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Clustering Based Energy Efficient Routing for Wireless Sensor Network Using Particle Swarm Optimization

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Abstract

The clustering strategy is the most effective and efficient way to preserve energy in the Wireless Sensor Network (WSN). However, the cluster heads in the hierarchical clustering approach use the majority of the energy that is required to carry out the operations. These operations include receiving the data from the sensor nodes, aggregating it, and then eventually transmitting it to the base station. When choosing the appropriate cluster head, you can play a significant part in reducing the amount of energy that is consumed by the WSN and, as a result, extending its lifespan. A technique for the selection of energy-efficient cluster heads that is based on the particle swarm optimization method is proposed in this study (PSO-EECH). For the method that has been proposed to measure the amount of energy used, we need to take into account the cluster distance, the distance between each sensor node and the nodes that are nearby, and the amount of residual energy that is left in sensor nodes. The aforementioned structure is also capable of doing cluster building, in which the non-cluster head node can follow its CH based on the determined weight function. The proposed PSO-EECH approach has been put through extensive testing, and the results have shown that it possesses a high degree of accuracy in every scenario. The outputs of the proposed algorithm are compared with those of other clustering-based algorithms already in existence, and the conclusions of this comparison have reported that our method outperforms the other existing methods.

Keywords: Cluster Heads, PSO, EECH, WSN

1. Introduction

In recent years, it has been stated that wireless application development and networking technologies have made substantial strides toward improvement. These are all raised as a result of the benefits which are supported by these technologies in comparison to wired networks. Examples of these benefits include the features of portability and easy installation facilities which are offered by these networks. Within the realm of wireless communication systems, wireless sensor networks, abbreviated as WSNs, have been hailed as a promising option for the foreseeable future. WSN is comprised of numerous sensor nodes, which, as the name suggests, are responsible for collecting data and transmitting it to the sink node, where it will undergo additional processing [1]. A wireless sensor network must not only have a detecting component, but it must also be able to interface with other devices, analyse the data, and store it. Each of the sensor nodes can communicate not just with one another but also with the base station.

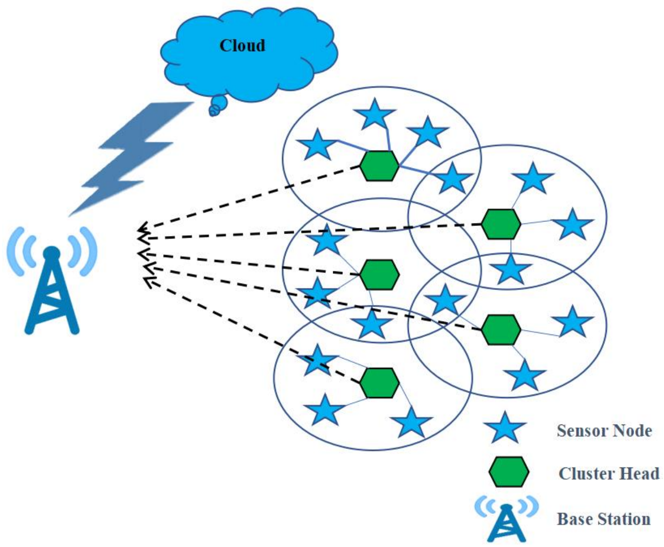

Figure 1. Cluster-based WSN Model

Energy consumption is a highly critical characteristic that needs to be handled effectively to boost network performance because sensor nodes are powered by batteries and cannot be replaced [2]. To optimize the conservation of power in wireless sensor networks (WSN), clustering sensor nodes into groups is a highly effective strategy. In hierarchical clustering, the network is initially divided into several subsets. Subsequent subsets are then created and organized accordingly [3]. Each cluster is led by a Cluster Head (CH), a designated node responsible for gathering data from its fellow cluster members, organizing this data, and transmitting it to the base station.

Even though clusters have a variety of benefits, it is essential to choose an appropriate cluster head to conserve energy and ensure the network's continued viability over its lifetime. This is because the cluster head has a direct influence on the sensor node energy levels of the other members. Particle Swarm Optimization, also known as PSO, is one of the most powerful nature-inspired algorithms available today [4,5]. It was developed with the goal of solving NP-hard problems in a manner that is both efficient and capable of avoiding local optima while achieving quick convergence.

The PSO technique was mostly utilised throughout this suggested work, which focused primarily on CH selection. The fitness function takes into account a number of parameters, including the distance between the CHs and the base station as well as the residual energy of the sensor nodes. This information is then used by PSO to arrive at a choice that is optimal [6]. The algorithm is thoroughly tested to be superior to other current optimization algorithms.

Introduced by Kennedy and Eberhart in 1995, Particle Swarm Optimization (PSO) is an algorithm for optimization based on the collective behavior observed in bird flocks and fish schools. PSO conceptualizes the process of optimization as a communal activity, where entities known as particles continuously modify their placement within a multi-dimensional space of potential solutions, aiming to identify the optimal solution. It is efficient because it takes into account the fact that every member of the swarm makes a contribution to the process of discovering the perfect area or zone for food [7]. As a result, it is able to effectively locate the optimum location. In order to accomplish this, they keep a record of both their own best-known location and the best-known location of the group, and they routinely update both records anytime there is a shift in any of the information contained in them. During each iteration, an adjustment is made to the velocity of a particle in line with Equation (1).

$$V_{i+1} = \sigma(V_i + C_1 * rand1 * (P_{best} - P_i) + C_2 * rand2 * (G_{best} - P_i)) \quad (1)$$

$$P_i = P + V_i \quad (2)$$

The optimal solution is discovered by comparing the fitness of the objective to the fitness of the particle that had the best answer so far. In Equation (2), P_i represents the particle's position, V_i its velocity, P_{best} its local memory space, and G_{best} its global memory space; the subscript I represents the ith particle in the search space. The latter is referred to as G_{best} and the former as P_{best}, both of which are used to store data. These numbers represent the unique answer for each particle, and their combined use allows one to determine a particle's new location by applying a simple algebraic formula to the particle's previous location and velocity [8,9].

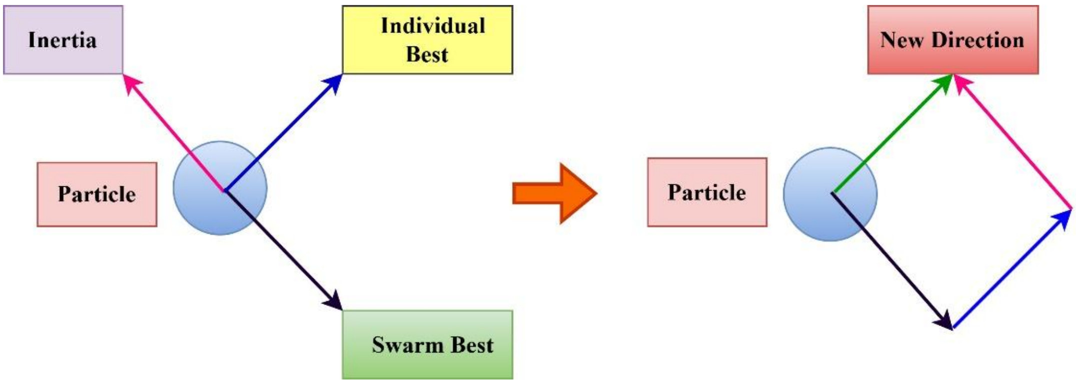

Figure 2. Velocity and Position Updates in Two-dimensional Particle Swarm Optimization

The particle's velocity depends on two components: the individual best P_{best} (Pi) component and the group G_{best} component, also called the social component. If a particle delivers the best solution, its value is added to the best. As shown in Figure 2, the PSO concept works because, during each iteration, the swarm particles advance in the direction of the optimal solution by altering their velocity in the local and global memory spaces [11].

The clustering algorithm in wireless sensor networks (WSN) primarily involves two crucial processes: the formation of clusters and the selection of Cluster Heads (CHs). Clustering helps eliminate energy wastage, which typically occurs during direct transmissions between sensors and the base station (BS). It also significantly improves the scalability of WSNs for real-world applications. Key considerations in the design of clustering algorithms include the maintenance of clusters, reselection of CHs, and determining the optimal cluster size. An essential goal in these algorithms is to establish selection criteria for CHs that maximize energy efficiency.

The main contribution of this article is as follows:

In this research work we have developed an effective particle representation and a new fitness function scheme is implemented in comparison with the current algorithms by considering distance parameters and residual energy [12,13,14].

For the proper selection and formation of cluster head in the heterogeneous WSN we have utilized particle swarm optimization technique to solve the energy issues in the sensors. It required a cluster structure in which the non-CH nodes are bound to a CH according to weight function, rather than cluster formation by a non-CH sensor node by only considering the distance as a parameter. It can lead to an imbalance in the load of CHs and may cause severe energy inefficiency [15,16,17,18].

The protocol we propose stands as a promising approach, particularly given the heterogeneous nature of sensor nodes in comparison to conventional wireless sensor networks (WSN). In such networks, sensors often have limited power and processing capacities, making energy conservation a critical priority. Additionally, it is vital to maintain a very low transmission power for each node to minimize interference.

The rest of this article is organized as follows: Section 2 describes the related literature work. Section 3 discusses about some of the methodology & certain assumptions considered for the WSN network, energy model and network model are outlined. In Section 4, the proposed model and its experimental results are highlighted for different scenarios. In the last, we conclude the research work highlighting the improvements in the results obtained.

2. Related Work

In wireless sensor networks (WSN), sensor nodes often operate autonomously across diverse geographical terrains. These nodes may function in environments ranging from artificial or natural landscapes, large infrastructures and underwater depths to conflict zones behind enemy lines. Effective communication between the base station (BS) and the sink requires specialized wireless routing protocols. WSNs typically manage hundreds or thousands of nodes using clustering methods. These clustered node systems fall into two broad categories: homogeneous and heterogeneous hierarchical systems. In homogeneous systems, all nodes are identical in terms of functionality and energy capacity. In contrast, heterogeneous systems comprise nodes that vary in battery life and functionality. For our project, we consider that both homogeneous and heterogeneous nodes are deployed distinctly. This submission includes a literature review of various studies published in this field.

Kulkarni et al. [19] presented PSO and analyzed the applications of WSN. In this study, we studied how PSO can be used to optimize the localization of nodes, the deployment of new nodes, the aggregation of data, and clustering while taking energy considerations into account. This evaluation brings to light open problems with WSN. Applications that operate at a high pace and in real-time were incompatible with each method.

Studies on PSO changes and their applicability in the actual world were scrutinized by Kothari et al. [20]. PSO has undergone rapid evolution, as evidenced by the development of two-step PSO and PSO-SVM (PSO-SVM). The incorporation of PSO into the algorithm that is considered to be the standard in the industry has also yielded outstanding outcomes. In this study, the most recent PSO updates were given, and the survey also analyzed the PSO's accuracy across fields. The absence of statistical information regarding typical PSO and its application in a variety of settings is a limitation of this work [20].

PSO swarm initialization, mutation operators, and inertia weight variants were the topics of research conducted by Imran and colleagues [21]. In this summary, the importance of mutation operators and the inertia weight parameter as essential components to improving PSO performance was highlighted. Other PSO variants were not investigated for this study.

In their study on the development of PSO-based clustering techniques, Alam et al. [22] discovered rapidly rising trends in the literature on SI, PSO paradigm, and PSO-based data clustering methodologies, which is evidence of the techniques' widespread use and acceptance. According to this research, the methodologies are novel, straightforward, and centred on collaboration and open communication. The applications of PSO clustering were discussed in this work. There is no attempt made to solve difficult problems. Esmin et al. [23] conducted a survey to investigate the different PSO variants for clustering high-dimensional data. This survey demonstrated how a variety of publications decreased the complexity of the data. Applications that are associated with clustering are still lacking.

Marini and Walczak [23] provided an explanation of how the PSO method can be used to handle problems involving chemometrics optimization. In this article, the significance of PSO meta-parameters is demonstrated by the use of specific cases in the areas of variable selection, the estimation of robust PCA solutions, and signal warping. This lecture provided an outstanding presentation of chemometrics works. However, it did not have any contemporary fields. The publication analysis in this survey does not take into account the annual exponential variation in the number of publications for each application area and version.

The history of the PSO algorithm as well as its theoretical analysis was discussed by Wang et al. [18]. The researchers' subsequent focus involved a thorough examination of the system's current attributes, including its algorithmic framework, topological structure, criteria for selecting parameters, approaches to multi-objective optimization, and the implementation of discrete and parallel Particle Swarm Optimization (PSO) techniques in engineering contexts. This overview also outlines areas for future research. The paper doesn't delve into analytical discussions. Cluster Heads (CHs) are initially selected based on a primary parameter, probabilistically, while secondary parameters are used for breaking ties. Unlike the LEACH protocol, which randomly selects CHs leading to uneven cluster sizes and premature node failure, HEED clustering extends the system's overall lifespan by ensuring better distribution of CHs across the network and minimizing communication costs. However, this clustering approach primarily focuses on a subset of parameters, which may limit the network's potential. These strategies, while effective in prolonging system lifespan, may not fully address all the demands of a wireless sensor network.

3. Methodology

The Energy Efficient Cluster Head Selection method we propose, utilizing the PSO algorithm, comprises two main phases: the appointment of the Cluster Head (CH) and the formation of clusters. In this algorithm, the decision to select a cluster leader hinges on evaluating the distance parameters and the cluster's remaining energy. During the CH selection phase, each sensor node first communicates its location and residual energy to the base station. This step is crucial for assessing whether the node possesses the minimum required energy threshold to be considered as a potential CH.

Some of the terminologies which are used in the algorithm are a set of the sensors used to deployed in the network are denoted as a set of sensor nodes S= (S1, S2….., Sn), and have a set of cluster heads denoted as C=(CH1, CH2, ... CHm), Dmax and Rmax refer to the maximum coverage range for sensor and the CHs respectively. The threshold distance is denoted as d0 and Th corresponds to the average threshold energy of the cluster head. ESi corresponds to initial energy of the sensor node and EChi corresponds to the existing energy of the cluster head.

The purpose of the proposed protocol is to improve energy efficiency by extending the lifetime of the network. This is accomplished by picking an appropriate cluster head from the standard sensor nodes in the network. Therefore, we look at the objective function F1 as the average distance that separates the cluster heads from the sink.

Let F2 be another objective function reciprocating all selected CHs' total current energy. This ratio needs to be maximized for efficient selection of the cluster head. That means the function F_2 has to be minimized. We regularize both the objective function in such a way that linear combination of these two should be minimized efficiently.

We regularize the two objective functions between 0 and 1 to minimize linear combinations of these two functions efficiently. These two functions are derived from the PSO-based approach. These two functions should be minimized for the proper selection of the cluster head problem.

$$\text{Minimize\_F} = \alpha * F_1 + (1-\alpha) * F_2 \tag{3}$$

$$\text{Subject to , Distance } (S_i, CH_j) \leq \text{dmax}, \quad \forall\ S_i \in S,\ CH_j \in C \tag{4}$$

$$\text{Distance}\left(CH_j, BS\right) \leq R_{max}, \quad \forall\ CH_j \in C \tag{5}$$

$$E_{ch} > T_h, \quad 1 \leq j \leq m \tag{6}$$

$$0 < \alpha < 1, \quad 0 < F_1, F_2 < 1 \tag{7}$$

Equations (3), (4), (5), (6), and (7) are constraints ensuring that all sensor nodes are within the intra-cluster distance, all cluster heads are within the communication range, and cluster heads have energy greater than the threshold energy. The fitness function denoted as F is a linear sum of two objective functions F1 and F2 respectively. α is the parameters which control the distance between the nodes and energy parameters respectively. E_{ch} is the energy of cluster head, T_h is the threshold and S_i is the ith sensor node. While dmax and R_{max} are the distance between cluster head & sensor node and distance between the base station and cluster head respectively.

3.1 Energy Model

The transmitter is comprised of a radio energy dispersal model which in addition has forward electronics ‘Eele’ that relies upon components such as coding, regulation, sifting and forwarding the signal and further enhancer relies upon the separation to the receptor and also fair bit error rate. Here, just free space model is utilized to have an experimental description. If the transmitter and receiver separation in the case that is not higher than d0 i.e. threshold separation then free space channel model with d2 energy loss is utilized and in case the transmitter and collector separation is extremely higher than threshold separation say d0 then multiple blurring way channel model is acquired i.e. d4 energy misfortune as in Equation (8). The energy model is utilized where the consumed energy is to send l-bit message over distance d:

$$E_{T_x}(l,d) = \begin{cases} l \times E_{elec} + l \times \epsilon_{fs} \times d^2 & \text{if } d \leq d_0 \\ l \times E_{elec} + l \times \epsilon_{mp} \times d^4 & \text{if } d > d_0 \end{cases} \tag{8}$$

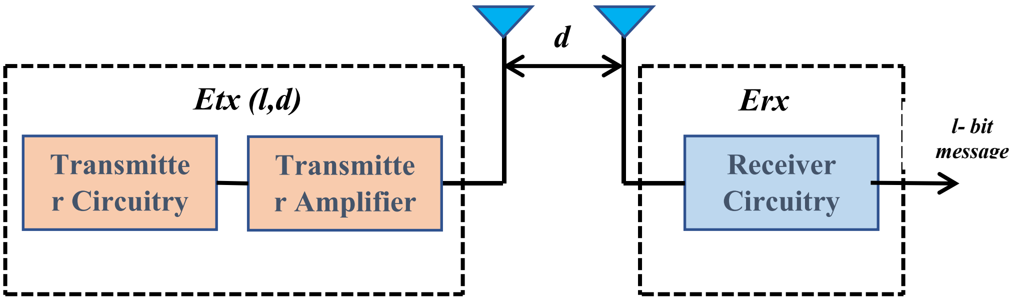

Figure 3. Energy Dispersion Model

In this context, E_{T_x}represents the energy transmitted, and E_{elec} is the energy dissipation per bit in both the receiver and transmitter units, typically set at 50 nJ/bit. While ϵ_{fs} and ϵ_{mp} is dependent on the transmitter amplifier model, as depicted in Figure 3. When the distance between the transmitter and receiver is less than a certain threshold, the free space model is applied. Conversely, for distances exceeding this threshold, the multipath model is used, as outlined in Equation (9), which calculates the energy based on these parameters.

$$d_0 = \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}} \tag{9}$$

Another side, the consumption of energy by receiver to receive l-bit-long packet is defined as shown in Equation (10) & listed in Table 1.

$$E_{Rx} = l \times E_{elec} \tag{10}$$

Table 1. List of Radio Parameters

Explanation	Symbols	Values
Energy utilized by amplifier to forward at shorter separation	fs	10pJ/b/m2
Energy utilized to forward/ receive the signal in electronic circuit is	Eelec	50nJ/b
Initial Energy of the sensor nodes	Einit	2J
Energy utilized by amplifier to forward to longer separation is	mp	0.0013pJ/b/m4

3.2 Network Model

In the energy model for the network, certain assumptions are made. The system is modeled on a free space basis, incorporating a receiver and transmitter with a critical separation distance, denoted as d0. Amplifier circuits are included at both the receiver (Rx) and transmitter (Tx). The Wireless Sensor Network (WSN) setup used for simulation takes into account various constraints and characteristics, which collectively contribute to shaping the framework of the model.

In our network setup, source nodes are distributed using a Poisson Homogeneous-Distribution. Each node has the capability to estimate distances to other nodes based on the power of received signals. Once deployed, sensor nodes are designed to remain stationary, functioning in either cluster head or normal sensor modes. The Base Station is stationary and strategically placed within the detection area. To reduce the total amount of data transmitted, a data-fusion technique is employed. The nodes in this network are homogeneous, possessing equal sensing and processing abilities, and the total number of sensor nodes exceeds that of cluster heads. Each node is equipped with a fixed communication range. Additionally, nodes are capable of monitoring their energy levels and know their transmission power, which is vital for calculating the energy expended in packet transmission.

Maximizing power efficiency in wireless sensor networks (WSN) is best achieved by organizing sensor nodes into clusters. This clustering method entails dividing the entire network into smaller units known as clusters. In each cluster, the appointed cluster head plays a crucial role in collecting and amalgamating data from other nodes in the group. Once this data is compiled, it is sent to the base station, which may occur either directly or via other cluster heads serving as intermediaries.

3.3 Derivation of the Fitness Function using Cluster Selection

In order to derive the fitness function value, it depends on the various parameters like average intra-cluster distance, average sink distance and energy parameter of the sensor nodes.

3.4 Average Intra-cluster Distance

It is the sum of the average distance of all the sensor nodes from the selected cluster head i.e. $\frac{1}{\mathrm{lj}}\sum_{\mathrm{i=1}}^{\mathrm{lj}} \mathrm{Distance\ (Si, CHj)}$. In the inter cluster, communication between the sensor nodes and the cluster head, some amount of energy is used to transfer the data from sensor node to cluster head. If an average distance is reduced between nodes and cluster head then some amount of energy will be saved. Hence, we need to select cluster head which is close to everyone.

3.5 Average Sink Distance

It is the distance ratio between cluster head CHj and base station to the total number of sensor nodes in CHj , i.e. $\frac{1}{\mathrm{lj}}\sum_{\mathrm{i=1}}^{\mathrm{lj}} \mathrm{Distance\ (CHj, BS)}$. In the data routing process, each Cluster Head (CH) transmits the aggregated data from its sensor nodes to the base station. To reduce energy consumption from CH to the base station, it's crucial to minimize the distance between all CHs and the base station. Therefore, the primary objective function is focused on decreasing both the average distance within each cluster and the distance between the cluster heads and the sink.

Thus, we can obtain the objective function 1 by simply adding the above two parameters to minimize the function expressed in Equation (11).

$$\mathrm{Minimize\ F1} = \sum_{\mathrm{j=1}}^{\mathrm{m}} \frac{1}{\mathrm{lj}} \left(\sum_{\mathrm{i=1}}^{\mathrm{lj}} \mathrm{Distance}\ (\mathrm{S_i}, \mathrm{CH_j}) + \mathrm{Distance}(\mathrm{CH_j}, \mathrm{BS}) \right) \qquad (11)$$

3.6 Energy Parameter

The current energy of the cluster head CHj is ECHj where j varies between $1 \le \mathrm{j} \le \mathrm{m}$, which have been selected from the sensor nodes in iteration. The sum of the total energy of all the selected cluster head nodes is given by $\sum_{\mathrm{j=1}}^{\mathrm{m}} \mathrm{ECHj}$. While selecting the cluster heads it's wise to select the cluster head which maximise the current energy of all the cluster head. So, in order to maximize energy, we have to take reciprocal of the sum of the current energy of the cluster heads. Therefore, our second objective function is defined by the Equation (12).

$$\mathrm{Minimize\ F2} = \frac{1}{\sum_{\mathrm{j=1}}^{\mathrm{m}} \mathrm{E_{CHj}}} \qquad (12)$$

In our proposed PSO-EECH algorithm we need to minimize the linear combination of the above two objective function together as they are not strongly conflicting to each other. Then, an optimum solution will be obtained by minimizing the fitness value. Lower the value of the fitness function better will be the particle position and hence, better cluster head will be selected.

Pseudocode of PSO Based Energy Efficient Cluster Head selection(PSO-EECH)

Input:

Initialise Sensor Nodes: S1..Sn, Swarm Size : NP, Dimension of particle: D=m.

Output:
Optimal Position of Cluster Heads CH={CH1,CH2,.... CHm}
Step 1: Initialize
Number of Cluster Heads m=D
Particles Pi ≤ Np
Step 2: For i=1 to NP do
Calculate Fitness F(Pi)
Pbesti= Pi
endfor
Step 3: Gbest = {Pbestk|Fitness(Pbestk) = min(Fitness(Pbesti))}
Step 4: for n=1 to max number of iterations
for i=1 to Np do
update Velocity
$V_1 + 1 = \sigma(V_i + C_1 * \text{rand} * (P_{best} - P_i) + C_2 * \text{rand} * (G_{best} - P_i));$
update Position
$P_i = P + V_i;$
If F(Pi) is less than F(Pbest)
Pbest = Pi;
endif
If F(Pi) is less than F(Gbest)
end
Gbest = Pi
endif
for k=1 to n
Calculate distance $(X_i, j(t+1), S_k)$
Xi, j (t +1)→{Sk| min(distance(Xi, j (t +1), sk),∀i,1≤ k ≤ NP}
endfor
endfor
Step 5: Stop

3.7 Cluster Formation

The objective function evaluates the quality of a particle's solution. In the context of cluster head selection, the objective function could be a combination of factors such as:

3.8 CH Residual Energy

Sensor node Si should join a cluster head CH by Equation (13) which has a high Residual energy than any other CH within the communication range.

$$CH_{Weight(S_i,CH_j)} \propto E\ Residual\left(CH_j\right) \tag{13}$$

3.9 Distance from Sensor node to Cluster Head

For reducing the energy consumption at the sensor node, sensor node should join the CH which is near to it’s communicating range as defined by Equation (14). Shorter the distance energy required is less.

$$CH_{Weight}(S_i, CH_j) \propto \frac{1}{Distance(S_i, CH_j)} \tag{14}$$

3.10 Distance from Cluster Head to Base Station

In order to transfer the data this is aggregated from the different sensor nodes to the base station. Hence, sensor nodes join the cluster head which is close to BS defined in Equation (15).

$$CH_{Weight}(CH_j, BS) \propto \frac{1}{Distance(CH_j, BS)} \tag{15}$$

3.11 CH Node Degree

A sensor node will join a cluster head which has a lower node degree than other cluster head by Equation (16) and (17).

$$\mathrm{CH_{Weight}}\,(\mathrm{S_{i,}\,CH_j}) \propto \frac{1}{\text{node degree}(\mathrm{CH_J})} \tag{16}$$

$$\mathrm{CH_{Weight}}\,(\mathrm{S_{i,}\,CH_j}) \propto \frac{\mathrm{E_{Residual}}\;(\mathrm{CHj})}{\mathrm{Distance(Si,CHj)} \times \mathrm{Distance(CHj,BS)} \times \text{node degree}(\mathrm{CHj})} \tag{17}$$

4. Results and Discussion

The proposed algorithm is tested using NS 2.33 and TCL script. The simulation has carried out for various nodes ranging from 300-700, with different cluster heads from 15 CHs to 50 CHs. It has been assumed that all the sensors nodes are having initially energy as 2J. During the simulation, we have used the following network parameters as listed in Table 2. Here, we have considered three network scenarios for the sensing field of area 200 X 200 m2. The position of the base station is also varied, from the centre location has X and Y coordinates as (100,100) and then the base station kept at the corner of the sensing field has X and Y coordinates (200X200) and then has kept outfield (300 X 300). Four different WSN scenarios are considered for the simulation WSN1, WSN2, WSN3 and WSN4.

Table 2. Simulation Parameters

Parameter	Value
Network topology	200 X 200 m2
Number of sensor nodes	300-700 nodes
Energy of Sensor nodes initially, Ein	2J
Base Station location	(100-300, 100-300)
Eelect	50nJ/bit
fsp	10pJ/b/m2
Eda	5nJ/b
mp	0.0013pJ/b/m4
Transmitter & Receiver electronics	50 nJ/bit
Transmitter amplification energy	100 pJ/bit/m2
dmax	100m
do	30m
Packet Length	4000 Bits
Message size	500 bits

Across the four wireless sensor network areas, labelled WSN1 to WSN4, the quantity of sensor nodes differs: WSN1 contains 300 nodes, WSN2 has 400, while WSN3 and WSN4 are equipped with 500 and 600 nodes respectively. Within each network, we designate 5-10% of the sensor nodes as cluster heads and execute the PSO-EECH algorithm 30 times for each network configuration.

We run the algorithm for more than 30 times and we test the result for different weighted factors for α from 0 to 1. When we simulated the result, the results obtained for the α=0.3 was better when compared to other factions. The various other parameters are run for the PSO algorithms and are listed in below Table 3.

Table 3. PSO Parameters

Parameters	Value
Number of swarm particles	30
Number of Iterations	100

C1	2.0
C2	2.0
A	0.3
D	15-50
Vmax	200
WC	0.7

It is to be noted that when the calculation for updated position, the new position of the particle may not be within the defined area i.e. (200 X 200). So, our proposed algorithm must be designed in such a way that it should round off the position within the target area. The absorption rule can be applied for the boundary condition. The rule is explained with the suitable example as shown below,

If the updated value exceeds the target area like (2.6,205), then the position of Y coordinate is greater than our range of 200, then our protocol will round off the value to the maximum value of 200 (2.6,200).

Suppose, the updated position will yield a negative value like (-4.2,87), in that case the newly updated position should be rounded off to zero (0,87).

However, the above type of decisions are going to happen very rare and the updated positions during the simulations will not go beyond the target area.

4.1 Performance Measurement in terms of Energy Consumption

Initially, we ran the PSO-EECH algorithm with a range of 300 to 700 nodes and 15 to 50 cluster heads to assess the overall energy consumption within the network under these varying conditions. The result is compared with the DSR, AODV, PSO-AODV, LEACH, PEGASIS and PSO-EECH are depicted in Figure 4, 5, 6 , 7 below.

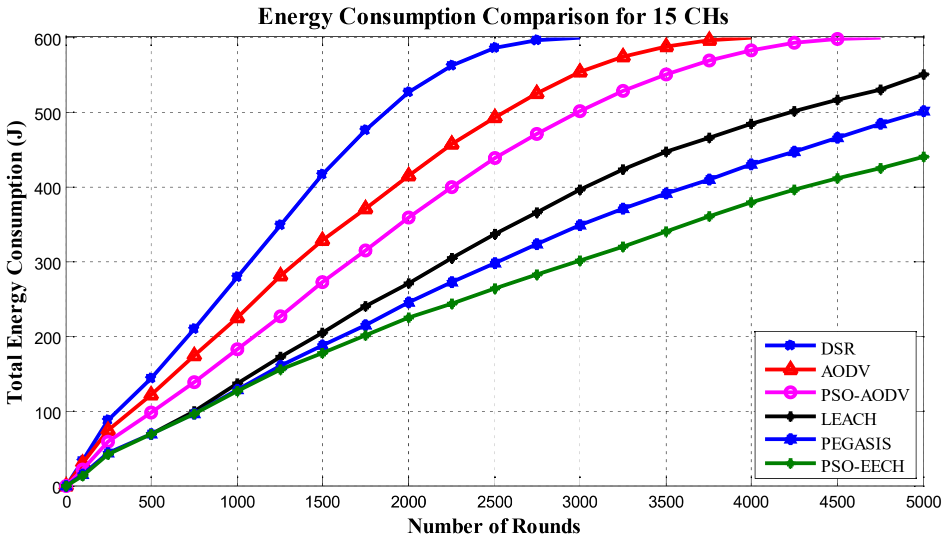

Figure 4. Total Energy Consumption for WSN 1 with 15 Cluster Heads

The Energy consumption of the PSO-EECH is less when compared with the other protocols as the number of rounds increased concerning 15 cluster Heads. There is a 26% increase in energy consumption with DSR, 21% with AODV, 17% increase in PSO-AODV, 7% increase in the energy consumption with the PEGASIS and 12% concerning LEACH as shown in Figure 4.

With the increase of sensor nodes to 400 and the Cluster Heads to 30,40 & 50. The energy consumption has increased in the PSO-EECH but, when compared with the DSR, AODV and PSO-AODV it is less by 28%, 20% and 15% respectively. LEACH and PEGASIS the energy consumption is less by 10% and 7% respectively which as shown in Figure 5,6 & 7 respectively.

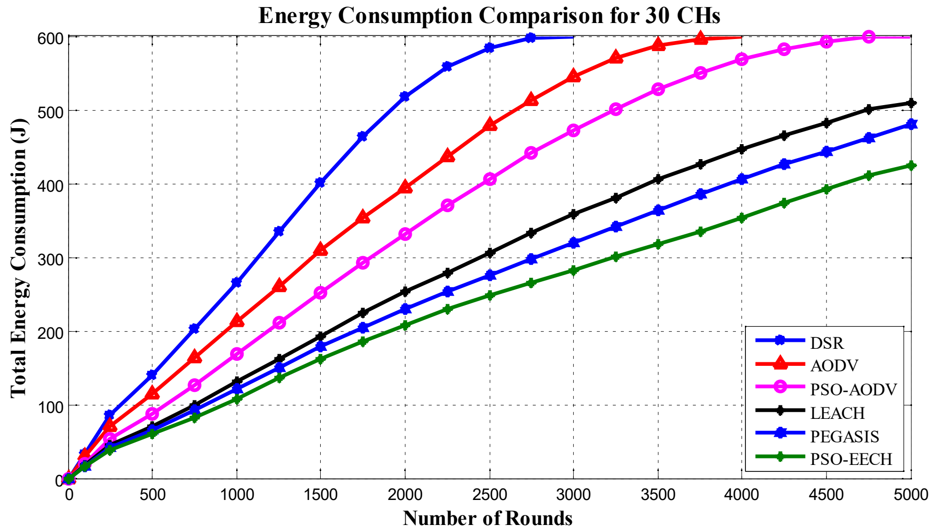

Figure 5. Total Energy Consumption for WSN 1 with 30 Cluster Heads

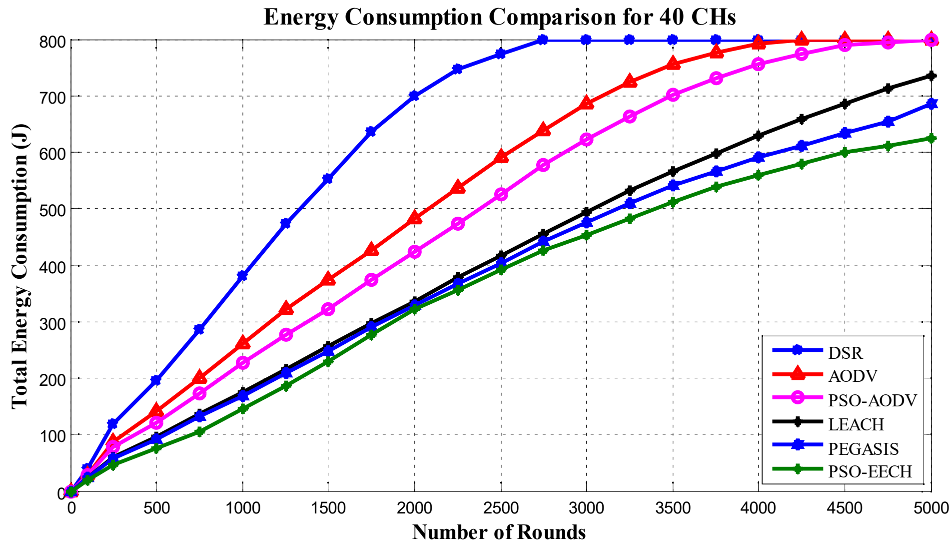

Figure 6. Total Energy Consumption for WSN 2 with 40 Cluster Heads

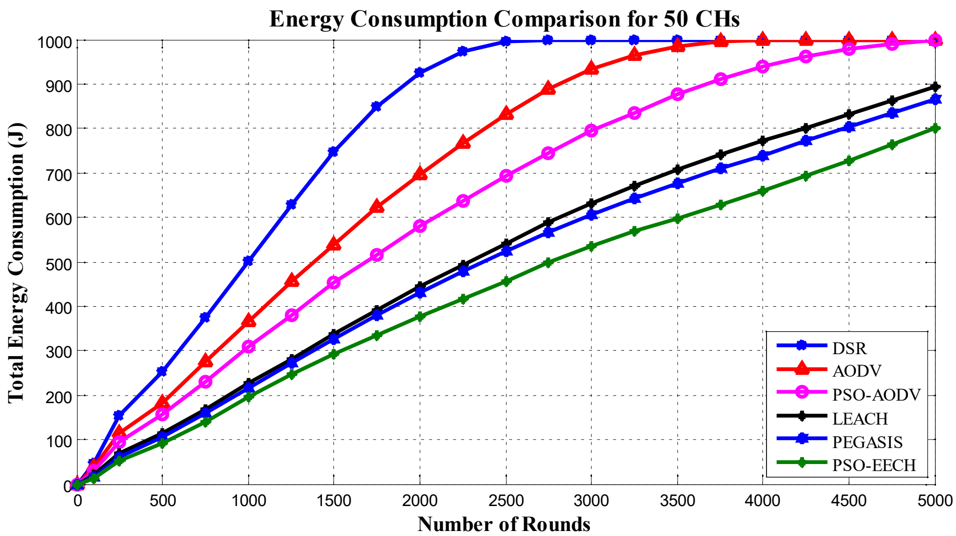

Figure 7. Total Energy Consumption for WSN 3 with 50 Cluster Heads

Table 4 . Comparison of Total Energy Consumption at round 5000 for 30 CHs in WSN#1

Number of Sensor Nodes = 300	Base Station center (100,100)	Base Station corner (200,200)	Base Station Outfield (300,300)
DSR	600.0	600.0	600.0
AODV	600.0	600.0	600.0
PSO-AODV	598.46	598.79	598.95
LEACH	510.48	550.89	589.46
PEGASIS	478.56	536.71	575.54
PSO-EECHs	427.12	489.54	523.16

The values are listed in the Table 4, 5 and 6 for all the cases. In the first scenario, the BS has kept at the Centre (100,100) and from the Figure 4 and 5 we observe that the PSO-ECHs outperforms the other algorithms with respect to the total energy consumption of the network.

Table 5. Comparison of Total Energy Consumption at round 5000 for 40 CHs in WSN#2

Number of Sensor Nodes = 400	Base Station center (100,100)	Base Station corner (200,200)	Base Station Outfield (300,300)
DSR	800	800	800
AODV	800	800	800
PSO-AODV	795.21	796.87	798.78
LEACH	738.14	761.56	778.27
PEGASIS	668.20	721.81	737.21
PSO-EECHs	623.63	652.84	700.33

Table 6. Comparison in terms of Total Energy Consumption at round 5000 for 50 CHs in WSN#3

Number of Sensor Nodes = 500	Base Station center (100,100)	Base Station corner (200,200)	Base Station Outfield (300,300)
DSR	1000	1000	1000
AODV	1000	1000	1000
PSO-AODV	988.21	991.28	997.87
LEACH	890.78	923.64	995.24
PEGASIS	861.87	898.97	958.27
PSO-EECHs	806.84	842.09	869.07

Figure 6, 7, and 8 demonstrate that as the network size expands, the efficiency of other algorithms diminishes. While the initial performance of PSO-EECH may not stand out, its significance becomes more pronounced with an increasing number of operational rounds and the depletion of sensor nodes' residual energy. The role of Cluster Head (CH) selection becomes increasingly pivotal in mitigating overall energy consumption.

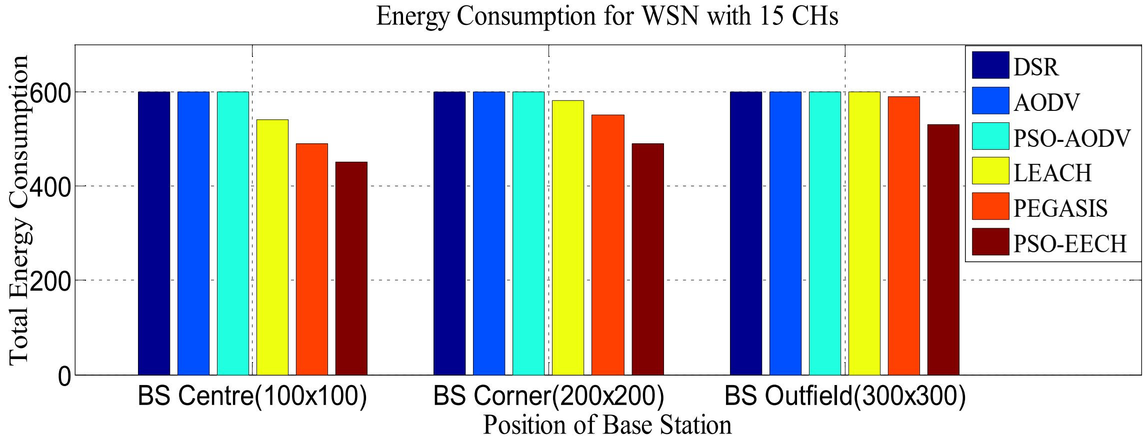

Figure 8. Total Energy Consumption for WSN 1 with 15 Cluster Heads

Hence, the proposed algorithm Energy Efficient Cluster Head selection utilizes the fitness function and selects the proper CHs. Subsequently, our algorithm was executed to compare total energy consumption across networks with 300 to 700 nodes and 15 to 50 CHs. We also altered the base station's position—center, corner, and outfield—to evaluate the PSO-EECH's performance under these different conditions. The outcomes of these variations are illustrated in Figures 8, 9, and 10, respectively.

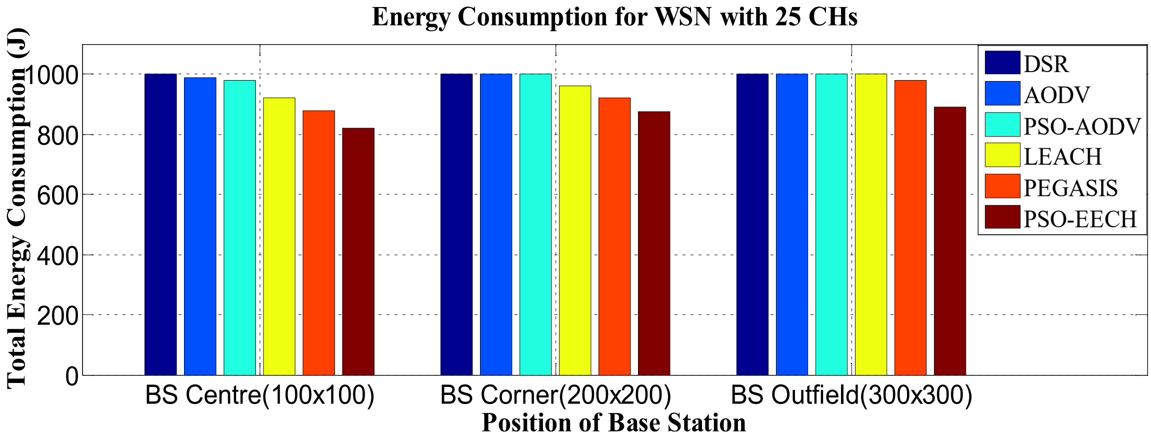

Figure 9 . Total Energy Consumption for WSN 3 with 25 Cluster Heads

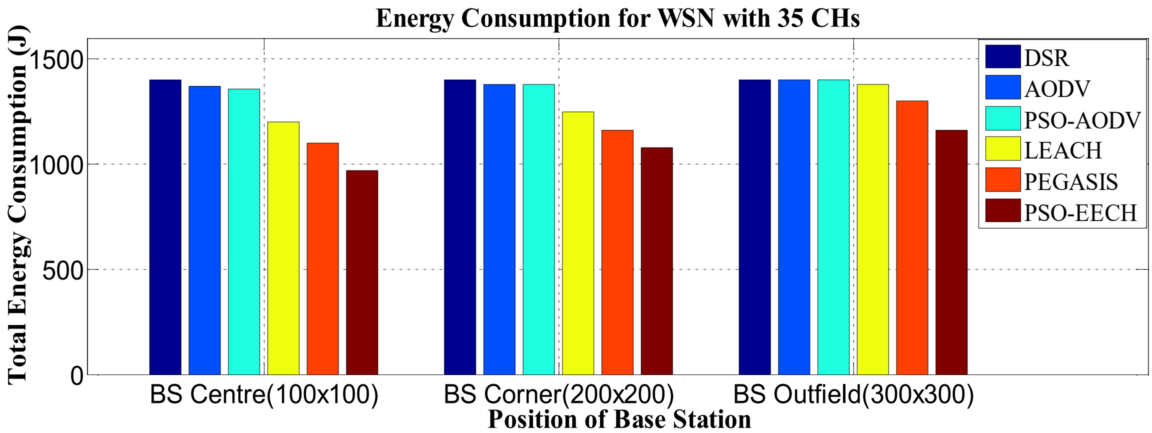

Figure 10. Total Energy Consumption for WSN 4 with 35 Cluster Heads

The energy consumption by the network at the end of 5000 rounds was calculated, and the results from Figure 8 to 10 show proposed algorithm presents a better solution with respect to energy consumption as compared with standard protocols.

4.2 Performance Measurement in terms of Network Lifetime

Next, we run the algorithm for comparing the network lifetime with respect to the number of rounds by varying sensor nodes from 300-500 and with CHs varying from 15-50 respectively. It can be observed from Figure 11, Figure 12 & Figure 13 respectively. Our proposed PSO-EECH outperforms the DSR,AODV & PSO-AODV and other clustering protocols like LEACH and PEGASIS.

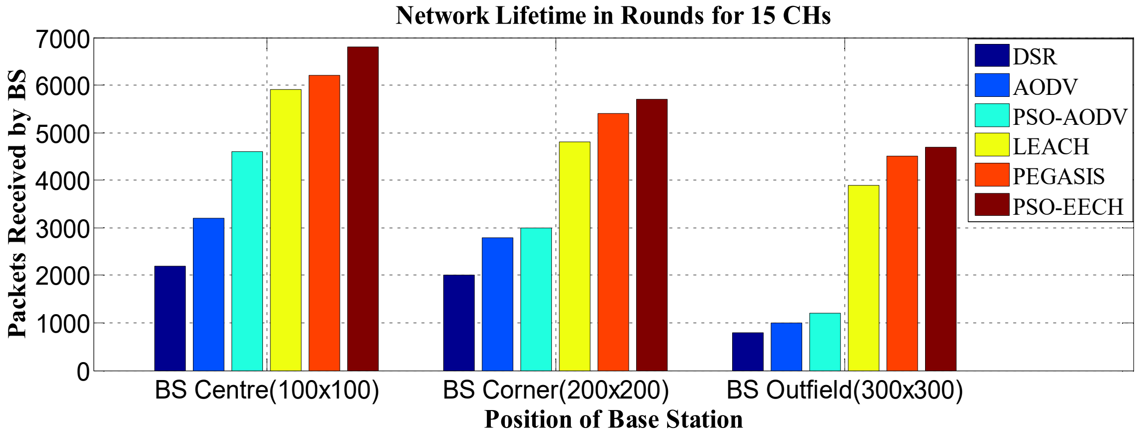

Figure 11. Network Lifetime in rounds for a 15 CHs in WSN#1

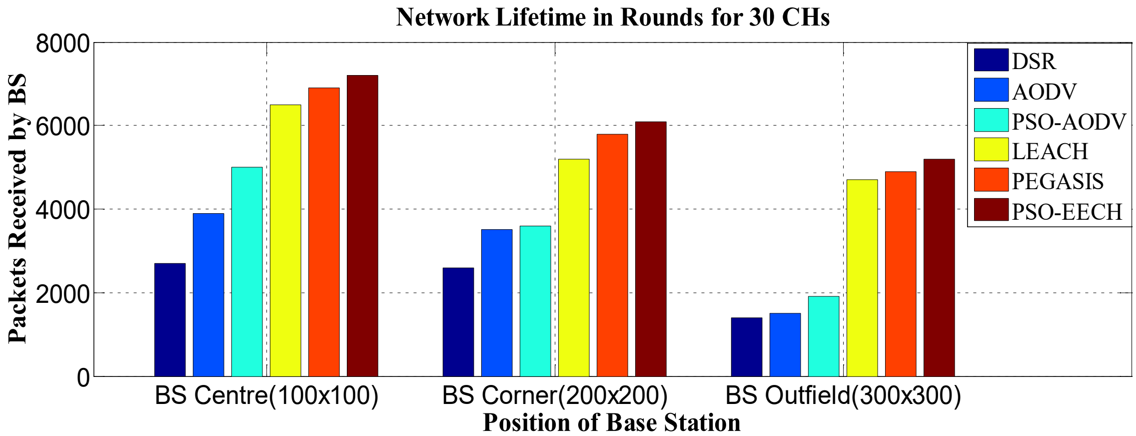

Figure 12. Network Lifetime in rounds for a 30 CHs in WSN#1

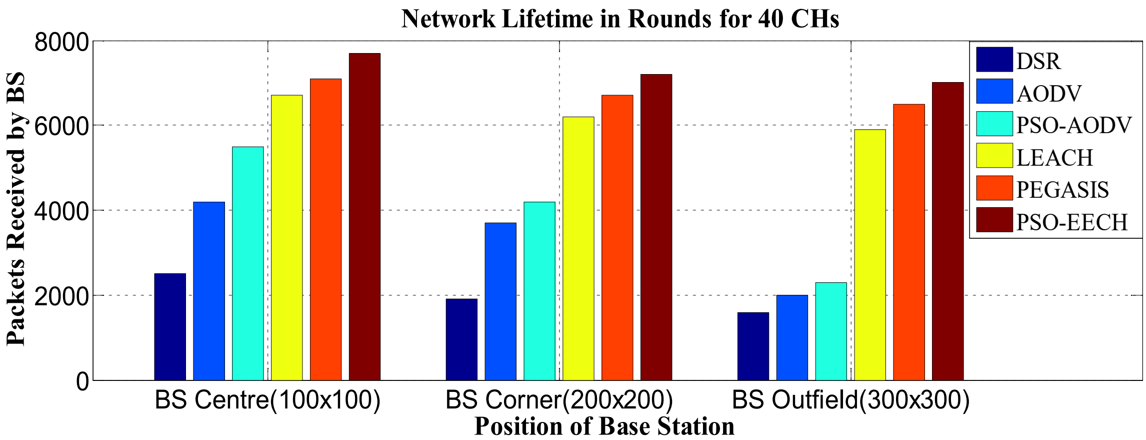

Figure 13. Network Lifetime in rounds for a 40 CHs in WSN#2

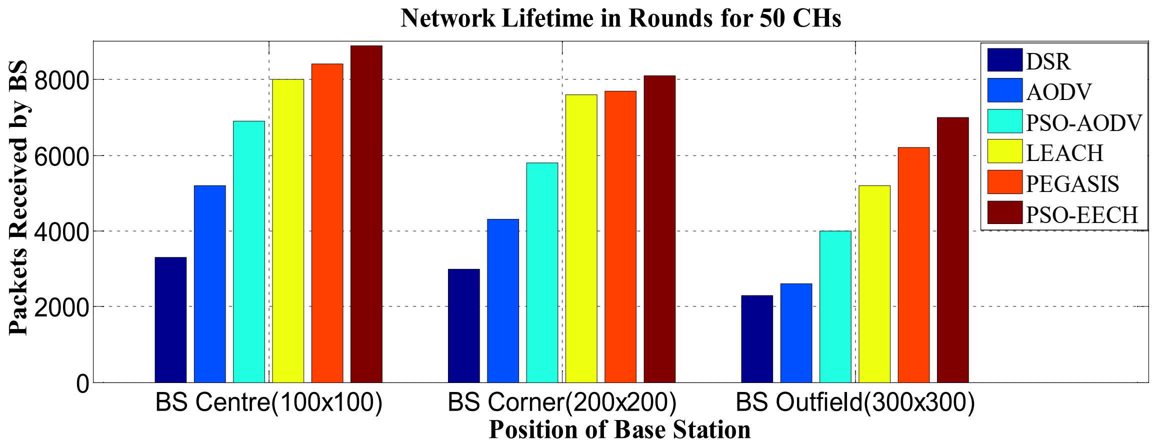

Figure 14. Network Lifetime in rounds for a 50 CHs in WSN#3

In essence, selecting a sensor node with low energy as a cluster head leads to rapid depletion and diminishes network efficiency. Conversely, our proposed PSO-EECH method prioritizes the selection of cluster heads from among the average sensor nodes that have higher residual energy, thereby enhancing the overall lifespan of the network. Figure 14 displays the outcomes of our algorithm runs with variable numbers of iterations, sensor nodes, and cluster leaders.

4.3 Performance Measurement in terms of Packets Received

The protocol's performance validation includes assessing packet reception at the base station across various scenarios, encompassing a range of cluster head quantities from 15 to 50 and varying numbers of sensor nodes between 300 and 500. Our proposed PSO-EECH protocol demonstrates a notable increase in the number of packets received at the base station, especially when compared with protocols such as DSR, AODV, PSO-AODV, LEACH, and PEGASIS. This enhanced performance is clearly illustrated in Figure 15, 16, 17, and 18, which display the comparative data outcomes.

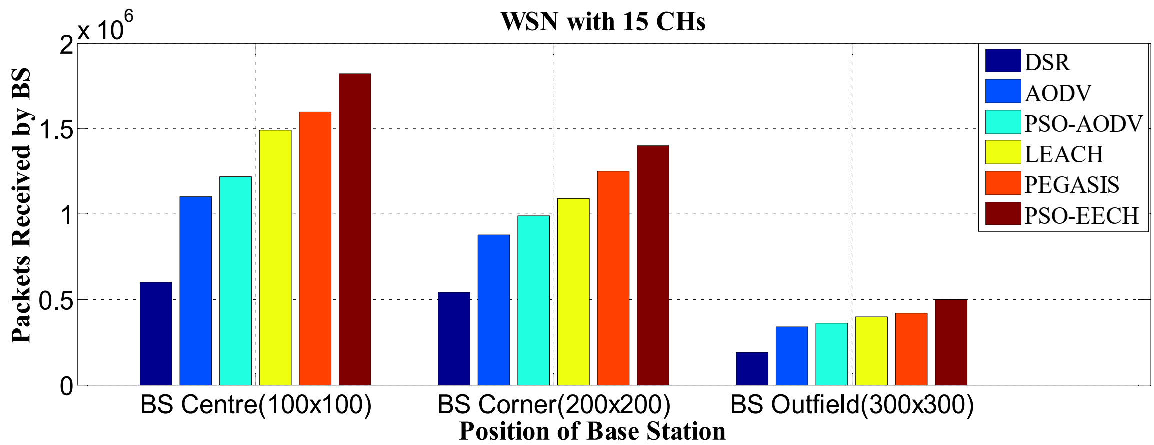

Figure 15. Packets Received by Base Station for a WSN#1 with 15 CHs

The results notably indicate that the total number of packets received at the base station is higher when it is centrally located in the target area (at coordinates 100,100), compared to its positioning at a corner (200,200) or in the outfield (300,300) of the target area. There is a more pronounced reduction in packet reception with other protocols than with the proposed PSO-EECH. This difference is attributed to the effective selection of cluster heads in the PSO-EECH method, facilitated by the use of an efficient fitness function.

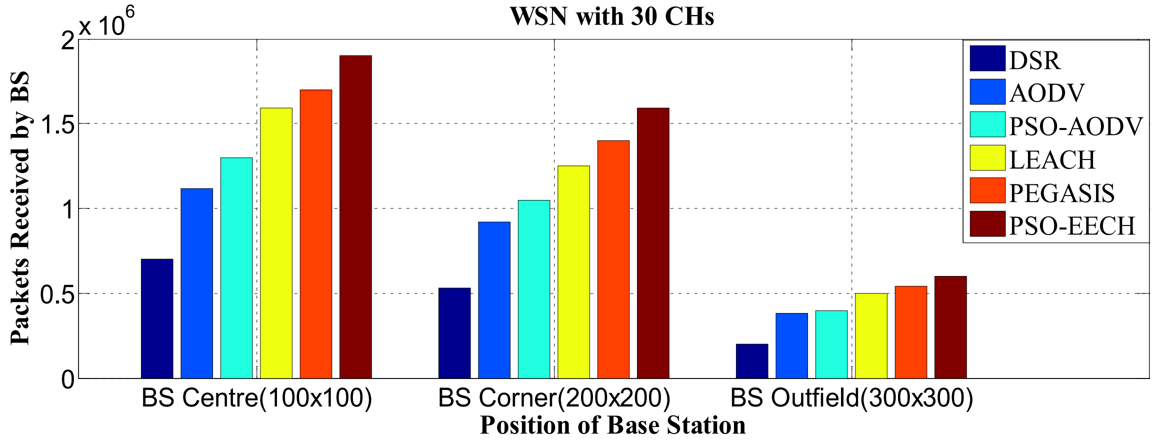

Figure 16. Packets Received by Base Station for a WSN#1 with 30 CHs

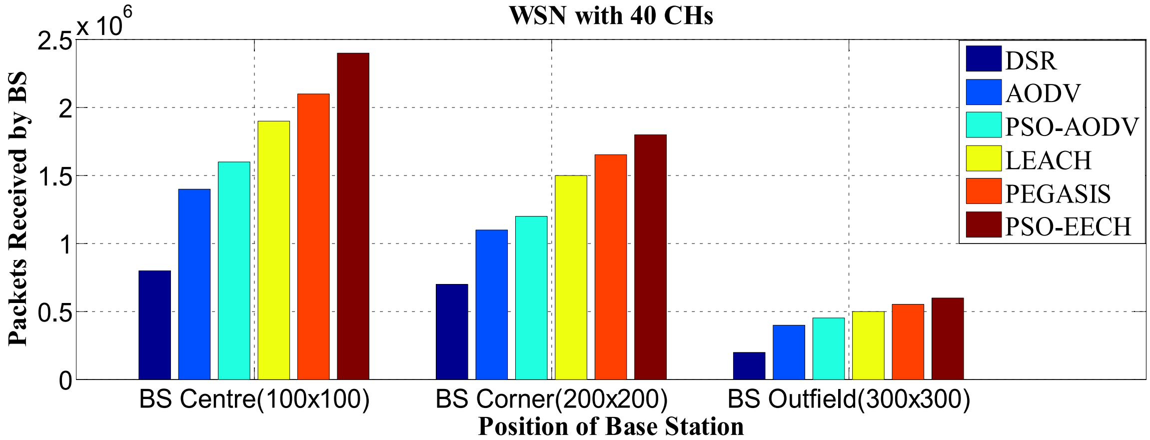

Figure 17. Packets Received by Base Station for a WSN#2 with 40 CHs

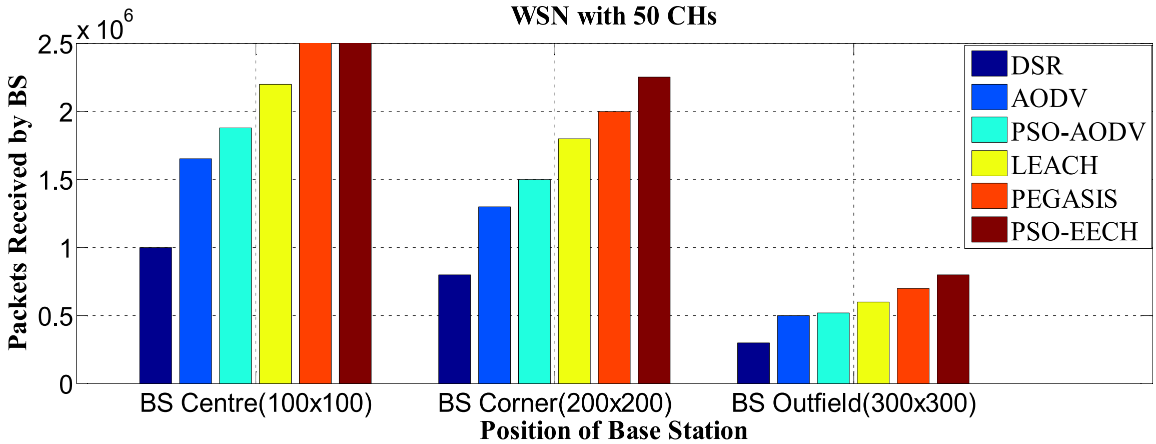

Figure 18. Packets Received by Base Station for a WSN#3 with 50 CHs

The decline in the packets is more with other protocols when compared to the proposed PSO-EECH due to the reason that in the proposed method, it takes proper selection of cluster heads with the usage of efficient fitness function as shown in Figure 18.

5. Conclusion

In this research, we have introduced a novel optimization technique known as "PSO-based Energy-Efficient Cluster Head Selection". Here, the PSO-EECH algorithm works with 2 phase cluster selection and cluster formation to provide an optimal routing for WSN. Wherein, the swarm method is used to select a suitable CH in the group of sensor nodes. Once the CH is selected then data from all the sensors will be sent to CH and it will then forward the data aggregated from the sensors to the base station. Hence, it has minimized the energy of all the sensors and hence the network life will be prolonged and the packet delivery ratio will increase drastically. In this simulation, we have taken 3 different WSNs scenarios with varying nodes, cluster heads and base station that have been considered implementation with performance evaluation of energy consumption. The performance has been compared by varying the base station at the corner, centre and outfield of the WSN and with other standard protocols of WSN such as LEACH and PEGASIS. Our proposed PSO-EECH has delivered the best performance in terms of network lifetime, energy consumption and the network throughput.

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