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ORIGINAL ARTICLE

# Optimal Selection of the Cluster Head in Wireless Sensor Networks by Combining Particle Swarm Optimization and Efficient Genetic Algorithm

Aliyu Zakariyya 1, Oyenike Mary Olanrewaju 2* and Bashir Ahmad Jamil 3

[1] Department of Computer Science, Federal University, 820101 Dutsin-ma, Nigeria.

*Corresponding author: Aliyu Zakariyya. Email: azakariyya@fudutsinma.edu.ng.

**ABSTRACT** – Wireless Sensor Networks (WSNs) have become a crucial component of numerous applications, including the military, healthcare, and environmental monitoring. A promising approach to increasing the lifespan of the sensor network is cluster-based WSNs. In WSNs, choosing the best cluster head is a crucial task that has an impact on the network's performance and energy efficiency. There are various issues with current methods for choosing the cluster head, including nodes dying too soon, uneven energy usage, and shorter network lifetimes. Moreover, traditional methods such as Randomized Clustering and Fixed Cluster Head are not effective in prolonging the network lifetime as they do not consider the energy consumption and residual energy of nodes. In this paper, an optimal selection of cluster head is presented where we combine the Particle Swarm Optimization (PSO) and Efficient Genetic Algorithm (EGA). Firstly, PSO is used to randomly select the cluster head and update the position of each cluster. Thereafter, EGA invokes its fitness values to select the best cluster head that transmits information to the base station. The simulation result shows that the performance improvement of the proposed method PSO_EGA in terms of network lifetime is 0.10% against Improve Cuckoo Search Algorithm (ICSA) and 0.20% against Hybrid Crow Search Algorithm (HCSA), packet to cluester head is 7% against ICSA and 16% against HCSA, packet to sink is 11% against ICSA and 22% against HCSA and number of alive node is 28% against ICSA and 48% against HCSA. Therefore, our proposed method outperforms ICSA and HCSA in terms of the aforementioned parameters.

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## INTRODUCTION

Wireless Sensor Networks (WSNs) have gained popularity as a result of the development of numerous applications. Without any infrastructure, these networks can be set up autonomously in most locations. They collect data on environmental phenomena for proper operation and event analysis, then transfer it to the base stations. The WSNs are made up of different sensor nodes that function as both relay nodes and sensor nodes with one another. However, the absence of infrastructure in these networks limits the sources, resulting in the nodes being powered by a battery with a finite amount of energy. It is not possible to recharge or replace the batteries due to the network's establishment in inaccessible places. Hence, improving the lifetime in these networks is, therefore, a crucial challenge. The sensor nodes use the most energy when transmitting data since the rate of energy consumption when sensing information and receiving information packets from another node is constant. In other to improved the lifetime of the sensor network clustering the network for selection of best cluster head that will route data to the base station is also difficult [1] [2].

Selecting a suitable cluster head (CH) to coordinate the communication and data transmission between the sensor nodes and the base station is crucial for WSNs. One of the challenges in these networks is to efficiently route data packets from sensor nodes to the base station or sink, in other to improved network lifetime [3] [12]. In a typical sensor network, nodes communicate with each other through intermediate nodes, called cluster heads, which forward packets to the sink. However, due to the limited energy resources of sensor nodes, it is important to minimize the number of hops between the sensor nodes and the sink [1], while ensuring that all packets are reliably delivered, making it an important factor to consider when thinking about energy efficiency in WSNs. In addition to achieving energy efficiency in the network, it is also necessary to mitigate CH selection that affects the WSNs technology. The clustering process was done where you partition the nodes into blocks which are is referred to as a cluster, and each cluster has a CH, where the CH is the one that collects the information from its members' nodes transmit it and transmit it to a base station or sink node. A WSNs frequently uses single-hop or multi-hop communication the base station receives data from the sensor node. The CH nodes that are far from the base station in a single-hop transmission pattern lose energy more quickly due to long-distance transmission as well as energy from the intra-cluster transmission, data aggregation, and inter-cluster relay[4]. So this paper provide an idea on how to overcome the above mention related problem in WSNs.

To address this challenge, this paper aims to investigate and develop a routing protocol that optimizes the packet transmission from the sensor nodes to the CH and from the CH to the sink. The proposed protocol should be able to efficiently route packets through the network, while improving the network lifetime and ensuring reliable packet delivery. The performance of the protocol is evaluated through simulations and compared with existing routing protocols to demonstrate its effectiveness.

The proposed algorithm will compare with Improve Cuckoo Search Algorithm (ICSA) and Hybrid Crow Search Algorithm (HCSA), there will be an expansion on the current understanding of the proposed algorithms, PSO_EGA Algorithm in terms of longest network lifetime, packect to CH, pakect to sink and most alive nodes. Our contributions are:

- The combination of these two algorithms to achieve an optimal selection of cluster head in WSNs.
- Provide a solution that balances the trade-off between network lifetime and network coverage.
- Evaluate and compare with the existing solution to demonstrate its effectiveness in improving the performance and efficiency in WSNs.

The body of this paper is structured as follows. Section 1 consist the introduce the overview of WSNs and its problems, in section 2 discuss the related works. In section 3 materials and methods are described. Section 4 the implementation and assessment of the suggested method are shown. Finally, draws the paper to completion.

## RELATED WORK

WSNs is a collection of sensor nodes that are connected wirelessly in other to monitor and gather data from the physical environment. The information gathered can be put to use in a number of different application, including industrial automation, healthcare, environmental monitoring, and military surveillance. However, the energy and computing resources, communication range, and reliability of WSNs are some of their limitations. Designing effective routing strategies to extend the network lifetime is difficult since sensor nodes have limited energy resources. Additionally, it is challenging to transmit data over long distances since the sensor nodes' communication range is constrained and their signal strength decreases with distance[2]. Therefore clustering process came into existence where the network is partitioned into specific number of clusters. Each cluster is having a cluster head where the cluster head is the node that transmit data from its cluster to the base station.

The CH is a designated node who serves as the coordinator for a collection of data from each sensor nodes for that clusters. A cluster head's primary responsibility is to oversee and organize communication between its cluster's nodes and the base station, it was in- charge of gathering and processing data across the network, based on factors including communication capability, closer proximity to the base station, and leftover energy, the CH is chosen [4]. Once selected, the CH become responsible for cluster formation, data aggregation, routing and network lifetime management. The CH is responsible for collecting data from cluster members and transmit the collected data to the base station [1].

The base station's location may have an effect on how much energy the CH uses. The energy needed for the CH to transmit data decreases with the distance between the base station and the CH. This is because the signal strength is stronger when the distance between the base station and the CH is smaller, which lowers the amount of transmission power needed by the cluster head. Conversely, the signal strength is weaker and the CH needs to raise its transmission power as a result of the larger distance between the base station and the CH, which increases energy consumption [8]. Therefore, optimizing the placement of the base station can improve the energy efficiency of the CH and extend the lifetime of the sensor network.

Particle Swarm Optimization (PSO) is a computational optimization algorithm that was inspired by the collective behaviour of bird flocks and fish schools. PSO is a population-based algorithm that uses a swarm of particles to explore the search space for finding the optimal solution to a given problem. Each particle in the swarm represents a potential solution to the problem, and the swarm moves towards the optimal solution by updating the position and velocity of each particle based on its own experience and the experience of its neighbours.

The author in [6] present a brief survey on how to address some problems in WSNs such as efficient deployment, node localization, clustering, and data aggregation using PSO, and also discuss its suitability in WSNs application and how those challenges are addressed by PSO. These surveys are focused on assisting researchers in locating available strategies to encourage feature research. The work by [7] present techniques for CH selection and packet retransmission using PSO and choice of CH according to the parameters such as the lowest average distance from the member node, residual energy, and the headcount on the possible head nodes. But the researcher should find a solution to reduce the complexity and increase the convergence rate of the proposed algorithm. A Multi-objective Particle Swarm Optimization (MOPSO) Multi-objective Data Aggregation 395 technique was presented by [13]. The major goal is to maximize the number of clusters in a WSNs in order to provide an energy-efficient solution. It is founded on the estimated node degree and node residual energy. It produces one set of solutions at a time. In order to increase network lifetime based on factors such as residual energy, distance to the base station, and intra-cluster distance from the cluster head, [1] describe a method for clustering the sensor network based on particle swarm optimization utilizing optimal fitness function. The simulation results show that the recommended technique outperforms protocols like LEACH, CHEF, and PSO-MV in terms of network lifetime and energy consumption.

Although PSO provides certain benefits, it also has some drawbacks. The algorithm's sensitivity to the original swarm configuration is one of its drawbacks. If the original swarm configuration is poorly thought out, the algorithm can end up converging to a local rather than a global optimum. The algorithm may experience premature convergence, in which case the swarm converges to a less-than-ideal solution before thoroughly exploring the search space. Several improvements, including hybridization with other optimization methods, adaptive inertia weight, and constriction factors, have been suggested to get around these drawbacks.

Genetic Algorithm (GA) is a heuristic search that draws its inspiration from the process of natural selection. It has been used in WSNs to address a variety of optimization issues, including routing that uses less energy, coverage optimization, and localisation. A population of potential solutions is first created, their fitness is assessed using a fitness function, and then additional generations of solutions are created using selection, crossover, and mutation operators. Until a stopping criterion is satisfied or a satisfactory solution is found, the process goes on. Energy-efficient routing is one of the most popular uses of GA in WSNs. In this situation, GA has been utilized to identify the most energy-efficient way for data transmission while providing acceptable network coverage and connectivity.

The author in [3] present a technique for energy-efficient data gathering whose aim is to reduce energy usage by managing the cluster count and its density based on the request sent by the base station using GA and also improve the network lifetime by using relay-node as routing element and Adhoc On-Demand Distance vector (AODV) algorithm was used to find the shortest path to send a packet to the base station. The researcher addresses its works in two phases, phase one is the setup phase where the cluster has been formed based on the request sent by the base station in a dynamic fashion in which only the nodes that meet the criteria for the request are permitted to take part in the clustering process other nodes will be in sleep mode. The second phase is the steady phase where the relay node is used as the routing element that collects aggregate information from CH and transmits it to the base station via other relay-node in a multi-hop fashion. The result shows that the proposed GA based on the energy-efficient data gathering (GAEEDG) technique is better than the existing LEACH and SEC in terms of increasing the energy usage of the nodes and also concerning network lifetime. But the researcher needs to improve the amount of packet loss of the sensor from the setup phase. The work by [10] present GA based on optimized clustering (GAOC) by considering residual energy, distance to sink, and node density in its formulated fitness function to solve hotspot problem and reduced the communication distance from a node to sink based on single sink and multiple sinks. According to the simulation research, the GAOC and MS-GAOC surpass cutting-edge protocols on the benchmark of various performance measures, including stability time, network lifetime, number of dead nodes per round, throughput, and network's remaining energy. But the algorithm has a problem with network coverage and sensor deployment.

Despite its benefits, GA has several WSNs-specific restrictions. The algorithm's accompanying processing expense is one of its main shortcomings. When working with a large number of sensor nodes, the process of establishing a new population and assessing their fitness might be computationally demanding. A proper fitness function that accurately reflects the optimization goals of the problem being solved is also necessary for GA.

The authors in [3] proposed an improved Cuckoo Search Algorithm (ICSA) whose aim is to balance the energy usage of the cluster head in other to maximize the network lifetime, the algorithm derived The cost function applied in the evolution of the cuckoo's nest and the fitness value for the selection of CHs are both described. The implementation was done using MATLAB and the simulation result shows that the suggested ICSA performed better compared to the current algorithms in terms of overall energy usage, residual energy, and network lifetime. But there is a need to improve communication between the CH and base station which consume energy.

The Cuckoo Search Algorithm is a population-based optimization method that takes inspiration from cuckoo birds' unique breeding habits. The fundamental principle of Cuckoo Search Algorithm is to employ a population of nests to look for an optimization problem's global optimum solution. However, Cuckoo Search Algorithm has various restrictions and flaws that could hinder its performance, similar to many other metaheuristic algorithms. Researchers have suggested many changes to the original CSA to solve these drawbacks. The following are some typical methods for enhancing the Cuckoo Search Algorithm, Local Search Techniques: To discover the global optimum solution, the Cuckoo Search Algorithm global optimization method relies on the exploration of the search space. It could not, however, be effective at utilizing the local search space. Therefore, to enhance the performance of the algorithm, local search techniques like hill climbing or simulated annealing might be used, Combining Cuckoo Search Algorithm with other metaheuristic algorithms: To make the most of their advantages and address their shortcomings, Cuckoo Search Algorithm can be combined with other metaheuristic algorithms as PSO, Differential Evolution (DE), or GA. The algorithm's capacity for exploration and exploitation may be enhanced by hybridization.

The authors in [12] proposed an ICSA whose aim is to balance the energy usage of the cluster head in other to maximize the network lifetime, the algorithm derived The cost function applied in the evolution of the cuckoo's nest and the fitness value for the selection of CHs are both described. The implementation was done using MATLAB and the simulation result shows that the suggested ICSA performed better compared to the current algorithms in terms of overall energy usage, residual energy, and network lifetime. But there is a need to improve communication between the CH and base station which consume energy.

The Crow Search Algorithm is an optimization algorithm that draws inspiration from nature and imitates the cunning foraging methods of crows. The program searches for the overall best solution to an optimization issue using a population of crows. However, CSA has various restrictions and flaws that could hinder its performance, similar to many other metaheuristic algorithms. Researchers have suggested a number of enhancements to the original CSA to solve these drawbacks, with the Hybrid Crow Search Algorithm (HCSA) being one of them. To enhance its performance, HCSA combines the Crow Search Algorithm with various metaheuristic optimization methods. The Crow Search Algorithm is frequently hybridized with other algorithms using a variety of methods, including. GA, PSO, and Ant Colony Optimization (ACO).

The work in [8] presented an energy-efficient data gathering using HCSA whose aim is to enhance the network lifetime and also provide a learning method that maximizes the lifetime of a network and to attain supreme energy efficiency. The implementation was carried out using MATLAB and the result was obtained by using the performance parameters including the overall amount of energy used, the number of active nodes, and the lifetime of the network when we compare it with the existing scheme the effectiveness of the suggested techniques are good. But there is a need to improve the amount of energy consumed during the transmission.

These methods can aid in enhancing the algorithm's efficacy and efficiency in locating the overall optimal solution.

## RESEARCH METHOD

As stated in this study an optimal cluster head selection approach is presented for wireless sensor networks by using PSO and EGA. Therefore PSO was used for optimal cluster head selection that takes care of intra-cluster communication and reduced energy consumption of the sensor node (SN) and the EGA was used for optimal path selection in other to transmit information from CH to the base station. This study was presented to improve network lifetime NL, energy consumption, and throughput. The proposed method has 4 steps:

I. Determine the optimal Clustering and CH selection using the PSO algorithm.

II. Wake-up sleep algorithm initialization.

III. Using efficient GA to select the best CH that performs the transmission to the BS.

IV. Simulation, assessment, and comparison of the suggested approach PSO_EGA with the prior HCSA and ICSA methods using the key WSNs criterion.

The CH has been selected based on the parameters which are residual energy of the sensor node, distance to base station and node density.

### PSO Clustering

The particles are produced at random during the clustering stage. Then, other nodes that are close to each cluster head are included as members of the cluster, and the fitness function is determined for each cluster head. Finally, the best points are chosen as the cluster heads. If the fitness function is superior to the best available globally, it is used instead. The process we are taking is the clustering cost function and evaluating based on the distance matrix, that is which one has the closest distance will be taken as CH. Updating the position depends on the residual energy of the sensor node that is the node that has the highest energy will be updated using the mathematical concept below and repeat the same process for the number of iterations, after that we are the global best position out of the number of iteration.

The mathematical model for selecting the position, the new position is created according to the previous velocity to the personal best and the global best so this will be the position the mathematical model will be.

The method use to find the updated initial position of SN can be described in Equation 1:

$$Xi(t+1) = Xi(t) + Vi(t+1) \quad (1)$$

Where $Xi$ represent the initial position of every node in the cluster, $t+1$ represent the updated position of node and $Vi$ represents the velocity of the node in position $i$.

The method used to find the updated velocity of the SN can be describe in Equation 2:

$$Vi(t+1) = \sum w * Vi(t) + C1 * Pi(t) - Xi(t) + C2 * G(t) - Xi(t)) \quad (2)$$

Where $C1$ represent the coefficient values from $0{,}1$

$Pi$ represent the best position and $Gt$ represent the global best position.

Where ∑w = sum of the 3 components parallel to the previous velocity, $Xi$→ $Pi$ and parallel to the vector $Xi$→$G(t)$

The general equation for updating the velocity of the particles.

$$Vij(t+1) = \sum w * Vij(t) + R1 * C1\,(Pij(t) - Xij(t) + R2 * C2\,(Gj(t) - Xij(t)) \quad (3)$$

Where R1 and R2 are uniformly distributed numbers in therange of 0.1.

Therefore, on every iteration of PSO position and velocity was updated the current best position will be $Pi(t) - Xi(t)$ for the global best $G(t) - Xi(t)$ and the SN again moves parallel to the updated velocity for the sensor node

$$Xij(t+1) = Xij(t) + Vij(t+1) \tag{4}$$

### Wake-up Sleep Initialization Algorithm

The wake-up sleep algorithm is used in WSNs to conserve energy and increase the battery life of individual nodes. The nodes in this algorithm periodically rise up from a low-power sleep mode for data sensing, processing, and transmission, and then go back to sleep to conserve energy. In industries where energy efficiency is critical, such as environmental monitoring, surveillance, and healthcare, the wake-up sleep algorithm is often utilized. This method reduces the amount of time nodes are awake and transmitting data, hence significantly extending the battery life of wireless sensor networks. This is how the algorithm functions. To save energy, the sensor node enters sleep mode.

1. Periodically, the node awakens to carry out a specified activity or check for new data to be relayed.
2. The node checks to see whether there is any data that can be transmitted, and if there is, it will turn on the radio and send it.
3. The node returns to sleep if there is no data to send in order to save energy.
4. Periodically, the node goes through this cycle again, waking up to carry out duties and provide data as needed.

In other to identify the sensor you must first ascertain the kind of sensor node and how it behaves in sleep mode. Sensor nodes typically use sleep modes to reduce power consumption and increase battery life. There are various sleep modes, including Deep Sleep Mode: When activated by a specific event, such as a timer or an external signal, the sensor node totally shuts down in this mode and only wakes up when prompted. Low-Power Sleep Mode. In this setting, the sensor node lowers its clock frequency, disables peripherals, and turns off unused circuitry to save power.

This algorithm will take place after the initial clustering the aim of this algorithm will make some only the transmission node will be active for every iteration the remaining nodes will be in sleep mode, which means the node that is performing the transmission will be awake while the remaining node will be on sleep-mode so that no energy consumption will be taking place on that corresponding node. The power consumption of the radio module, the node's duty cycle, and the length of the wake-up phase must all be taken into account when calculating the energy consumption during the wake-up state in a WSNs. Determine the node's duty cycle, which is the proportion of time the node spends awake. The formula below can be used to compute this: $duty_{cycle} = \frac{wake_{uptime}}{wake_{uptime}} + sleep\_time$ where wake-up time is the duration of the wake-up state and sleep time is the duration of the sleep state. Use the following calculation to determine the amount of energy used while awake:

$\text{Energy} = \text{power usage} * \text{the duration of the awake node.}$

### Use of Efficient Genetic Algorithm for Optimal Selection

In this portion some of the parameters that we need to improved are network lifetime, packet to cluster head, packect to base sation and number of alive node. GA that is specifically created to be efficient in terms of time and resource utilization is referred to as an efficient genetic algorithm in WSNs. This is crucial for WSNs since they frequently operate in dynamic and unpredictable contexts and are resource-constrained. EGAs are a type of genetic algorithms that employ a number of methods to enhance the effectiveness and efficiency of the conventional genetic algorithm. The parameters utilized in EGA vary depending on the implementation and problem domain. However, a few typical EGA variables are Population size, Selection operator, Crossover operator, Mutation operator and Fitness function.

Population size: The population was initially injected with a set of randomly created individuals at the beginning of the genetic algorithm, and at the end of each generation, the individuals are assessed according to their fitness function. In order to produce a new set of offspring individuals for the following generation, the individuals with the highest fitness values are chosen for reproduction. Their genetic information is then integrated by crossover and mutation operators. For a set number of generations or until a termination criterion is satisfied, the processes of selection, crossover, and mutation are repeated.

Selection operator: A crucial element that determines which members of the population will be chosen to reproduce and pass on their genetic information to the following generation is the selection operator. The selection operator is in charge of producing a new population made up of the best members of the previous generation and of preserving population variability.

Crossover operator: The parent individuals' chromosomes are divided into one or more crossing locations by the crossover operator. The genetic material from the parents is then swapped to make new offspring chromosomes after the chromosomes are split at the crossover spots. The new offspring individuals are then produced using the new offspring chromosomes.

Mutation operator: The key element that makes arbitrary alterations to a population member's genetic makeup is the mutation operator. The algorithm is kept from being stuck in local optima by the mutation operator, which adds new genetic variety to the population. The way the mutation operator operates is to randomly pick one or more genes from a person's chromosome and alter their values. The mutation rate is a factor that establishes the likelihood of a gene changing. Typically, a modest mutation rate is used to prevent the algorithm from adding an excessive amount of random diversity to the population.

We are having threshold and the corresponding particular node has to be achieved before it will be selected as CH so this will be in an efficient genetic algorithm therefore efficient genetic algorithm we are using the objective function (OF) and the cost function (CF) so this objective function and cost function will be adapted from cuckoo search algorithm where selecting eligible CH, the fitness function of each node will be calculated based on the following expression:

$$fitness = a1 * f1 + a2 * f2 + a3 * f3 \tag{5}$$

If the fitness is evaluated from the genetic algorithm then we are calculating the cost function

where $a1, a2, a3$ are constant and its value is between 0,1 values of $a3$ equals to $1 - a1 - a2$

where $x1$ denotes maximum average Euclidean distance between nodes

where $x2$ indicates the relationship between the total energy of all nodes, the total energy of all network nodes, and the total energy of all CHs.

Where value of $\beta$ is 0.5 order to minimize intra-cluster distance and choose the best position-based CHs, the maximum value of the function $x1, x2$ is used. This lowers energy usage.

$$Cost = \beta * x1 + * (1 + \beta) * x2 \tag{6}$$

## EXPERIMENTAL RESULT

The algorithm was simulated using MATLAB software where 100 nodes were randomly deployed over a network area of size 250*250 and the base station was located 125*250 the simulation parameters are from the table below.

**Table 1.** Parameter list used in the experiment

| Parameters | Value |
|---|---|
| Network area | 250* 250 |
| Number of sensor nodes | 100 nodes |
| Location of a base station | 125*250 |
| The initial energy of the sensor node | 2j, 200j |
| % of CH | 5-25 |
| Eelec | 50nj/bit |
| Efs | 10pj/bit/m² |
| Emp | 0.0013pj/bit/m⁴ |
| Do | 87.00 |
| Dmax | 25m |
| Packet length | 400bit |

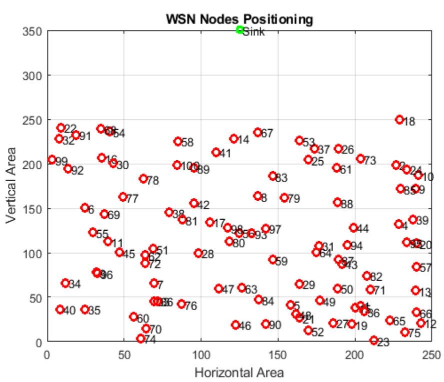


**Figure 1.** Sensor node deployment

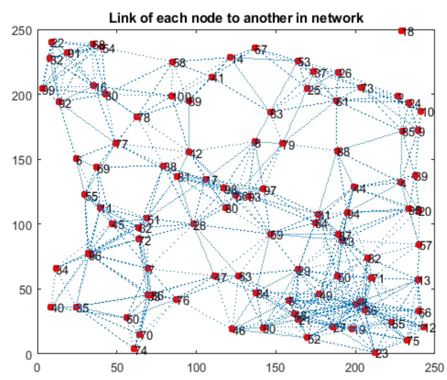


**Figure 2.** Bi-Directional Link

The first initialization was the deployment of SN on the network topology where we have a set of 100 nodes and 1 sink that deployed randomly, after that we're evaluating the bi-directional link of the SN i.e the node that can directly communicate with each other wirelessly that will be Figure 1 and 2.

Figure 1 indicates an implemented network topology with a total of 100 sensor node which are randomly deploy and a base station. Figure 2 we're evaluating the bi-directional link which indicates the nodes that's are directly communicate with each other from the topology where we have the diagrams from the above. After that, we're taking the initial clustering by using the PSO algorithm and taking the clustering cost function where the evaluating for the distance matrix i.e which node has the closest distance that will be considered as CH.

PSO parameters: Suppose the initial position, random position number of CH for 100nodes we're taking 10 CH, so those are the CH that is randomly generated on the topology then we're taking the cost function and which node has the best cost function that will be updated and after that the main loop will be started for every iteration of elicity we are taking the updated position after were evacuating the cost function and repeat the process for the number of iteration.

After that we're taking the global best position out of the number of the iteration we're taking that will be considered. Figure 3 shows PSO clustering of 100 nodes where the clusters will be split into 10 groups for the entire network.

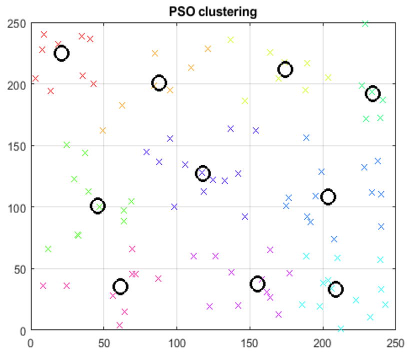


**Figure 3.** PSO Clustering

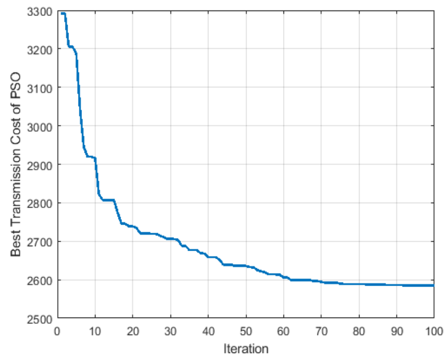


**Figure 4.** Transmission Cost

Best transmission cost as the number of iterations is increased the transmission cost is going to be reduced so that we can get the best position of CH which was shown in figure 4. Those 10 CH will be split again into 4 levels whereby each level was based on the distance between the cluster head to the base station. To form the distance of 100 so 75-100 is level 1, 50-75 is level 2, 25-50 is level 3 and 0-25 is level 4.

After that wake-up sleep algorithm will be stated whereby when there is a transmission from a particular level only the CH of that level will be active the remaining nodes of every level will be in sleep mode. Therefore for every number of processes, we are going to have a condition to elect the node that will perform the transmission so the election of this node will be handled by the use of EGA.

### Network Lifetime

Figure 5 illustrates the performance of the suggested Efficient PSO_EGA in terms of network lifetime from the experiment as the number of the round's going to increase automatically the network lifetime is going to be reduced these are the default procedure but compares with HCSA and ICSA. The first node died at round 575 out of 1000 rounds for the proposed algorithm while for the ICSA the first node died at round 565 out of 1000 rounds and lastly for the HCSA the first node died at round 555 out of 1000 rounds so compared with HCSA and Improve cuckoo the proposed PSO_EGA performed better than the existing protocols.

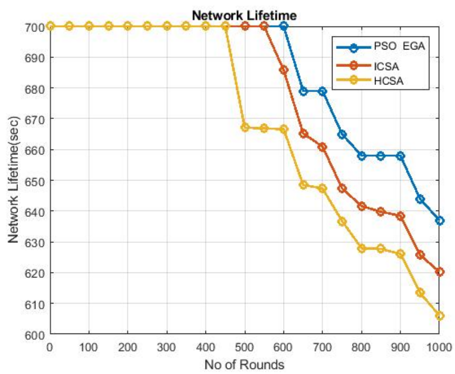


**Figure 5.** Network Lifetime

### Throughput

Figure 6 illustrates the effectiveness of the suggested Efficient PSO_EGA in terms of throughput as the number of rounds going to increase the concatenation number of packets received having the throughput will increase by 2Mbit/second for the proposed method while for the ICSA received the packet by 1.45Mbit/second and lastly for the

HCSA received packet having the throughput by 1.39Mbit/second so we have achieved better performance from the proposed PSO_EGA compared with the existing method.

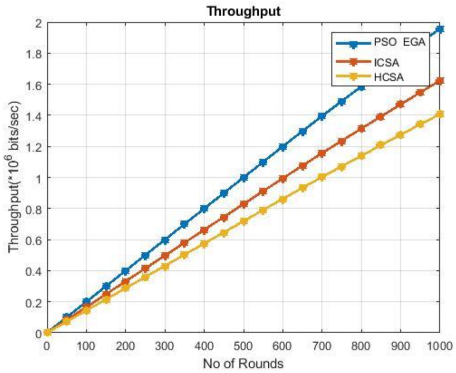


**Figure 6.** Throughput

### Number of Cluster Head

Figure 7 illustrates the effectiveness of the suggested Efficient PSO_EGA in terms of the number of CH, so CH selection has to be increased in order we have maintained the CH in higher order compared with the existing method. When the existing ch died we have to choose another ch based on the parameters residual energy, distance to base station and node density. In addition, also our proposed method has selected CH in higher order.

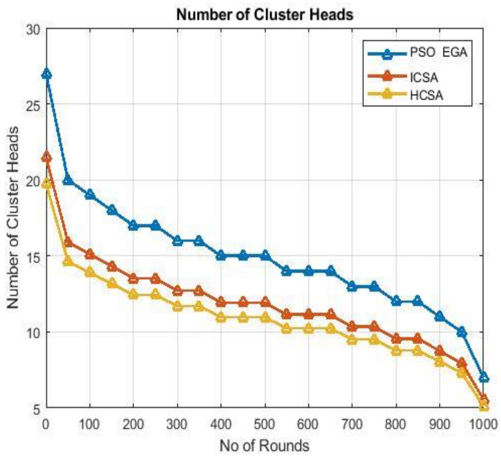


**Figure 7.** Number of Cluster Heads

### Packet to Cluster Head and Packet to Sink/Base Station

Figure 8 and 9 illustrate the effectiveness of the suggested PSO_EGA in terms of a packet to CH and Packets to sink/ base station in fig 8 packet to CH in our proposed method the amount of packet received from normal node to cluster head was 9500 packet in 1000 rounds, while ICSA received 8800 packet from normal nodes to cluster head in 1000 rounds and lastly for HCSA received 7900 packet in 1000 rounds. That will be the total packet transmit from the sensor node to CH while in 9 is the packet transmitted from the CH to sink that's a destination. In our proposed method, ICSA, HCSA the amount of packet received from the CH to the sink node was 9000, 7900 and 6800 packets was sent to the destination in 1000 round so our proposed method performs better compared to the existing method in terms of packet to cluster head and packet to sink node.

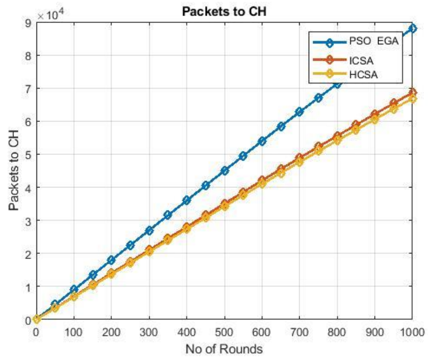


**Figure 8.** Packet to CH

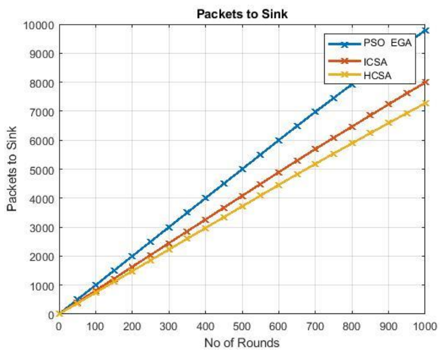


**Figure 9.** Packet to Base Station

### Energy Consumption

Figure 10 illustrates the effectiveness of the suggested PSO_EGA with regard to energy usage we are having the very lowest energy consumption by using the wake-up sleep algorithm compared with the existing method we have reached 65, 40, and 30 percent of energy saving as compared with the existing method which are ICSA and HCSA.

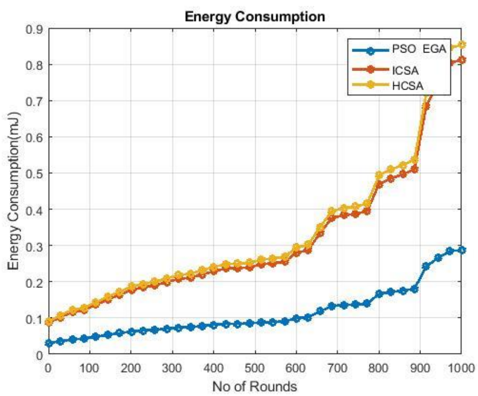


**Figure 10.** Energy Consumption

### Packet Delivery Ratio

Figure 11 illustrates the effectiveness of the suggested PSO_EGA regarding the ratio of packet deliveries as the number of rounds going to be increased on the network automatically we are going to have the highest data delivery ratio that will be saturated as we compare with the existing method.

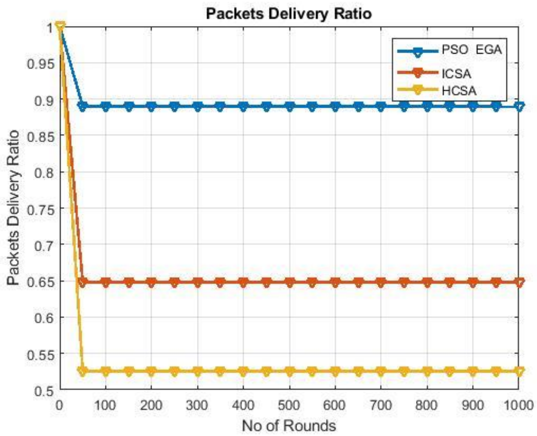


**Figure 11.** Packet Delivery Ratio

### Number of Live Nodes

Figure 12 illustrates the effectiveness of the suggested PSO_EGA in terms of the number of alive nodes in our proposed method first node dies at around 575 of out 1000 rounds and also 88 nodes are still alive out of 100 nodes that we deployed while in improved cuckoo search algorithm the first node dies at round 480 out of 1000 rounds and also 60 nodes are alive out of 100 nodes that deployed and lastly in HCSA the first node die in round 390 out of 1000 rounds and also 40 node are alive out of 100 sensor node deployed after the complete round so compared with the existing method our proposed PSO_EGA perform better.

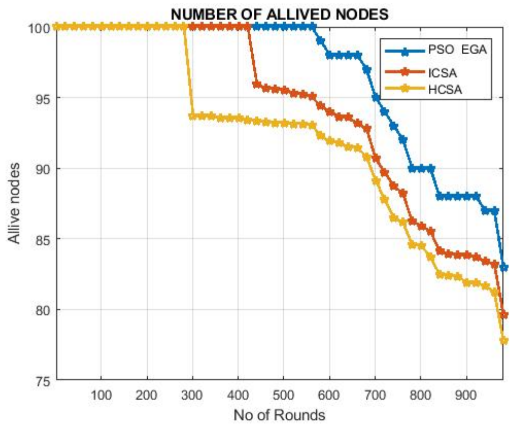


**Figure 12. Number of Alive node**

### SUMMARY OF THE RESULT

The simulation experiment was based on PSO_EGA in comparison with the previous methods such as the HCSA and ICSA. The experiment parameters used in this simulation are shown in Table 1. For PSO_EGA in terms of energy consumption the proposed method has the lowest energy consumed which reduce by almost 65 percent from the energy compared to the previous method and in terms of network lifetime in the proposed method the first node died at round 575 out of 1000 rounds, For PSO_EGA in terms of pakect to cluster head our proposed method transmit 9500 pakect to ch out of 10,000 while in ICSA transmit 8800 pakect, and HCSA transmit 7900 pakect. in terms of packet to base station our proposed PSO_EGA transmit 9000 pakect out of 10000, ICSA transmit 7900 and HCSA transmit 6800 and in terms of alive nodes our propose PSO_EGA has 88 nodes that are still alive out of 100 sensor node deployed, ICSA has 60 nodes that are alive while HCSA has 40 nodes that are alive. So based on the comparison our proposed method performs better in each scenario.

### CONCLUSION

In this paper, we proposed an optimal selection of the CH in WSNs by combining the PSO and EGA to prolong the lifetime of the sensor network. Firstly, PSO is used to randomly select the cluster head and update the position of each cluster. Thereafter, EGA invokes its fitness values to select the best cluster head that transmits information to the base station. The parameters used for selecting the cluster head was based on residual energy, distance to base station ann node density. As a means of validation, HCSA, ICSCA, and routing methods were replicated and their performances were compared with the developed EGA protocol using network lifetime, energy consumption packet to CH, packet to sink and number of alive nodes as metrics. The simulation result shows that our proposed PSO_EGA outperform the existing ICSA and HCSA in optimal selection of the CH in WSNs. The application of this approach in practical scenarios could also be explored to evaluate its real-world performance. Overall, the study provides a useful framework for researchers and practitioners working in the field of wireless sensor networks to enhance the performance and miximize the packect delivery ratio of the sensor node.

### Conflict of Interest

It is stated by the authors that they have no competing interests.

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## REFERENCES

[1] H. Yetgin, K. T. K. Cheung, M. El-Hajjar, and L. H. Hanzo. "A survey of network lifetime maximization techniques in wireless sensor networks." *IEEE Communications Surveys & Tutorials,"* vol. 19, no. 2, pp. 828-854, 2017.

[2] S. Randhawa, and S. Jain. "Multi-objective Data Aggregation for Clustered Wireless Sensor Networks." In *Progress in Computing, Analytics and Networking: Proceedings of ICCAN 2017*, pp. 393-406, Springer Singapore, 2018, doi: https://doi.org/10.1007/978-981-10-7871-2_38 393-406.

[3] T. Sujithra, and R. Venkatesan. "Genetic algorithm based energy efficient data gathering in wireless sensor networks." *International Journal of Applied Information Systems*, vol. 11, no. 2, pp. 1-7, 2016

[4] S. R. Nabavi, V. O. Moghadam, M. Y. F. Hendi, and A. Ghasemi. "Optimal selection of the cluster head in wireless sensor networks by combining the multiobjective genetic algorithm and the gravitational search algorithm." *Journal of Sensors*, vol. 2021, pp. 1-16, 2021, doi: https://doi.org/10.1155/2021/2292580.

[5] B. Singh, and D. K. Lobiyal. "Energy-aware cluster head selection using particle swarm optimization and analysis of packet retransmissions in WSN." *Procedia Technology, vol.* 4, pp. 171-176, 2012, doi: 10.1016/j.protcy.2012.05.025.

[6] R. V. Kulkarni, and G. K. Venayagamoorthy. "Particle swarm optimization in wireless-sensor networks: A brief survey." *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), vol.* 41, no. 2, pp. 262-267, 2010, doi: 10.1109/TSMCC.2010.2054080.

[7] P.C.S. Rao, P. K. Jana, and H. Banka. "A particle swarm optimization based energy efficient cluster head selection algorithm for wireless sensor networks." *Wireless networks, vol.* 23, pp. 2005-2020, 2017, doi: 10.1007/s11276-016-1270-7.

[8] P. K. Kodoth, and G. Edachana. "An energy efficient data gathering scheme for wireless sensor networks using hybrid crow search algorithm." *IET Communications*, vol. 15, no. 7, pp. 906-916, 2021, doi: 10.1049/cmu2.12128.

[9] M. Elhoseny, A. Farouk, N. Zhou, M-M. Wang, S. Abdalla, and J. Batle. "Dynamic multi-hop clustering in a wireless sensor network: Performance improvement." *Wireless Personal Communications, vol.* 95, pp. 3733-3753, 2017, doi: 10.1007/s11277-017-4023-8.

[10] S. Verma, N. Sood, and A. K. Sharma. "Genetic algorithm-based optimized cluster head selection for single and multiple data sinks in heterogeneous wireless sensor network." *Applied Soft Computing*, vol. 85, no. December 2019, pp. 1-21, 2019, doi: https://doi.org/10.1016/j.asoc.2019.105788.

[11] A. Rostami, and M. H. Mottar. "Wireless sensor network clustering using particles swarm optimization for reducing energy consumption." *International Journal of Managing Information Technology, vol.* 6, no. 4, pp. 1-15, 2014, doi:DOI : 10.5121/ijmit.2014.6401.

[12] G. P. Gupta, "Improved cuckoo search-based clustering protocol for wireless sensor networks." *Procedia Computer Science, vol.* 125, pp. 234-240, 2018

[13] Y. Lu, J. Chen, I. Comsa, P. Kuonen, and B. Hirsbrunner. "Construction of data aggregation tree for multi-objectives in wireless sensor networks through jump particle swarm optimization." *Procedia Computer Science, vol.* 35, pp. 73-82, 2014