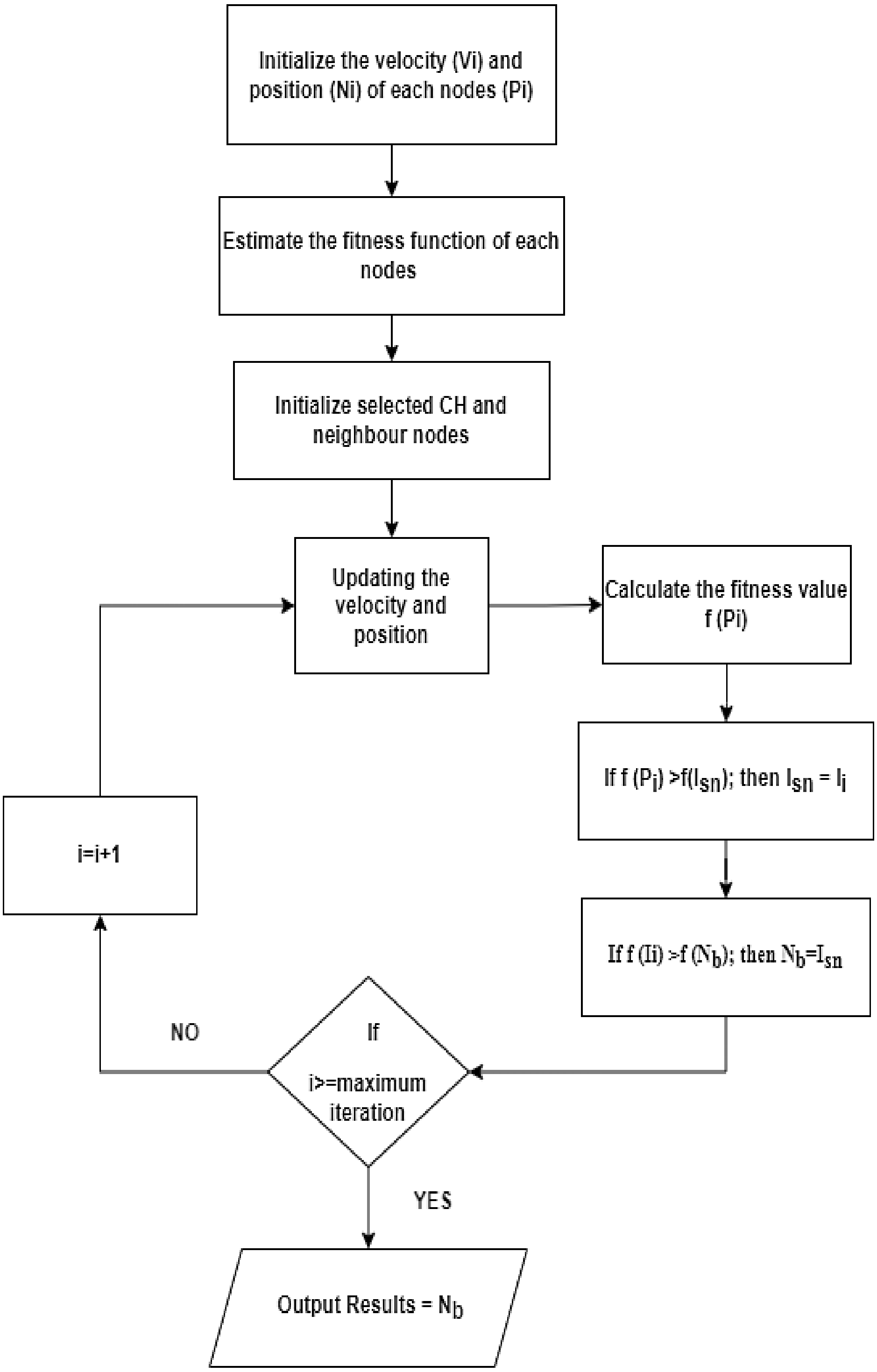

Figure 2. Flow Chart of PSO based Clustering

$$Delay_j = \frac{\max_{i=1\ to\ M} \tau_{i,j}}{M} \tag{32}$$

where $\tau_{i,j}$ is the maximum delay of all i-th member nodes in the j-th cluster.

3.5.2 Optimized Machine Learning Model based CH selection

Machine learning (ML) models have lately achieved significant advancements in several practical applications. However, these models are very susceptible to internal parameters, specifically known as hyperparameters. This study introduces a novel approach in the clustering process of Mobile Ad hoc Networks (MANETs) by utilizing machine learning (ML) to classify nodes as either regular nodes or Cluster Head nodes. The classification is based on chosen metrics that are used as features. By utilizing machine learning methods such as Support Vector Machines (SVM), decision trees, neural networks, ensemble learning, K-nearest neighbors (KNN), and naïve Bayes, we may attain high classification accuracy.

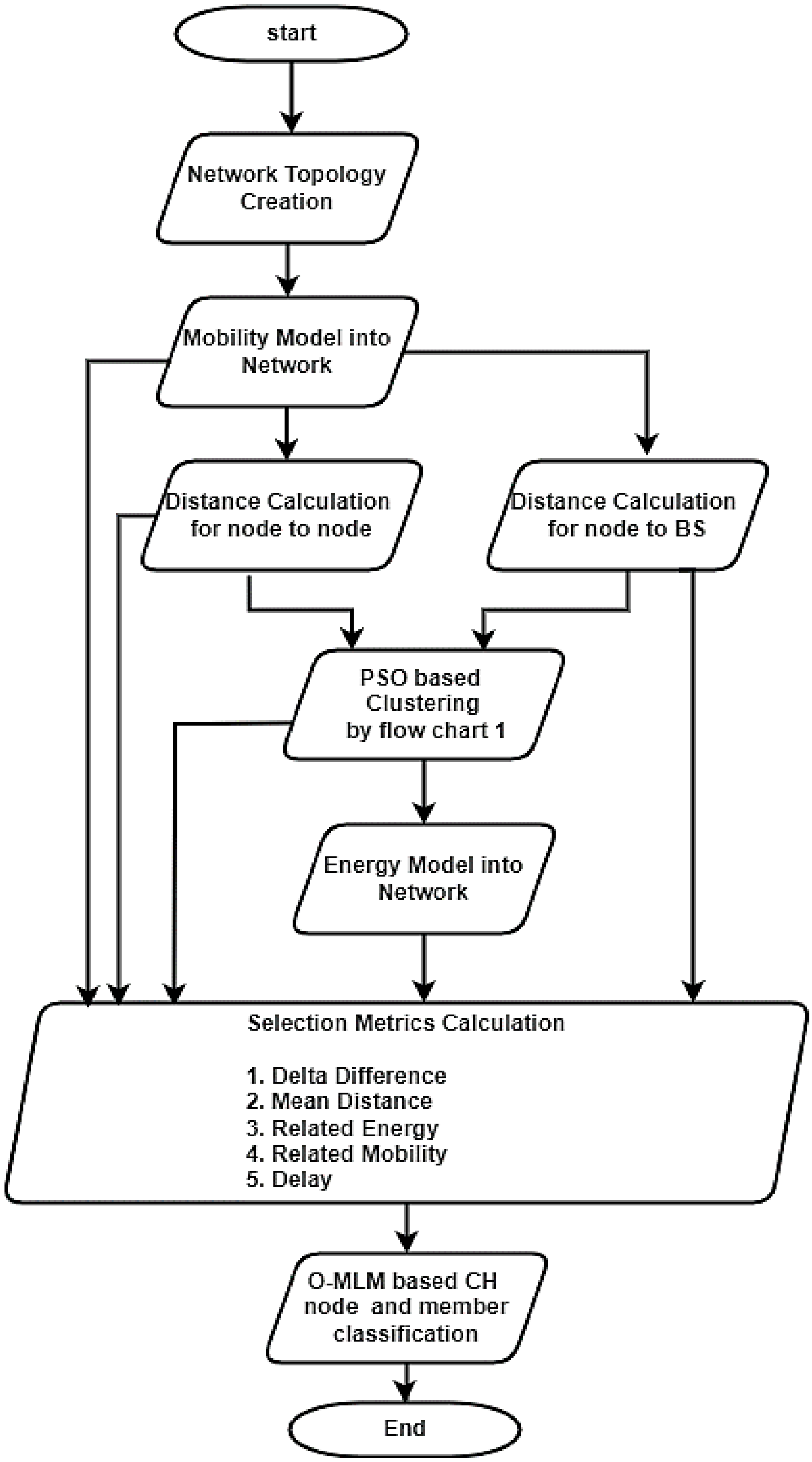

Figure 3. Proposed HDOMLM based Clustering and CH selection

The accuracy is mostly determined by the features or qualities of the data and its application [7]. It is not optimal for every context and every feature. To address this issue, we are now deploying the optimized Machine Learning model (O-MLM). In this approach, the ML model may be selected by optimizing the hyperparameters to achieve the best classification accuracy and minimize the loss simultaneously. This O-MLM algorithm chooses the most optimal machine learning model together with their respective hyperparameters for the training process, based on the available ML models.

Derivation of selection metrics as features for the machine learning model is the primary part of this Optimized Machine Learning Model (O-MLM). Delta difference, Average Distance, Related Energy, Related Mobility, and Average transmission Delay are features taken for the learning model. After the cluster formation using PSO, the Leading node selection is performed for all the cluster members in each cluster [28]. The features are extracted for these cluster members as selection metrics of Delta difference, Average Distance, Related Energy, Related Mobility, and Average transmission Delay as described below. Once these features are extracted from the nodes gathered information, we use the O-MLM model to predict whether the particular feature set belongs to a normal node or a leading node. The o-MLM model is trained with pre-labeled features. The formation of the O-MLM model is described in the following section.

Machine learning algorithms can efficiently allocate network demand and reduce energy consumption throughout the network, hence prolonging its lifespan. In contrast to static clustering approaches, machine learning algorithms may adjust to fluctuating network circumstances, including variations in node density and energy levels, by re-selecting cluster heads as necessary.

O-MLM automatically performs model selection on several classification model types using different hyperparameter values, based on the provided predictor and response data. The system uses Bayesian optimization to choose models and their corresponding hyperparameter values. It then calculates the cross-validation classification error for each model.

Once the optimization process is finished, O-MLM provides the model that has been trained on the full data set and is anticipated to accurately categorize fresh data [29-32]. To train its Gaussian process model of the objective function, Bayesian optimization uses objective function evaluations. A new feature of Bayesian optimization is the acquisition function, which determines the next point to assess.

The acquisition function can balance sampling at low-modeled objective functions with investigating unmodeled areas. O-MLM's Bayesian optimization maintains a multi-tree Bagger objective function model. This means the objective function model splits by learner type and becomes a Tree Bagger ensemble for regression for each learner.

3.5.2.1 Bayesian Optimization

The objective of hyperparameter optimization in machine learning is to identify the hyperparameters of a specific machine learning algorithm that yield the optimal performance, as evaluated on a validation set. Bayesian methods, as opposed to random or grid search, maintain a record of previous evaluation outcomes [33]. They utilize this information to construct a probabilistic model that links hyperparameters to the likelihood of achieving a certain score on the objective function.

$$P(score|hyperparameters) \qquad (33)$$

This model is called a "surrogate" for the objective function and is represented as p(y | x). Optimizing the surrogate is simpler compared to optimizing the objective function, and Bayesian approaches involve identifying the next set of hyperparameters to assess the actual objective function by picking hyperparameters that yield the highest performance on the surrogate function. The Bayesian optimization algorithm is shown in Algorithm 1.

Algorithm 1. Bayesian Optimization of Hyperparameters

i. Construct a surrogate probability model of the fitness function

ii. Predict the best score by providing surrogate hyperparameters

iii. Apply these hyperparameters to the true objective function

iv. Update the surrogate model incorporating the new results

v. Repeat steps 2–4 until max iterations or time is reached

Two fundamental decisions must be taken while undertaking Bayesian optimization. A prior completed utility that articulates beliefs almost the optimized function must be chosen first. We decide on the Gaussian process erstwhile for its elasticity and controllability. Second, select an acquisition function to build a utility function. We used Expected improvement for acquisition.

3.5.2.2 Acquisition Function

Typically, acquisition functions rely on past observations and the hyperparameters of the Gaussian Process (GP). We represent this reliance as $a(x;\{x_n,y_n\},\theta)$. There are multiple widely favored options for the acquisition function. In the context of the Gaussian process prior, these functions are exclusively dependent on the model using its predictive mean function $\mu(x;\{x_n,y_n\},\theta)$ and predictive variance function $\sigma^2(x;\{x_n,y_n\},\theta)$. As we move forward, we will represent the best current value as $x_{best} = \underset{x_n}{argmin}\,\{f(x_n)\}$, and the cumulative distribution function of the standard normal will be denoted as $\Phi(.)$. Specifically, the Expected Improvement function is utilized in the job that we are doing [34]. An evaluation of the expected amount of progress in the objective function is performed by the 'expected-improvement' family of acquisition functions. This family of functions disregards values that increase the objective. To put it another way, the location of the lowest posterior mean is what we mean when we talk about x_{best}. The lowest value of the posterior mean is denoted by the symbol $\mu Q(x_{best})$ [32]. Consequently, the anticipated enhancement is provided by,

$$a_{EI}(x;\{x_n,y_n\},\theta) = \sigma(x;\{x_n,y_n\},\theta) * \left(\gamma(x)\Phi(\gamma(x)) + \mathcal{N}(\gamma(x);0,1)\right) \quad (34)$$

The overall process of HDOMLM-based cluster head selection is shown in the flow chart of Figure 3.

4. Results and Discussion

In this section, we are evaluating the proposed HDOMLM-based clustering in MANET. To evaluate the performance of the proposed system we are comparing the results of earlier works of CH [35] and ANFIS-EESC [36] with the proposed HDOMLM. For the simulation of the work, we are using a simulation tool of MATLAB 2020a version in Inter® Core™ i3-5005U CPU of 8GB RAM, 64-bit operating system. The simulation settings for the MANET model and Energy model are given in Table 1 And Table 2 respectively. Table 3 for the parameter settings of PSO and O-MLM optimization functions.

Table 1. Network Model Configurations

Parameter	Value
Network Length x Width	200 x 200 m
Coverage Range	50 m
Number of Sensor Nodes	50
Number of Sink Nodes	1
Sink Coordinate(X,Y)	(100,100)
Nodes Mobility	Random Way Point Model
Velocity of node	20 ms^{-1}
Percentage of CH	0.1
Number of Cluster Levels	5
Delay per meter distance	0.01s
Ideal Degree of Node	45^o

For training in the optimized machine learning model (O-MLM), we considered random network node configurations with 100 scenarios to create the database. In the database, for each scenario, we are considering the 50 nodes in the network. Each node has 5 selection metrics to classify as a normal node or cluster head node. The training input information for a single node is 5. A total of 100 scenarios and 50 nodes have a 5000x5 dimensioned database for training and 5000x1 for training labels with classes of either 1 or 2. Class 1 denotes that the node belongs to normal and class 2 is considered as CH nodes.

Table 2. Energy Model Configurations

Parameter	Value
Initial Energy (E_o)	0.03 J
Energy dissipates per bit (E_b)	50 nJ/bit
Energy loss of multi-path fading (E_{mp})	0.0013 pJ/bit/m^4
Data Aggregation Energy (E_g)	5nJ/bit
Packet Size (K_{bits})	6400
Number of Rounds	1000

Table 3. Optimization Parameters

	Parameter	Value
PSO	Number of Clusters	5
	Number of Iterations	100
	Number of population	50
	Inertia Weight Damping Ratio	1
	Inertia value of Weight	0.72979999
	Learning Coefficient of Personal	1.4961962
	Learning Coefficient of Global	1.4961962
O-MLM	Optimizer	Bayesian optimizer
	Max Objective Evalations	20
	Min Training Set Size	100
	Number of Folds	5
	Prior Probability	Empirical

4.1. Performance of Network Topology and Clustering with CH selection

In Figure 4, we show the generated network topology of MANET nodes with random generation of position for the X-axis and Y-axis within the area of 200x200m which we configured in the simulation. In this simulation network, single sink BS is located in the center of the network in a fixed manner.

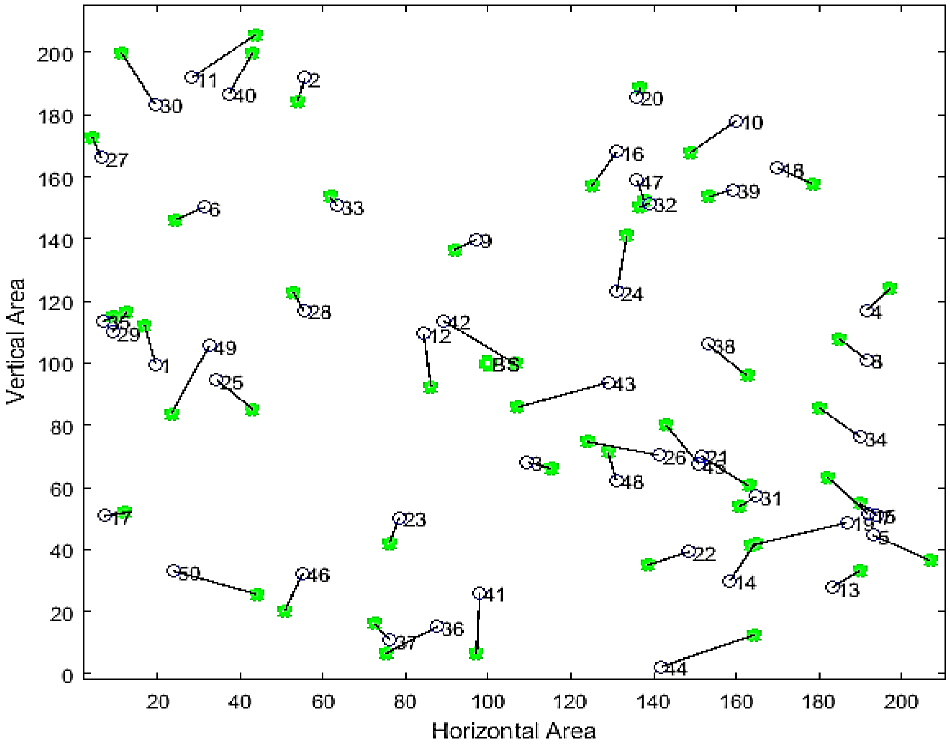

Figure 5. Mobility Applied model of MANET

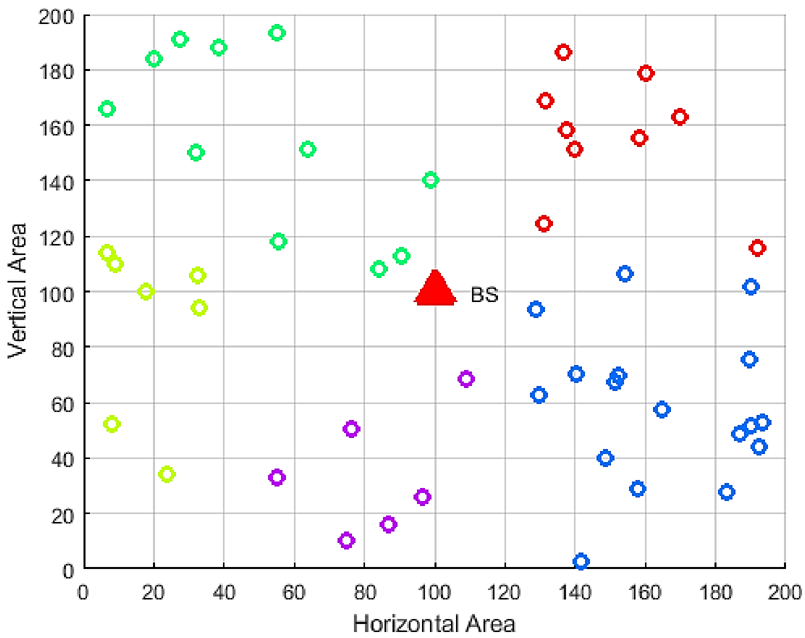

Figure 6. PSO based initial Clustering

To increase the lifetime of the network and the acceptability of nodes to BS we positioned BS in that place.

Mobility is generated using a Random Waypoint model in the created network topology as shown in Figure 5. The initial node's position is represented as a blue circle and the corresponding moved position is denoted as a green pentagon marker which is linked with its initial location shown as a black line in Figure 5.

The clustering is performed using PSO at the beginning round of the process using the optimization cost function of transmission distance. The number of nodes in Figure 4 is assigned as five groups of nodes named clusters with 5 different colors shown in Figure 6. Each color has unequal members within the clusters because it depends on the distance of nodes i.e. mobility. As we see from Figure 6, the nodes are grouped with communication range based link establishment shown in Figure 7.

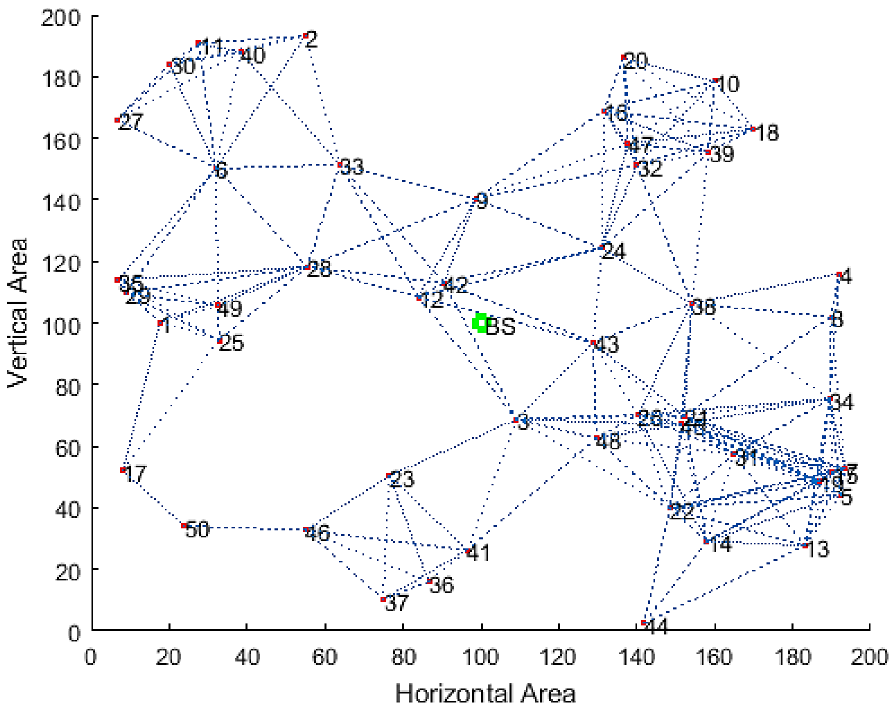

Figure 7. Link Established with communication range R=50m

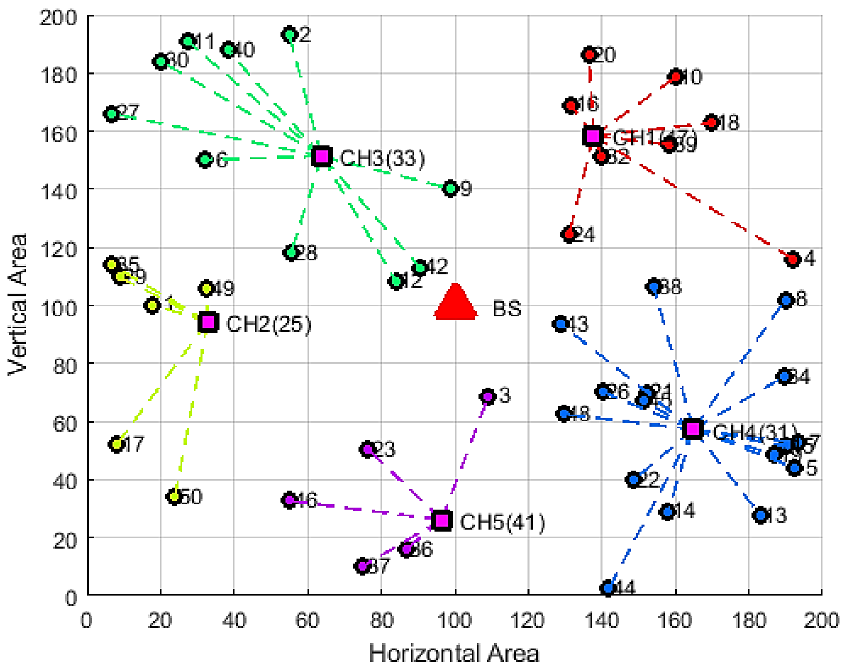

Figure 8. Proposed CH selected at round 1

Figure 8 depicts the CH selected in the network configured for the beginning round. For each cluster, the best CH is selected using our proposed HDOMLM algorithm. To select the CH node from the formed PSO clusters, the multiple selection metrics are evaluated as delta difference, mean distance, related energy, related mobility, and transmission delay.

These metrics are used as features in the optimized machine-learning model. After the updation of selection metrics, based on the features the nodes will be classified and marked as CH or normal which is shown in Figure 9 at the round of 1000.

4.1.1 Performance comparison for different Number of Rounds

The lifespan of each node that makes up a heterogeneous WSN has a significant impact on the network's longevity. Two main criteria determine a network's lifetime: (i) the total amount of energy used during a round and (ii) the total amount of energy available for usage.

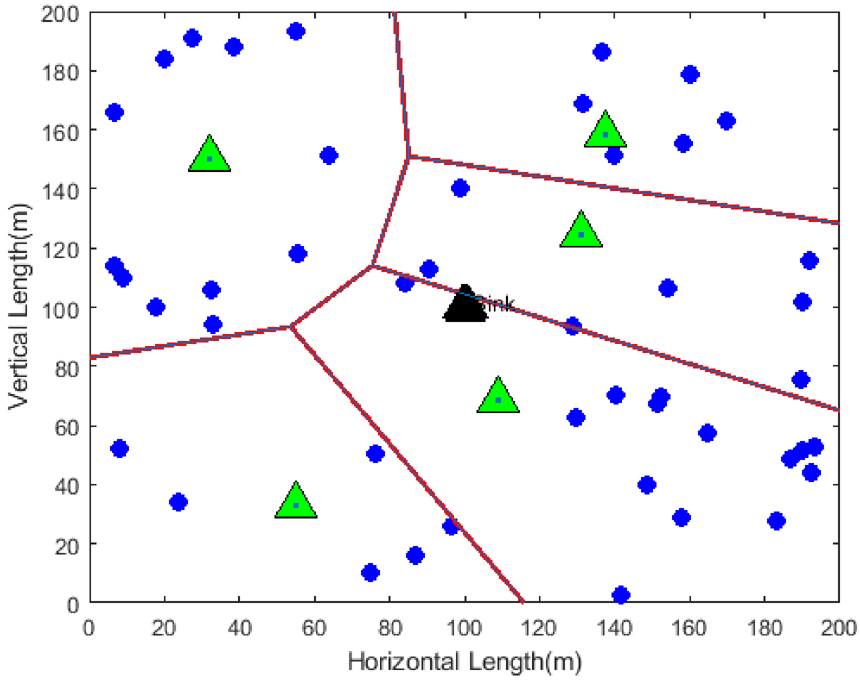

Figure 9. Proposed CH selected at round 1000

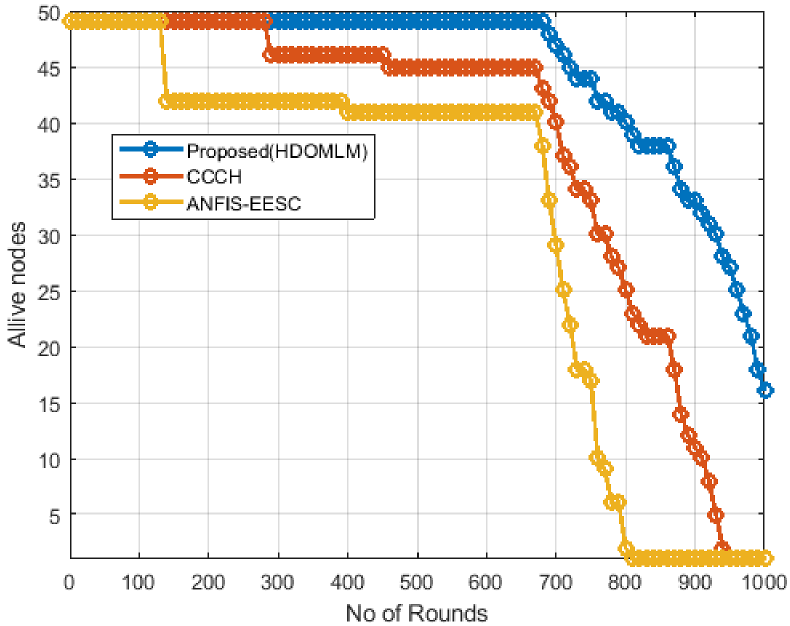

Figure 10. Network Lifetime interms of Alive Nodes

The type of service a network offers determines how long it will last. Since the performance of the network drops as soon as a single node dies, it is frequently imperative that every sensor node survive for as long as possible. It matters in this case to know whenever the first node fails.

As compared to CCCH and ANFIS-EESC, Fig. 10 demonstrates that HDOMLM has more live nodes every round. This is because CCCH selects CHs without considering the nodes' remaining battery energy.

Figure 11 illustrates the overall energy usage of several protocols during the lifespan of the network. In the CCCH and ANFIS-EESC protocols, all the chosen cluster heads (CHs) send their combined data straight to the base station (BS), resulting in higher battery energy consumption. However, HDOMLM addresses the issue of imbalanced energy consumption by employing rapid prediction of Cluster Heads (CHs). It attains equilibrium in the distribution of energy usage among the Cluster Heads (CHs) and extends the overall lifespan of the network.

The Energy Tax is calculated by dividing the energy spent by the network to transmit a packet to the sink by the product of the total number of distributed nodes and the number of packets received effectively by the sink [33].

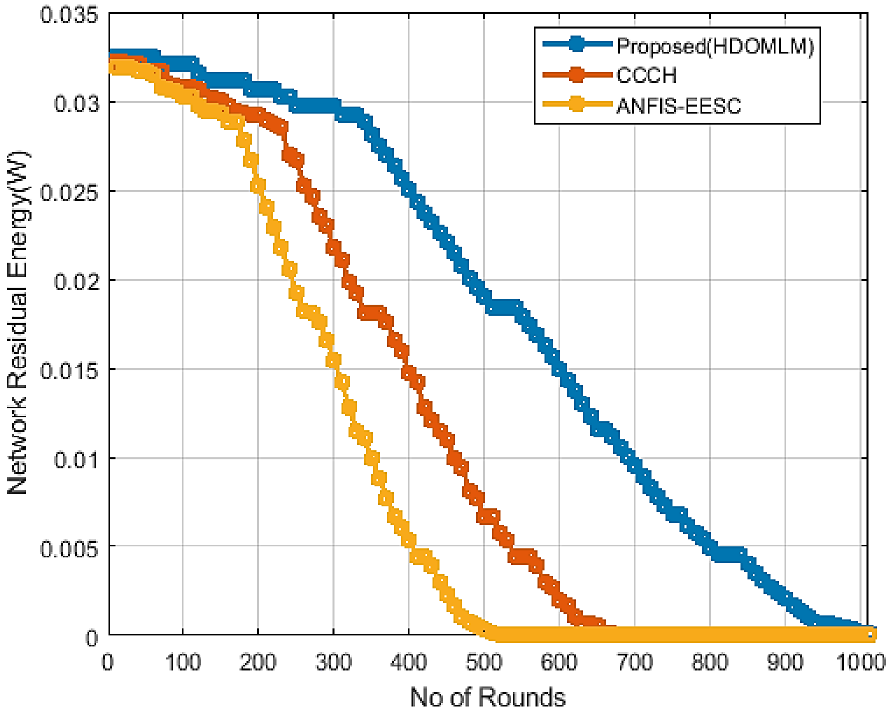

Figure 11. Network Lifetime in terms of Residual Energy

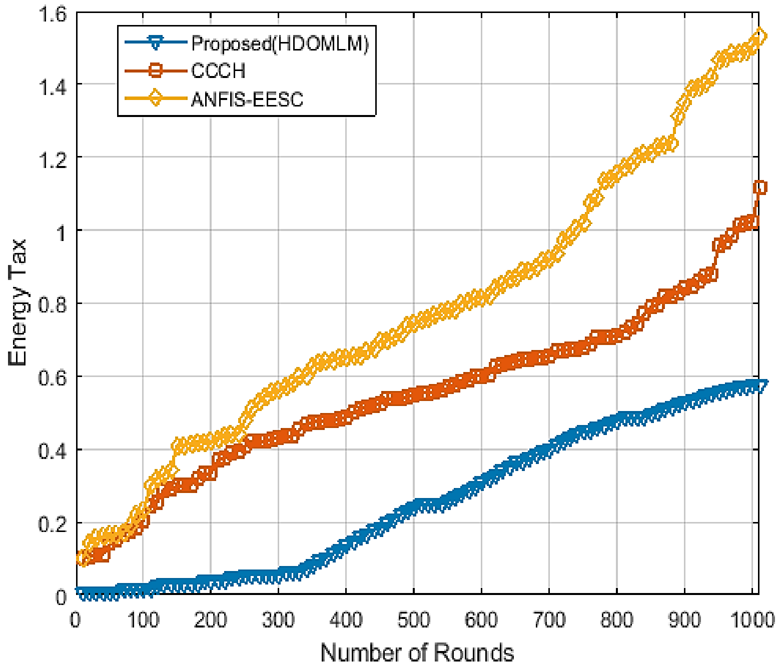

Figure 12. Energy Tax Vs Number of Rounds

Figure 12 illustrates a progressive increase in the energy tax over the three methods. This is due to the correlation between the number of rounds and the growth in successfully transmitted packets from the source to the destination. Consequently, there is a corresponding rise in energy consumption during the transmission and reception of these packets. Out of the three different procedures, HDOMLM has the lowest energy tax in comparison to the others.

As the number of rounds increases, the packets received in the receiver of BS increase due to transmission occurring after every CH selection. With a communication range of R=50m in this simulation, the nodes can get highly available links to forward the packets to the selected path neighbors. This is shown in Figure 13 with the comparison of the proposed HDOMLM with CCCH and ANFIS-EESC. From these three curves, the proposed method attains the highest Packet delivery than the other two methods with a minimum difference of 1000 packets to a maximum difference of 2500 packets.

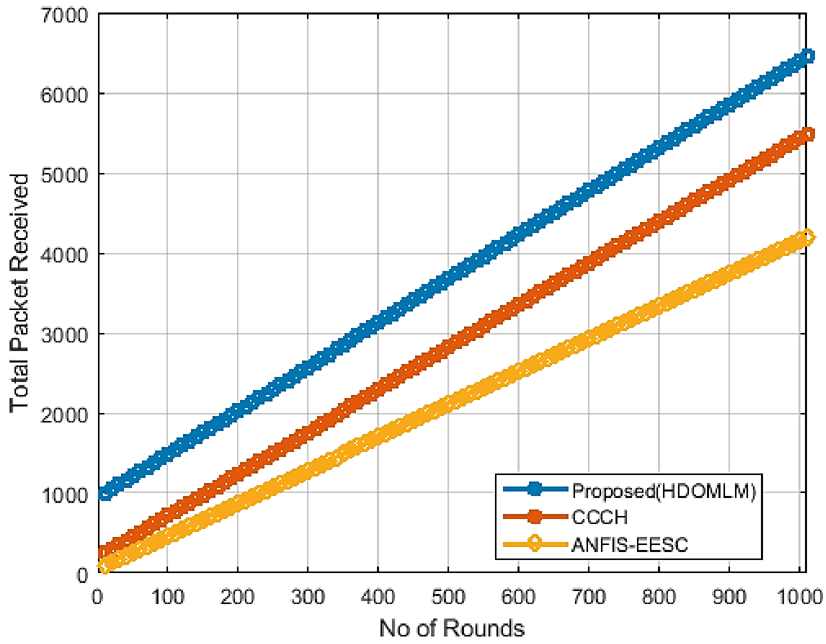

Figure 13. Packets Received at BS Vs Number of Rounds

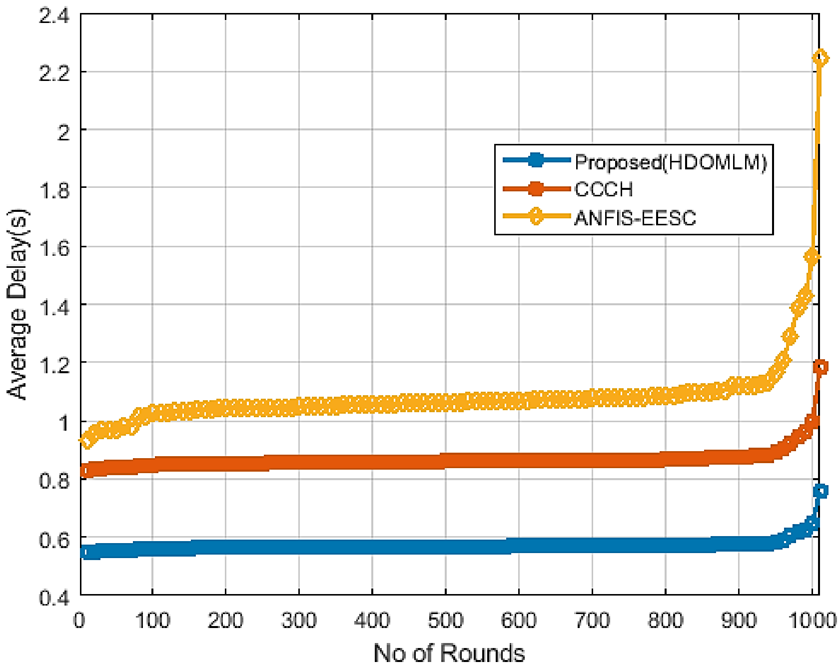

Figure 14. Average End-to-End Delay Vs number of rounds

Mean end-to-end The typical amount of time it takes for a packet to get from its origin node to its destination sink is known as transmit delay. Figure 14 shows the average end-to-end delay with different protocols by increasing the number of rounds with the increasing curve of delay due to the factor of cumulative time calculated in every round.

As the best, the CH selected from the highest metrics is easy to predict using HDOMLM which obtained the lowest delay in the blue marked line of Figure 14. As the rounds increase, energy consumption is increased which impacts the CH selection duration. The delay was reduced than the other two protocols of CCCH and ANFIS-EESC with 0.4s and 1.4s difference than HSOMLM respectively.

Figure 15 depicts the performance of time consumption in every round. As the rounds increased, the time consumption increased due to multiple node evaluation. As rounds increase, the capability of a node to be selected as CH is reduced as decreasing of energy, increasing of distance. This will make the repetition in the selection process and transmission. Even though our HDOMLM getting reduced time complexity than CCCH and ANFIS-EESC by 100s and 150s correspondingly.

4.2 Performance comparison for different Number of Nodes

As the number of nodes increases, the number of alive nodes in the network increases, due to the cumulative energy available to the nodes. Only some of the nodes are involved in the communication which leads to an increase of live nodes in the network. Figure 16 illustrates the network lifetime as increasing nodes with the increasing curve line for all three protocols. HDOMLM is getting the highest lifetime than the other two methods of CCCH and ANFIS-EESC of 162 and 223 nodes difference of lifetime at 400 nodes deployment.

Figure 17 shows the performance of residual energy by increasing the number of nodes in the network. As the nodes increase, the remaining energy in each round increases due to the inactive of highly non-communicating nodes involved in the transmission. In other protocols, moreover, all the nodes are involved in the selection of CH nodes which is replicated in Figure 17 for the other two methods. But in the proposed HDOMLM, only the corresponding nodes information is gathered and prediction will be taken over for the specific node's energy which automatically saves the other nodes battery life.

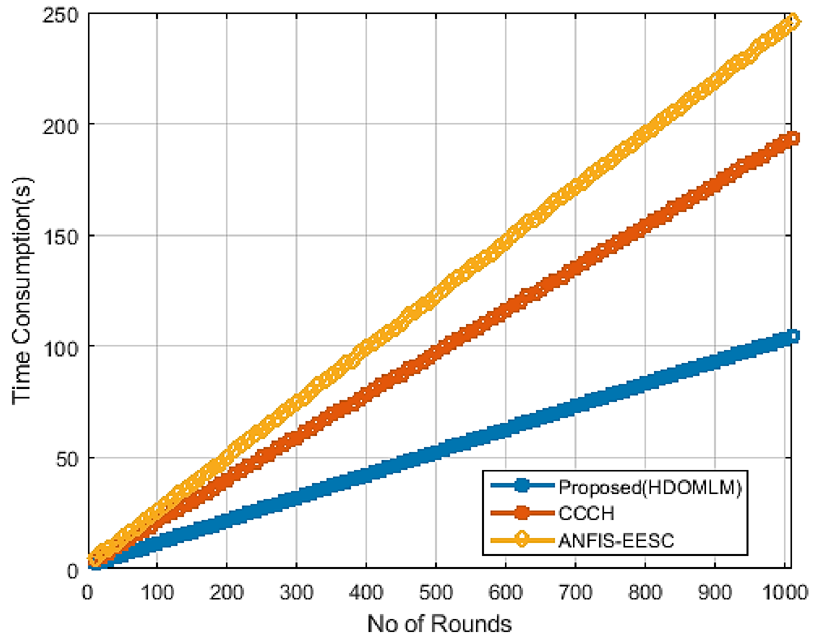

Figure 15. Time Complexity Comparison

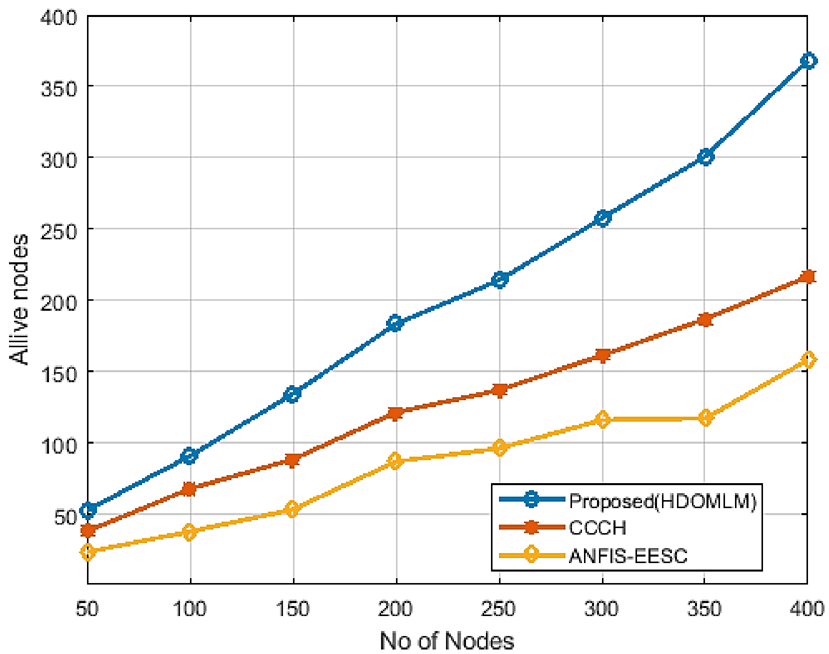

Figure 16. Alive Nodes Vs Nodes Deployment

Table 4. Sample Training data of O-MLM

S.No	Delta Difference	Mean Distance	Related Energy	Related Mobility	Transmission Delay	Class Label
1	**8.282877**	**0.544444**	**0.177778**	**0**	**0**	**2**
2	28.18314	0.736111	0.455556	0.002137	0.034402	1
3	27.85697	0.85	0.455556	0.001653	0.026603	1
4	36.98853	0.827778	0.455556	0.00236	0.037981	1
5	21.62178	0.738889	0.455556	0.0015	0.024138	1
6	10.08948	0.138889	0.455556	0.001071	0.017233	1
7	**7.339835**	**0.016667**	**0.177778**	**0**	**0**	**2**
8	28.85827	0.425	0.455556	0.002286	0.036799	1
9	29.73845	0.811111	0.455556	0.001584	0.025495	1
10	28.81437	0.252778	0.455556	0.0018	0.028971	1
11	28.46728	0.147222	0.455556	0.001703	0.030143	1
12	34.01818	0.241667	0.455556	0.001466	0.02595	1
13	**5.921404**	**0.352778**	**0.177778**	**0**	**0**	**2**
14	42.36541	0.111111	0.455556	0.00236	0.041775	1
15	24.9938	0.802778	0.455556	0.001441	0.025508	1
16	16.09644	0.138889	0.455556	0.001103	0.01953	1
17	40.06615	0.783333	0.455556	0.002199	0.038933	1
18	21.13001	0.405556	0.455556	0.000801	0.014178	1
19	22.77754	0.216667	0.455556	0.001304	0.023079	1
20	**5.595669**	**0.197222**	**0.177778**	**0**	**0**	**2**
21	12.53824	0.297222	0.455556	0.000357	0.006326	1
22	40.96507	0.483333	0.455556	0.00236	0.06757	1
23	29.07836	0.358333	0.455556	0.001458	0.041747	1
24	23.32992	0.480556	0.455556	0.001581	0.045269	1
25	11.92073	0.116667	0.455556	0.000696	0.019942	1
26	27.82305	0.530556	0.455556	0.000938	0.02687	1
27	21.99071	0.341667	0.455556	0.001234	0.035337	1
28	**10.52849**	**0.147222**	**0.177778**	**0**	**0**	**2**
29	10.49287	0.483333	0.455556	0.000666	0.009854	1
30	34.18968	0.605556	0.455556	0.001677	0.024813	1
31	18.51124	0.825	0.455556	0.000921	0.013627	1
32	31.80792	0.769444	0.455556	0.001671	0.02472	1
33	22.09075	0.527778	0.455556	0.000551	0.008149	1
34	31.51917	0.533333	0.455556	0.001317	0.019488	1
35	**6.262997**	**0.147222**	**0.177778**	**0**	**0**	**2**

36	59.88969	0.219444	0.455556	0.00236	0.034917	1
37	16.97307	0.630556	0.455556	0.000572	0.008458	1
38	24.20513	0.722222	0.455556	0.000802	0.011868	1
39	34.65828	0.038889	0.455556	0.001652	0.024441	1
40	43.7464	0.255556	0.455556	0.002016	0.029826	1
41	20.14356	0.202778	0.455556	0.000882	0.014627	1
42	34.95453	0.358333	0.455556	0.001518	0.025178	1
43	35.77777	0.041667	0.455556	0.00236	0.039148	1
44	14.33816	0.716667	0.455556	0.000689	0.016057	1
45	**4.86126**	**0.266667**	**0.177778**	**0**	**0**	**2**

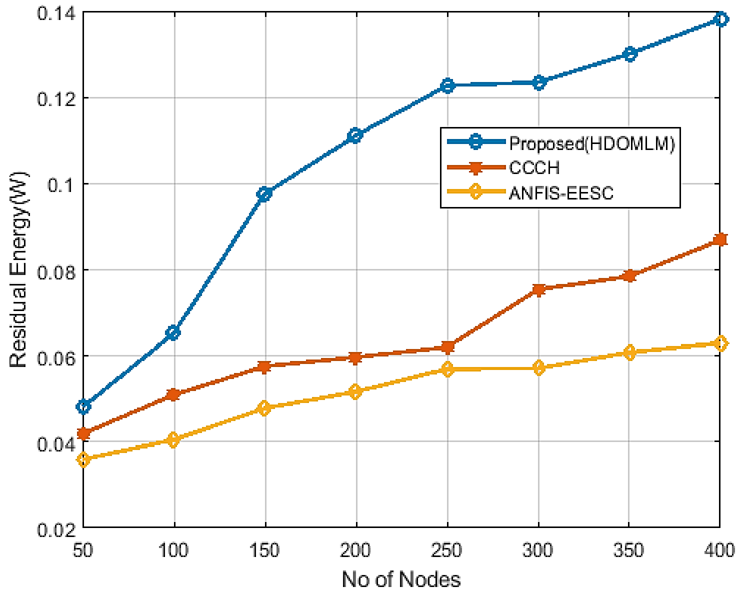

Figure 17. Residual energy vs nodes deployment

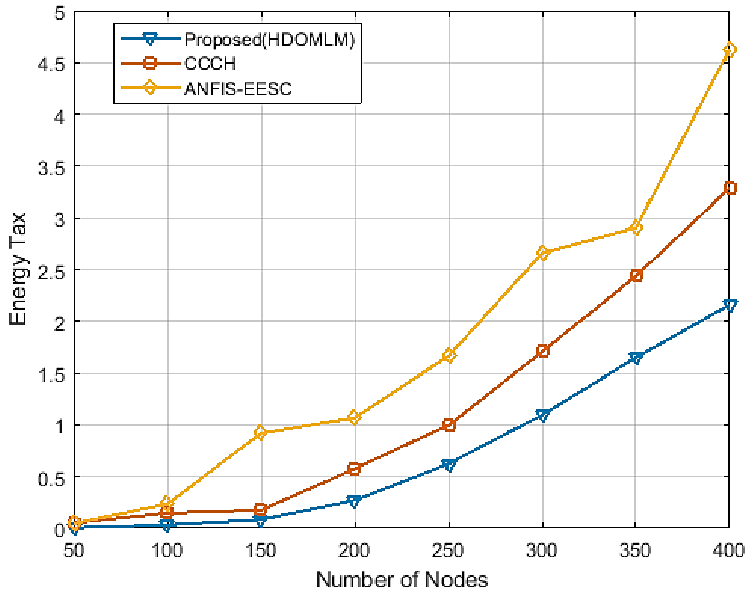

Figure 18. Energy Tax Vs number of nodes

Table 5. Performance Comparison for HDOMLM

Number of Nodes	End-to-End Delay	Alive Nodes	Residual Energy	Time(s)
50	0.72529	50	0.097623	2.287419
100	0.741029	91	0.122722	16.57749
150	0.833472	135	0.130121	31.0563
200	1.056586	184	0.123497	45.39378
250	1.110372	214	0.111119	59.65935
300	1.374562	268	0.138084	74.13664
350	1.52304	321	0.048084	88.27833
400	1.719303	368	0.065201	102.3044

Table 6. Quantitative evaluation of proposed HDOMLM of 400 nodes network scenario

Metrics Methods	Network Lifetime	Energy Tax	Average Delay(s)	Throughput (Kbps)	Average Inter-cluster distance (m)	Average Intra-cluster distance (m)	Load balancing probability	Selection Time(s)
ANFIS-EESC	0.3875	4.65	2.18	32.58	35.66	29.7	0.8239	248.7693
CCCH	0.5450	3.43	1.22	39.44	46.27	26.4	0.8847	189.0742
Proposed HDOMLM	0.9075	2.15	0.78	54.21	58.45	16.5	0.9462	102.3044

Figure 18 illustrates a progressive increase in the energy tax of the HDOMLM, CCCH, and ANFIS-EESC protocols. This is due to the fact that when nodes are deployed from sparse to dense, the total amount of nodes capable of forwarding packets likewise grows, resulting in higher energy usage for sending and receiving packets. Out of the three treatments, HDOMLM has a reduced energy burden. The CCCH and ANFIS-EESC protocols are built on sender interaction, where senders communicate with neighboring nodes to get forwarding information for selecting suitable relay nodes. This interaction results in higher energy consumption. ANFIS-EESC may not efficiently transfer packets along the ideal path due to a lack of global viewpoint, resulting in significant energy consumption. Due to the lack of restrictions on the forward direction in CCCH protocol, packets are transmitted in unneeded directions, resulting in an increase in energy consumption. However, HDOMLM operates as a coordination-based procedure, allowing routing decisions to be made by the receivers themselves. This eliminates the need for information maintenance and results in a protocol with minimal energy consumption.

In Table 4, multiple metrics for different nodes are listed. The delay for 50 nodes network is 0.7s and 400 nodes is 1.7s which means only 1 s delay increased even increasing of nodes to 8 times than 50 nodes. The following Table 5 shows the training data information that we used in the O-MLM for the classification of normal nodes and CH nodes.

In Table 6, we have shown the quantitative analysis of the proposed HDOMLM and compared it with earlier implementations of CCCH and ANFIS-EESC.

In this Table 6, we show the metrics of network lifetime, energy tax, average delay, throughput, inter and intra-cluster distance, load balancing probability, and CH selection time for 400 nodes of the network scenario. The network lifetime is measured by the ratio of the number of alive nodes to the total number of nodes. As the ratio increases the network lifetime will increase and it is 0.9075 in our proposed HDOMLM. This is 40% and 58% lifetime savage than CCCH and ANFIS-EESC respectively. The energy tax of our proposed HDOMLM is 2.15 which is 1.28 and 2.5 less than the existing methods of CCCH and ANFIS-EESC correspondingly. The average delay is reduced to 0.78s in our proposed

HDOMLM and it is less than the CCCH and ANFIS-EESC delays of 1.22 and 2.18 respectively. The highest throughput of 54.21×10^3 bps is achieved using our proposed model HDOMLM and it is 41% higher than other existing methods. Higher inter-cluster distance and lower intra-cluster distance signifies the better performance of clustering. The proposed HDOMLM attains this effective distance of 58.45m inter-cluster distance for a 200x200 m network area and 16.5m of intra-cluster distance for 50m of communication range. The load balancing is a major factor in depicting the data distribution in the communication among different clusters. 0.8239, 0.8847, and 0.9462 of load balancing probability is achieved by ANFIS-EESC, CCCH, and proposed HDOMLM respectively.

7. Conclusion

A novel approach can be observed for optimizing the selection of Cluster Heads (CH) by considering energy efficiency. This is achieved through the utilization of a Machine Learning algorithm called HDOMLM. As far as we know, this is a novel machine-learning method used for the selection of cluster heads in mobile ad hoc networks (MANET). The suggested study aims to address the issue of energy usage in MANET (Mobile Ad hoc Network). The PSO algorithm is employed for the initial clustering process, considering factors such as node distance, position, and speed to optimize cluster formation. The Hybrid Dual Optimization of Machine Learning Model approach is employed to pick the Cluster Head (CH) from the nodes by classifying the features. O-MLM utilizes five distinct selective metrics as features by extracting the attributes of energy, mobility, delay, distance, and delta speed that are linked to the problem at hand. The performances are evaluated through the monitoring of Alive Nodes, Energy Consumption, Network Lifetime, End-to-End Delay, Number of Successful packets received, and overall time consumption for CH selection. These metrics of HDOMLM are compared with earlier works of CCCH and ANFIS-EESC. At 1000 rounds, the alive node is 15 for 50 network nodes in HDOMLM and it is 0 at 800 rounds for ANFIS-EESC and 0 at 910 rounds for CCCH. Network lifetime is increased and at the same time, residual energy is retained as 1.16X10-4. The network lifetime of the proposed HDOMLM is improved by 40% and 58% than the earlier implementation of CCCH and ANFIS-EESC respectively. The throughput of 54.21x103 bps is obtained using the proposed HDOMLM and it is 41% higher than the ANFIS-EESC method. 0.78s of average delay is measured using HDOMLM and it is 37% lower than CCCH and 65% lower than ANFIS-EESC methods. For future work, we will concentrate on secured communication with intrusion detection methodologies.

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K.S. Nirmala Bai - Investigation, Formal analysis, Conceptualization, Writing – original draft. M.V. Subramanyam: Validation, Methodology, Writing – review & editing, Supervision. Both the authors read approved the final version of the manuscript.

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Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

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