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OA-PU Algorithm-to Enhance WSN Life Time with Cluster Head Selection

D. Nageswari[1,*], R. Maheswar[2] and P. Jayarajan[1]

[1]Department of ECE, Sri Krishna College of Technology, Kovaipudur, Tamil Nadu, 641042, India
[2]School of EEE, VIT Bhopal University, Bhopal, Madhya Pradesh, 466114, India
*Corresponding Author: D. Nageswari. Email: nageswaripapers@gmail.com
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Abstract: Clustering is the most popular strategy for increasing the lifetime of a wireless sensor network, which immediately leads to a stronger routing process. This process requires the processing of sensor nodes into clusters and assigning relevant cluster heads to each cluster. This paper aims to implement a new hybrid algorithm called Over taker Assisted Political Update (OA-PU) for selecting an efficient cluster head. This cluster head is selected based upon four factors, namely energy, distance, cluster radius, and time. The hybrid algorithm is a combination of the Fusion Rider Optimization Algorithm (F-ROA) as well as a nature-inspired Political Optimization Algorithm (PO). Fusion-ROA depends on groups of riders that are attempting to reach the goal and PO is a state of the art meta-heuristic optimization methodology for global and structural analysis performance prediction in the WSN environment. In terms of alive node analysis, cost function analysis, and energy analysis, the proposed OA-PU outperforms conventional approaches. Consequently, the lifetime of WSN is increased and an optimal system is developed.

Keywords: Alive node; political optimization; cluster radius; cluster head overtaker

1 Introduction

The network lifespan is considered a valid indicator of network efficiency in wireless sensor networks (WSN). The network runtime is defined by the time it takes for a particular amount of nodes to perish source of power exhaustion [1]. Particularly, protocol assessment is a key issue in WSN since it is necessary for reducing traffic interruption and increasing network lifespan [2]. For prolonging network lifetime and preserving network energy balance, topology management based on hierarchical classification techniques is frequently utilized [3]. Cluster head node selection is a crucial element for regulating topology in hierarchical clustering methods. During the last few decades, several hierarchical clustering methods have been suggested in the literature for topological power. Hierarchical clustering method LEACH, in particular, is considered as the gold standard for topology management [4]. Although the network's endurance was extended, a part of the network's sensor nodes died prematurely because of the randomization involved in the gathering of cluster heads [5].

Behavioral and physiological factors may be sensed and tracked using numerous sensor nodes (SNs) in the WSN. The evolution of sensors has made WSN currently available in a compact SN format with wireless networking hardware [6]. LEACH-C or centralized LEACH is an enhanced form of LEACH that uses the simulated annealing technique to choose optimal cluster head nodes [7]. In general, the grey wolf optimization algorithm (GWOA) can prevent local optimal control detection stagnation. A higher degree of convergence towards the optimal stage was achieved yet the degree of testing recommended by GWOA is insufficient while performing cluster head selection [8].

The local search technique obtained through Cuckoo Search Optimization Algorithm (CSOA), is also insufficient. Thus, for increasing network lifetime and managing resources in the network, the discovery constraint of GWOA and the exploitation limitations of CSOA under cluster head selection must be efficiently managed [9,10]. The artificial bee colony (ABC) algorithm is a meta-heuristic intelligent swarm system inspired by the natural behavior of bees gathering honey [11]. In comparison to other swarm intelligence approaches, the artificial bee swarm algorithm can produce strong optimization outcomes by balancing local discovery and global growth. Around the same time, it has a small number of parameters and is easy to use. The secure transmission process is the final stage of each round in the clustering-based technique. The member nodes send perceived data to the related cluster head in this process, as well as the cluster head then sends the collected information to the base station [12].

Overall, the interval between member nodes as well as their respective cluster heads is short, and intra-cluster contact is accomplished with a single hop. The gap between the cluster heads and the base station is usually very large. If single-hop connectivity is used, the cluster head's energy utilization would be increased unnecessarily. The distance between the cluster head as well as the base station in large-scale WSNs can also surpass the sensor node's full radio range [13]. As a result, hierarchical clustering protocols typically require a routing algorithm to determine the best route between each cluster head and the base station, allowing the cluster head to transmit data to the base station in several hops. This way, the cluster head will resist using too much energy when it is far away from the base station [14].

Sensor nodes in the same cluster can interact directly with each other, dividing the wireless sensor network into clusters. Based on the intensity of received signals, a sensor node selects which cluster to enter [15]. Sensor nodes in the same cluster choose a cluster head randomly after entering the cluster to collect and relay data to the base station as in Fig. 1. Since the cluster head consumes more energy, it must be replaced regularly to decrease power consumption [16]. Each sensor node transmits its location to the base station during the implementation stage. The base station then selects cluster heads based on their power levels and placements, and the chosen cluster heads begin transmitting data to the base station. This method can successfully extend the system's lifetime, but it has the disadvantage that remote cluster heads use high energy.

Cluster head selection is a difficult process as it has several problems including energy consumption, reduced lifespan, data transmission, execution time, and residual energy. By reducing the cluster head selection time the energy consumption can be reduced and thereby increasing the life span of WSN. Henceforth, a hybrid algorithm called Over Taker Assisted Political Update (OA-PU) is developed by combining the concepts of Fusion Rider Optimization Algorithm (F-ROA) and nature-inspired Political Optimization Algorithm (PO) to reduce energy utilization and increase network life-cycle. To choose a CH, parameters like energy, distance, cluster radius, and time are used. Hereby, the OA-PU ensures that CHs delivered aggregate data successfully to the Base Station (BS). The suggested model maintains a high coverage ratio and eliminating redundancy. The threshold value of residual energy is calculated using our current method. In terms of alive socket analysis, decision variables analysis, and conceptual design, the functionality of the OA-PU is contrasted to that of standard techniques.

The literature works related to our research are reviewed in the second section. Section three describes the network and energy consumption models of our proposed Optimization scheme. The proposed algorithm is simulated and compared to other existing methods in the fourth section. Section six concludes the paper with the obtained results and outlines the future scope of this research work.

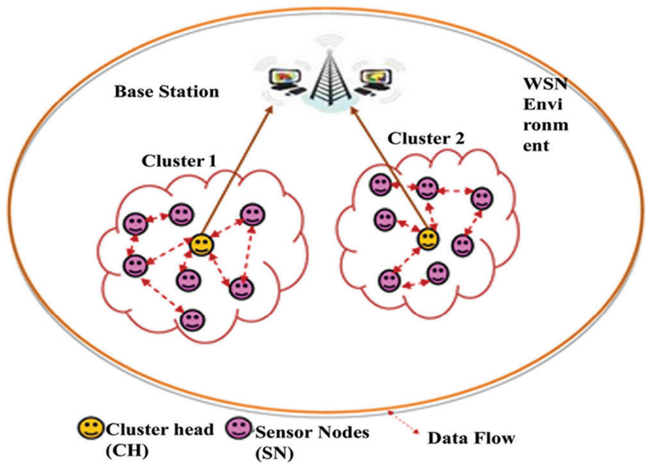


Figure 1: Cluster performance in WSN environment

2 Literature Review

Pitchaimanickam et al. [17] proposed a hybrid approach for choosing the best CH called Harmony Search Algorithm-Particle Swarm Optimization (HSA-PSO) by integrating HSA as well as PSO. This approach increased the effectiveness of searching while also extending the lifespan of the SNs. The HSA could use high-searching power, while the PSO moved from one region to the next in search of the best approach with better results. However, this technique was restricted to a single region and could not be applied to other areas.

For controlling network resources, Yanwen et al. [18] established the Software-defined Network dependent Energy Consumed Connected K-Neighborhood (SDN-ECCKN) algorithm. The devised algorithm was implemented using ECCKN as a foundation. This approach has many advantages, including network lifetime monitoring, energy management, the number of live nodes, as well as individual node control, but it was not applicable in complex WSNs.

RE-LEACH is a LEACH-based protocol proposed by Pandey et al. [19]. The authors made this protocol by obtaining low-overhead and energy-efficient. Cluster configuration, reappointment, and data transfer are the three steps of this protocol. This method also incorporates the process of reappointment. If a node has more remaining energy than the others, it is assigned to complete the mission several times. By avoiding node death, the mechanism will extend the life of a WSN.

Miao et al. [20] have offered a remedy of energy gaps in WSNs caused by strong traffic near BS. The authors employed the Grey Wolf Optimization (GWO) approach for routing and clustering to high efficiency. The GWO method employs two fitness factors for both routing and clustering procedures. The routing fitness feature is built around two goals: total distance traversal and hop distance minimization. The aggregating objective function distributes the entire load based on the distance between portals and BS, and for clustering and routing, the population’s best solution is picked.

To extend the lifetime of WSN networks, Sahoo et al. [21] proposed a hierarchical clustering method based on a genetic algorithm (GA). WSN clusters are dynamically optimized using the GA-centered self-organizing network clustering approach. The proximity of nodes, estimated energy consumption, base station size, and residual energy variables are used to configure an optimum dynamic network configuration. A cluster head is a node in a cluster that has balanced these variables during the optimum cluster setup period. More clusters are generated if the sensor field is quite far away from the base station, to keep the metabolic rate as high as possible and extend the WSN's longevity.

Swarm intelligence-based forwarding (SIF) is proposed by Barzin et al. [22]. SIF forms clusters using an efficient clustering algorithm, and then suitable CHs are chosen. This method produces both a balanced and accurate number of clusters. This routing scheme's key goal is to extend the network's lifespan, and it can be used for a wide range of applications. An effective clustering strategy, as well as a topology control system, forms the foundation of this scheme. To determine the optimum number of clusters, the clustering strategy is used. In addition, sensor nodes (SNs) in the configuration control mechanism determine the most effective route based on the optimum forwarding contact location. This protocol's key feature is that it uses as few resources as possible while extending the network's lifetime.

Sharmin et al. [23] propose a method to the routing hole problem in WSNs caused by energy depletion. The paper successfully resolves the problem of the network lifespan being prematurely terminated because the BS is located far away. The suggested scheme preserves connectivity while conserving electricity. The number of sensor nodes (SNs) in a WSN has an impact on the network's performance. As a result, we must achieve the optimal node degree while using fewer resources. Moreover, a routing system requires the least amount of transmitting capacity. In WSNs, the proposed scheme executes efficient data monitoring activities with optimum sensor nodes.

3 The Proposed Hybrid Algorithm Termed Over Taker Assisted Political Update (OA-PU)

The proposed method provides a hybrid algorithm called over taker assisted political update (OA-PU) to identify the cluster head based on fusion-rider optimization algorithm (F-ROA) and political optimization algorithm. This system uses the k-means clustering technique to create the clusters within the sensor nodes. This technique improves energy consumption as well as network lifetime by considering CHs neighboring nodes. The primitive descriptions of the used F-ROA and PO optimization Algorithms are discussed first in this section for a better understanding of their benefits and limits.

In the typical WSN setting, there are multiple difficulties to be solved to enable better efficiency and energy optimization. The CH of a WSN is normally determined by factors such as energy, distance, cluster radius, and time. The parameters are taken into account as WSN is integrated with k-means clustering tools. The main goal of this effective CH selection using Fusion-ROA and PO is to minimize the distance between nodes, reduce execution time, as well as increase residual energy. The proposed CH selection model is a parametric representation. The batch size in a WSN often fluctuates, and CHs are chosen from the WSN's total sensor nodes. When choosing a CH in a WSN, performance metrics such as node distance, latency, and spectral efficiency are taken into account, as previously indicated. As a consequence, only CHs may connect to the BS directly, and the access of all other nodes has been prohibited. When the characteristics from both WSN and IoT networks are integrated, the CH selection in WSN systems becomes more complicated. As a consequence, factors including energy, distance, cluster radius, and node time are used to calculate a low and mid-rate. This non-linear issue will be solved using our suggested OA-PU.

3.1 Model of a Network

WSN comprises a group of stationary sensor nodes, each with its unique set of capabilities, designated by Sn. During data transfer, a node might operate as both a CH and an active sensor. Sensor location, topological features, data sensing, frequency hopping, and environmental impact are often connected to the WSN. The sensors are positioned at random or manually in application regions. Clustering is done by using a variety of sensor nodes. It's a fantastic concept for prolonging the life of WSN. During the clustering phase, sensor nodes are gathered and a CH is chosen using the k-means clustering method, with the count denoted by Sc. This CHS is compatible with any cluster. In a cluster, the nodes are grouped such that they are as close to CH as feasible. The sensor nodes collect data on a particular region and send it to the CH during the operation. Furthermore, the collected data is sent to the BS by the particular CH. In the current study, Fig. 2 illustrates the CHS of a WSN with many sensor nodes and a consolidated BS.

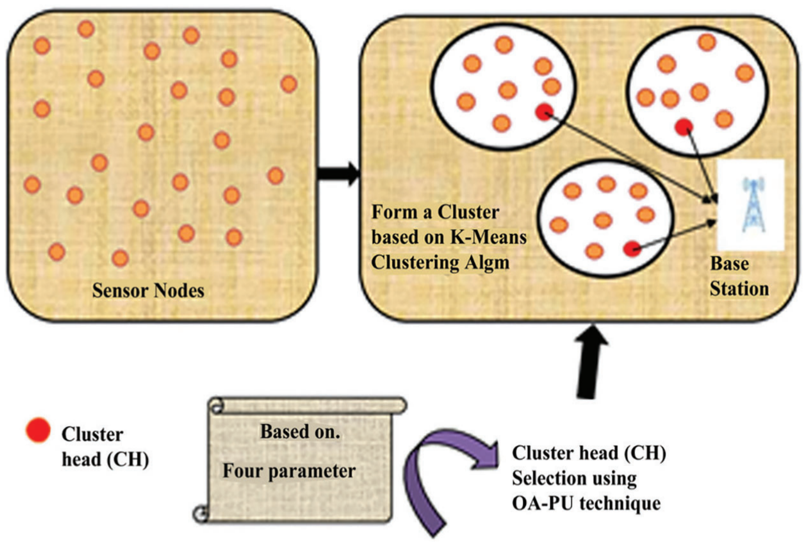


Figure 2: Architecture of the proposed system

3.2 Cluster Formation

Selecting the correct cluster counts: In WSN, the cluster's conceptual identity accounts are based on energy efficiency analysis. The use of a rational cluster count will improve network connection reliability while also extending network lifetime and balancing node energy loss. In inter-cluster communication, this architecture uses the multi-hop networking mode. D_j is determined by the interval between the BS and the severe CH, which is classified as several hops. D_j = k. *le*, where k is the cluster count and *le* is the equal distance length.

$$e_{mh} = e_{rx} + e_{da} + e_{tx} \tag{1}$$

In Eq. (1) e_{mh} is the overall energy costs across the clusters. The efficiency of received data is defined by e_{rx}, the distance between sensor nodes is represented by e_{da}, and the efficiency of transmitted data is determined by e_{tx}.

K-mean clustering: A k-means clustering algorithm is used to cluster the current results, which is described as follows: K-means is a classic data mining clustering algorithm that is often used to cluster massive amounts of data. This algorithm was first proposed by Mac Queen in 1967 and is known to be a simpler, non-supervised learning algorithm for resolving issues on recognized clusters. In a repeating method, the provided data items are categorized into k distinct clusters by resolving to premature convergence. As a result, the generated cluster's outputs are separated and compressed. Fig. 3 shows the k-means clustering structure.

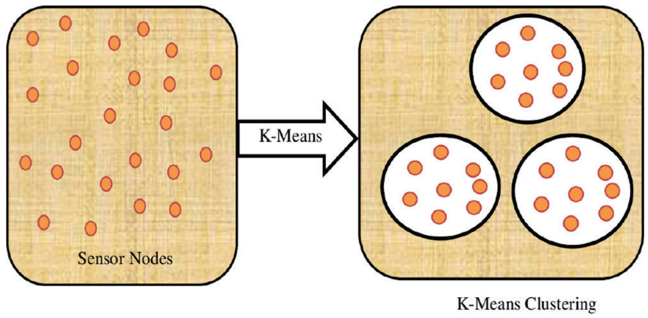


Figure 3: K-means clustering structure

This algorithm is made up of two distinct steps. The k pre-determined and fixed centers are selected at random in the first step. The stage after that delivers all data items to the nearest data center is referred to as the transport stage. The distance measure is typically used to compute the distance between each data object as well as the cluster head. The first stage is complete and an early collection is carried out, with all data items contained within a few clusters. The average of newly formed clusters has been recalculated in this manner. This procedure is iterated indefinitely before the minimal criterion function is achieved. The following are the measures involved in k-means clustering:

Input: k is the count of ideal clusters.

Output: k groups of clusters

Step: 1 from the specified nodes, choose k data objects at random as initial cluster heads.

Step: 2 Proceed;

Step: 3 Calculate the distance between each data object dbj($1 \leq j \leq n$) and the entire cluster heads k Ci($1 \leq i \leq k$), and allocate the data objects to the nearest cluster with dbj as mentioned (2).

$$I = \sum_{j=1}^{k} \sum_{x \varepsilon C_j} (\|x - \beta^2\|) \tag{2}$$

Step: 4 the cluster head is recalculated for each cluster i ($1 \leq i \leq k$).

Step: 5 Repeat when there is no change in the cluster head.

3.2.1 Calculation of the Number of Nodes in the Best Cluster

The competitive radius is used to describe the relationship between the cluster node count as well as the distance to BS (3)

$$G_j^{\wedge} = \left(1 - \tau \cdot \frac{ge_{mx} - ge_{(BS)}}{ge_{mx} - ge_{mn}}\right) \cdot G_0 \tag{3}$$

Eq. (3) is the node's first competitive radius, in which the element τ takes the competitive radius scope as well as calculates the distance effect within it. Based on the rise in element, the distance effect on competition radius increases. G_0 is the maximum competitive radius, ge_{mx} and ge_{mn} are the minimum and maximum distances from all nodes to BS. As $G_j^{\wedge}$ increases, the variance spectrum of Li decreases, and vice versa.

G_0 also has a direct effect on Li's worth. The competition radius of the cluster is equal to the spacing between the BS and the cluster, according to Eq. (3).

3.2.2 CH Selection

Following the creation of clusters, the best CH for data transmission must be chosen. This paper attempts to choose the best CHS by considering the fitness parameters such as energy, distance, cluster radius, as well as time, which have already been identified as issues when selecting the CH.

Since the shortest path selection improves the presentation of data transfer, the distance can be reduced. The use of energy by each node is another incredibly serious issue. As a result, the knowledge flow is the most important complexity with the least amount of energy and the shortest range. Since the clustering rate has increased over time, we need to determine the cluster radius. Almost all optimization algorithms place a high value on distance, cluster radius, and energy consumption when making a decision about which CH to use. As a result, various objectives must be met to extend the node's mortality rate. Finally, while choosing the CH from a group of sensor nodes, energy, proximity, cluster field of view and duration must all be taken into account.

Fig. 4 depicts the OA-PU methods' block structure, with Fusion-ROA considering two parameters: distance and energy, as well as PO, which specifies the cluster radius and time factors. These two algorithms illustrate how cluster heads are chosen in each cluster based on four variables in the WSN environment.

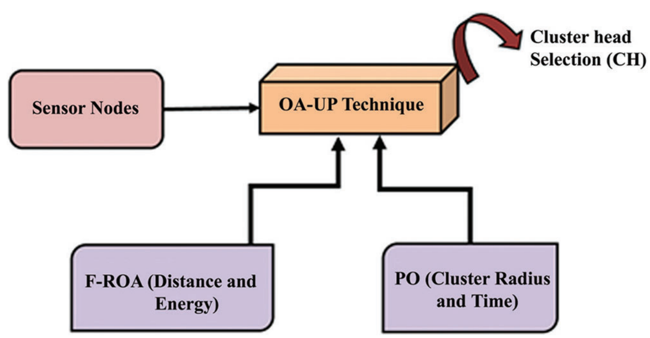


Figure 4: Block diagram of OA-PU techniques

3.3 Fusion Rider Optimization Algorithm (F-ROA)

The Fusion rider optimization algorithm (F-ROA) is based on a unique computer approach known as fictional computing, which employs a series of processes to improve the system performance using fictitious facts and concepts. F-ROA relies on groups of riders that are attempting to accomplish the goal. To achieve this, F-ROA uses rider groups that go on a path to accomplish a shared goal. The number of groups in F-ROA is four, with equal riders allocated in each.

F-ROA is a novel computational algorithm based on the motivation of a group of riders who drive together towards a certain destination to achieve the cluster head position. They are divided into four classes, with the number of riders spread evenly among the four groups. Bypass rider, follower, over-taker, and intruder.

Riders create a multi-technique, with the proper formulation of the pedal, speed, guiding, and throttle being the most essential considerations while accomplishing the goal. Riders manage their position at each iteration by managing these characteristics and then start the well before strategy depending on the current energy rate, which is perpendicular to the direction between the rider's goal and present location.

The current leading rider is listed based on the current achievement rate. This procedure will continue until the riders have been given the full amount of time. Following that, the cluster head is declared alongside the leading operator.

The optimal cluster counts k objective function OC_1 is given in Eq. (4). The optimal CH selection objective function OC_2 is described in Eq. (5). The overall energy efficiency is described by Eg_{tot} and the number of clusters in the environment is represented by f_3.

$$OC_1 = \min(Eg_{tot}) \tag{4}$$

$$OC_2 = \min(f_3) \tag{5}$$

In general, a WSN is made up of groups of clusters, each of which has its CH that acts as a coordinator for collecting data from sensor nodes and transmitting it to the BS. As a result, selecting the right CH, which has an impact on deciding the network's overall system performance, is important. F-ROA is used to choose the best CH from a cluster of nodes. While F-ROA has many advantages for solving complex problems, it still needs to be improved to reach its full potential. In reality, the handling of community updates has been improved.

Rider's position update: The pioneering rider is decided by upgrading the rider's placement in each series, as shown in Fig. 5.

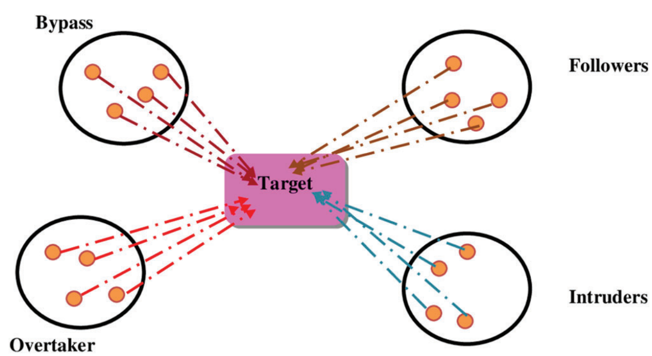


Figure 5: Rider positions

Update procedure for bypass riders: Since they bypass the usual path and do not join the leading riders, the bypass rider's location is updated at random. This is represented in Eq. (6).

$$A = 2 \times f \tag{6}$$

Update procedure for follower*:* Since the up comer's position is changed by tracking the leading rider's position, this type of rider reaches the goal easily and quickly. The location update of the follower is determined based on the coordinate cluster head selector for the accurate estimation in P and is specified in Eq. (7).

$$B_\beta = |e \times T_\beta - T| \tag{7}$$

Update procedure for overtaker: The relative progress rate, path predictor, and coordinate cluster head selector are all important factors in the overtaker upgrade process. The overtaker's location change model is written in this manner Eq. (8).

$$B_{\propto} = |e \times T_{\propto} - T| \tag{8}$$

Update procedure for the intruder: When it attempts to take the leading rider position, the intruder uses the same mechanism as a follower to update its position. The method of updating the intruder's location is depicted as follows Eq. (9)

$$B_{\pi} = |e \times T_{\pi} - T| \tag{9}$$

Algorithm 1: Contains the pseudo-code for the proposed F-F-ROA

Input: Riders' directions are random, r^t

Output: Rider in the lead, r^i

Step:1 Assign the cluster.

Step:2 Distribute the rider's parts.

Step:3 Determine the clustering rate

While $J < J_{off}$

for x = 1 to r

Update the rider for the bypass role as specified Eq. (6)

Update the location of your followers as specified Eq. (7)

Update the location of the overtaker as required Eq. (8)

Update the intruder's location as desired Eq. (9)

Riders are ranked based on their cluster rate.

Update the rider conditions.

Return z^l

S = S + 1

End for

End While

End

Each cycle t is compared to the preceding repetition t−1 to check if the current t produces an improvement. If the analysis is correct (getting the proper suggestion compared to the previous t−1), the process is carried out as usual. If not (the solution has not been enriched), the parameter trail is set to 0 and the iterations proceed. If the trail is greater than 5, the overtaker update is carried out as above Eq. (8). The suggested OA-PU is depicted in flow chart form in Fig. 6. In the optimization approach, the following parameters are considered.

Energy: Energy consumption of non-CH nodes: After the CH has been selected; each non-CH node decides which CH will be unified in the new stage. The CH is chosen based on the estimation of the received transmitter capacity. As a result, the energy use up of a non-CH node updating the cluster can be calculated as follows:

$$g_{t'} = 2m_1 g_e + m_1 h_b H_a^2 \tag{10}$$

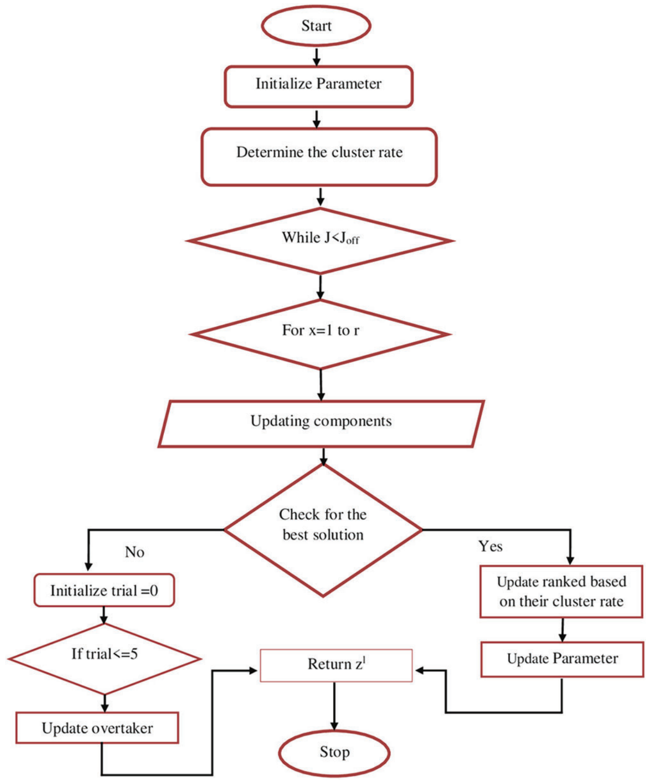


Figure 6: Flow diagram for the proposed system

The total energy required to create a cluster is calculated as follows:

$$g_t^{all} = q\left[g_t + \left(\frac{v}{q} - 1\right)g_{t'}\right] \tag{11}$$

where g_t stands for CH energy consumption, $g_{t'}$ for non-CH energy consumption, v stands for total nodes, q stands for cluster number, and g_t^{all} stands for total energy consumption.

Energy consumption of CH nodes*:* The energy used by CH in any area is calculated as follows:

$$g_t = m_1 g_a\left(\frac{v}{q} - 1\right) + m_1 h_s H_{BS}^4 + m_1 h_b H_c^2 \tag{12}$$

$$Energy(E) = g_t' + g_t^{all} + g_t \tag{13}$$

Distance: When data must be transferred from one node to the next, distance is a major factor. The distances are calculated using the wireless network, which is in control of the nodes' mobility depending on their locations, velocity, as well as acceleration. The interval between the CH M_j is calculated as follows:

$$Distance(D) = \left\{ \frac{1}{|M| \times l} \sum_{j=1}^{|M|} \sum_{\substack{n = 1 \\ i \varepsilon n}}^{v} \frac{z(M_j) l_n}{l} \right\} \tag{14}$$

V denotes the overall number of nodes, as well as M j, denotes the jth CH.

3.4 Political Optimization Algorithm (PO)

To find the optimal result based on the fitness value, the suggested Political Optimization Algorithm (PO) is used. Each agent provides the solution in the proposed hybrid approach. For the fitness function, the optimal solution has the fewest set of data with the highest connection efficiency and kinetically selected CHs with the maximum residual energy. The foremost process is concerned with energy conservation and they recognize that reducing the optimal number of CHs will minimize energy consumption. Eq. (15) is an illustration of this.

$$Y = \frac{Number\ of\ optimal\ cluster\ (c)}{Size\ of\ set\ of\ CH\ contestants\ (s)} \tag{15}$$

Senor nodes or various sensor nodes (i.e., parties) in a cluster are shown in Fig. 7. a) Population initialization. Political parties PS1, PS2, PS3, etc. are represented by the small circle. C1, C2, and C3 are the three clusters represented by the big circle. b) Within each cluster, neighbors of various political parties perform canvassing efforts. c) The efficiency of selected cluster heads and nodes is calculated. Finally, based on the node quality, update the cluster head's locations.

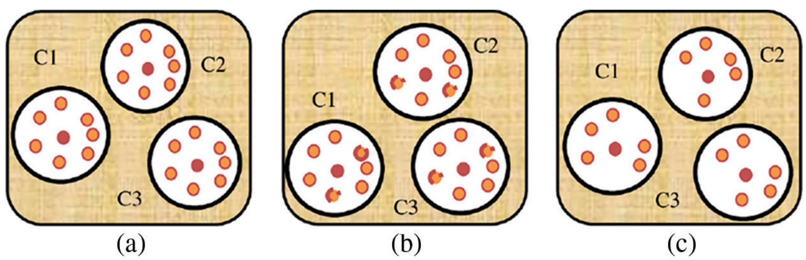


Figure 7: Structure for PO (a) cluster initialization (b) canvassing (c) Head selection

Even though the traditional PO model produces adequate results, it suffers from fitness function and is also prone to local optima that delay the optimization process. As a result, the PO definition is merged with the current WOA system, resulting in improved convergence as well as optimal outcomes. Certain search problems have been stated to benefit from hybrid optimization algorithms. The incredible hunting method of humpback whales is the most powerful motivating factor. They follow the predator's movements and encircle it. The current optimal option, according to this technique, is the one that is closest to the target being sought. Eqs. (16) and (17) depict this behavior), where i defines the current iteration, A and E denote coefficient vectors, J denotes the optimal option so far, || denotes the absolute value, and "." denotes a unit by element multiplication."

$$D = |E.J(i) - J(i)| \tag{16}$$

$$J^{(i+1)} = J(i) - A.D \tag{17}$$

It is important to note that J must be modified if the best outcome becomes available. The vectors C and E are enumerated according to Eqs. (18) and (19), where q is minimized from 2 to 0 for different iterations as well as f is the random vector in [0, 1].

$$A = 2_q.f - q \tag{18}$$

$$E = 2.f \tag{19}$$

The search agent location is modified in the current hybrid system based on the PO update that is specified in Eq. (21), where J_1, J_2, as well as J_3 are enumerated as per Eqs. (18)–(20) and D_1, D_2, and D_3 are enumerated as per Eqs. (20)–(26).

$$D_a = |E_1 \cdot J_a - J| \tag{20}$$

$$D_b = |E_2 \cdot J_b - J| \tag{21}$$

$$D_c = |E_3 \cdot J_c - J| \tag{22}$$

$$J_1 = |J_a - A_1 D_a| \tag{23}$$

$$J_2 = |J_b - A_2 D_b| \tag{24}$$

$$J_3 = |J_c - A_3 D_c| \tag{25}$$

$$J^{(i+1)} = \frac{J_1 + J_2 + J_3}{3} \tag{26}$$

Algorithm 2: Contains the pseudo-code for the proposed PO.

Input: J_i
Output: $\check{J}_i$
$\check{J}_i$ Represents the most effective search agent
while $i < i_{max}$
For every search agents
update q, A, and E
if $1(|A| \geq 1)$
update the current exploring agent's location using Eq. (16)
else if $1(|A| \geq 1)$
Evaluate J_1, J_2, and J_3 in Eqs. (23)–(26)
In Eq. (21), use PO update to change the location
end if 1
Check to see how the search agent goes outside the search area.
Evaluate the search agent's ability.
If a better solution is available, update $\check{J}$
end while

The hybrid scheme was created by combining the algorithms, all of which are innovative optimization approaches. In this scenario, both approaches concurrently offer the optimal best outcomes in each round of repetition; the best outcome is picked in each round of repetition by assessing the guidelines established by both refinements. Furthermore, the best solution is given to both algorithms to produce optimal solutions that are much better than the previous optimal solutions, as well as the cycle is repeated until the maximum number of iterations is reached. To solve a wide variety of optimization problems. There are several complex problems for which conventional methods are unable to have the optimal solution at any given time. The most recent meta-heuristic optimization techniques are F-ROA and PO. In the optimization approach, the following parameters are considered.

Cluster radius: In a WSN, clustering is the effective approach for extending the network lifespan. It requires forming clusters of sensor nodes as well as selecting cluster heads (CHs) for each cluster.

$$ClusterRadius(CR) = \sqrt{\frac{\sum_{j}^{m}(y_j - y_0)^2}{m}} \tag{27}$$

Measures the distance between nodes in the cluster and the cluster head. The square root of the cluster's maximum position from some point.

Time: The hierarchical clustering solution for WSN and its round duration are quantified using the initial useable capacity of sensor nodes, as well as the aggregate energy consumed by CH and non-CH nodes in around. For the first round of the setup process, nodes are designated as CH.

$$Time(T) = T_{setup} + T_{steady} \tag{28}$$

The operations carried out in a round are split into two phases: setup and steady-state. In the setup process, clusters are formed, and in the steady-state phase, sensed data is transmitted to its expected destinations.

4 Result and Discussion

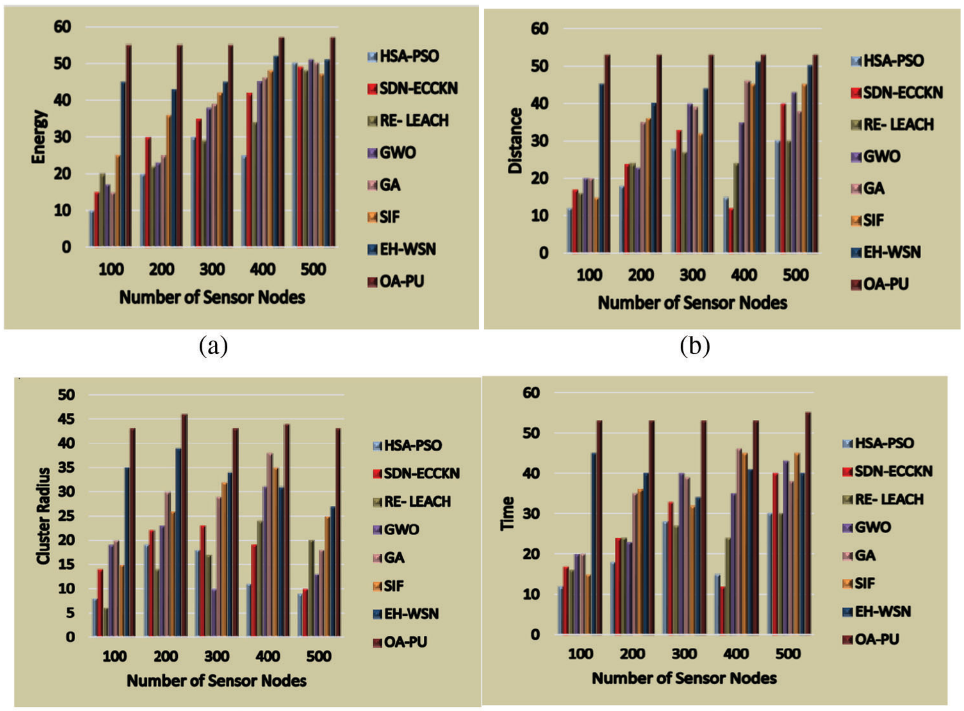
The OA-PU technique was used to apply the presented cluster-head selection model in the NS-3 device, and the results were observed. Energy, distance, cluster radius, and time were used to compare the performance of the adopted strategy to that of other existing techniques such as HSA-PSO, SDN-ECCKN, RE-LEACH, GWO, GA, SIF, and EH-WSN. The study was carried out in two experiments: one with 100 nodes and the other with 500 nodes, with the number of rounds, varying from 20, 30, 40, 50, 60, 70, and 180, etc. In a 100 × 100 m^2 network topology, 50 sensor nodes are randomly distributed.

Three performance standards are included in the LEACH-M simulation experiments: network lifetime, energy consumption, and the number of data received at BS. The other two indexes, except for energy consumption, are assessed using the assessment criteria, the first node dies (FND), half of the nodes alive (HNA), and the last node dies (LND) (LND). LEACH-M receives more data at BS when compared to LEACH-C and EE-LEACH. When the area is increased to 300 × 300 m^2, however, the number of data packets sent to BS decreases. This is because, in the WSN as a whole, fewer alive nodes are transmitting their sensory data to BS after some nodes die early. Simulation parameters are given below Tab. 1.

Table 1: Simulation parameters

Parameters	Value
Simulation area	100 m × 100 m
Number of nodes	500
Transmission speed	Millisecond's
Number of CHs	10% of total nodes
Data packet	500 bytes
Initial node energy	5.5 J

In the analysis, the proposed OA-PU system was compared to the HSA-PSO, SDN-ECCKN, RE-LEACH, GWO, GA, SIF, and EH-WSN schemes with various numbers of sensor nodes in the network. Fig. 8 shows the energy, distance, cluster radius, as well as time of the proposed OA-PU scheme and the compared HSA-PSO, SDN-ECCKN, RE-LEACH, GWO, GA, SIF, and EH-WSN schemes with varying numbers of sensor nodes in the network.



(a) (b)

(c) (d)

Figure 8: Performance of proposed parameters. (a) Energy (b) Distance (c) Cluster radius (d) Time

The four network parameters were found to be superior with the proposed OA-PU on average with the compared systems since it can manage various sensor node characteristics that assist in cluster head selection. It's also effective at maintaining the pace of utilization as well as the amount of exploitation suffered during the network's collection of productive cluster heads. Fig. 9 depicts the evaluation of the performance of the proposed algorithm contrasted with the existing algorithms.

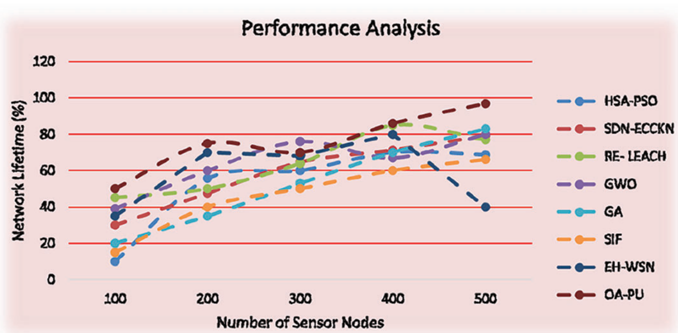


Figure 9: Performance analysis of proposed system

$$Lifetime = E + D + CR + T \tag{29}$$

The suggested OA-PU scheme facilitates the creation of a combination between the extraction and discovery rates introduced by the basic F-ROA as well as PO algorithms, which results in a higher percentage of sensor nodes. The number of lost nodes in the network visualized during deployment of the proposed OA-PU structure and the compared HSA-PSO, SDN-ECCKN, RE-LEACH, GWO, GA, SIF, and EH-WSN methods. Initially, the network's number of sensor nodes is zero. When the number of rounds is raised from 0 to 500, however, the number of missing nodes continues to rise. While performing the planned OA-PU method, the proportion of lost nodes in the network is still decreased on average with the analyzed HSA-PSO, SDN-ECCKN, RE-LEACH, GWO, GA, SIF, and EH-WSN systems. The percentage of lost nodes in the network fully drains only after 480 cycles, whereas, the percentage of packet loss visualized during the execution of the analyzed HSA-PSO, SDN-ECCKN, RE-LEACH, GWO, GA, SIF, and EH-WSN S systems. The suggested OA-PU scheme achieves a significant reduction in the number of packet losses due to the addition of four parameters in balancing mechanisms, which extends the network lifetime.

5 Conclusion

In this research, a novel hybrid clustering method based on fusion –rider optimization algorithm (F-ROA) and political optimization algorithm (PO) known as OA-PU has been created with four stages: cluster construction, separation and merging, collecting CH, and data processing. In terms of energy, distance, cluster radius, and time metrics, the proposed model selects the best cluster head. Initially, the cluster of nodes is formed using used the k-mean clustering algorithm. A probabilistic model for selecting the appropriate number of clusters has been added to this. The purpose of this screening process was to separate as well as merge cluster structures based on experimental results, as well as to achieve the network's non-uniform clustering layout. Eventually, the time lag optimized data energy storage system was employed in the spectrum sensing stage to decrease the information fusion effect on the node mobility. As a result, the proposed method reduced energy utilization since the execution time is less. Simultaneously, the reduced energy consumption leads to enhance the longevity of the network. Furthermore, the proposed OA-PU algorithm checks whether the collected data reached the appropriate BS. Also, maintains a high coverage ratio and eliminating redundancy. However, proper channel allocation is needed for a strong probability of effective reporting. Albeit, the proposed algorithm efficiently reduces energy utilization and enhances the lifespan of the network, energy storage efficiency and efficient reporting chance are not addressed because the focus of this article is limited to leftover energy that has not been harvested and that does not include self-interested successful production models. Therefore the future research will be based upon the limitations of this approach.

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