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Research Article

Utilization of Tabu Search Algorithm in IoT-Equipped WSN for Energy –Efficient Cluster Head Selection

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ABSTRACT

The Internet of Things (IoT) has brought transformative changes to various areas of human life, enabling the interconnection of sensor nodes to monitor and manage remote environments for applications like precision agriculture, wildlife conservation, and intelligent forestry. However, the limited battery life of these sensor nodes reduces network longevity, necessitating ongoing maintenance. To address this, energy conservation and provisioning are critical. Among these, clustering plays a vital role in maximizing energy efficiency and extending network lifespan. Despite various clustering methods proposed to enhance energy conservation, the improper selection of Cluster Heads (CH) often leads to an energy-hole issue, degrading network performance. CHs are pivotal in managing communication within clusters and eliminating duplicate data transmission, thereby optimizing energy use. To overcome this challenge, we propose a Tabu Search-based technique for energy-efficient CH selection in IoT-enabled wireless sensor networks(WSN). Our approach involves two phases: cluster formation using Euclidean distance and CH selection through Tabu Search. Simulated using Python, the proposed Tabu Search algorithm's performance is benchmarked against existing methods such as SWARAM, HSWO, EECHIGWO, and EECHS-ARO. Results show that our approach significantly improves network performance and energy efficiency.

Keywords: IoT; Energy Conservation; WSN; Clustering; Tabu Search Method.

1. INTRODUCTION

The IoT is a rapidly evolving study topic in academia and industry. Due to invention of IoT it has tremendous impact on people's lives. IoT enhances life efficiency. In IoT, physical objects have computing capabilities, communicate and exchange data seamlessly. Application of IoT includes in many areas like healthcare, commerce and retailing, smart grid, agriculture, country border surveillance and smart homes [1-3]. Data that are collected from surrounding environment by the dispersed sensor nodes in WSN comes to the central node for analysis. Wireless sensor networks rely heavily on communication elements to transmit and receive data wirelessly [4-6]. Advanced technologies led to small sensors with low-power. Many industries employed WSN real-time applications such as industrial automation and intelligent infrastructures defence systems.

Because of limited memory capacity, battery capacity and limited processing power it is very difficult to increase network lifetime using resource-constrained sensor nodes. Several approaches are being suggested to

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extend the network's life. Energy conservation is crucial in data transmission for Wireless Sensor Networks [7-9]. Routing plays a vital role in WSN. Every day, the number of sensor nodes increases from a few to thousands, enabling multi-hop communication between them. The sensors depend on batteries, which cannot be refilled or replaced. To address energy issues in WSN clustering method and hierarchical routing has used in previous studies. Clustering methods can help to save energy while also increasing network durability.

One of the important strategies to reduce energy consumption is clustering, by eliminating redundant data transport between nodes. In WSN sensor nodes are divided into numerous clusters. Every cluster has a Cluster Head (CH), who communicates with the other Cluster Members (CM). Previous techniques often use optimization algorithms to provide CH selection options. The optimization method selects the best answer from a set of alternatives. Various optimization methods, such as whale optimization algorithm [10], coati optimization algorithm (COA) [11], golden jackal optimization (GJO) [12], artificial bee colony (ABC) [13], marine predator optimization (MPO) [14], and particle swarm optimization (PSO) method [15], have been used to identify optimal CH. However, optimization strategies used for CH selection are time-consuming to reach convergence. Because a result, the sensors battery deplete rapidly.

In order to address the issue, we recommend using the Tabu Search (TS) approach to determine the optimal CH within clusters and thereby prolong the networks' lifespan. TS has a faster convergence time during CH rotation as compared with other optimization techniques. Rapid convergence enhances network performance and adaptability. Fast convergence improves network performance and adaptability. This work focuses on network and system flexibility. The primary contribution of this paper is as follows:

- Clusters are formed by computing the distances between network nodes. Later, CH is determined in nodes using the TS technique.
- The CH selection model, which is based on the TS method can improves network longevity and throughput.
- Using fitness function with distance and energy makes CH selection more efficient.
- The TS method is evaluated in comparison with SWARAM, EECHS-ARO, HSWO, and EECHIGWO.

This study represents the following sections: Section 2 represents a survey of literature on various optimization methods and strategy of CH selection. Section 3 includes the Network Model. The proposed TS algorithm technique is described in Section 4. Section 5 discusses the performance of the proposed TS method. Section 6 discusses the conclusions and future directions.

2. RELATED WORKS

Because there are only a few battery-powered sensor nodes in remote locations, energyefficient solutions are essential in wireless sensor networks. CH selection improves stability of networks by forming clusters within the network region. While there are numerous designs for selecting CH, improving energy in WSNs remains a challenge.

Cherappa et. al.[16] introduced clustering method which associates sailfish optimization algorithm (ASFO) with routing protocol to increases efficiency. ASFO employed K-ASFO to choose the optimal CH among the nodes, effectively transmitting data with the CMRP routing protocol. The performance of ASFO was assessed using MATLAB simulations, with a comparison to KSOA and WOA based on packet delay, power consumption, PDA, network lifetime, throughput, and PLR. The ASFO method achieved as 93.19% accuracy rate, surpassing KSOA and WOA benchmarks.

Sindhuja et al. [17] proposed using African vulture optimization to identify energy efficient cluster heads for data aggregation in WSN (MOCHSAPGAN-AVO). This approach determine the optimal routing path and transfer data to the base station. Simulation results in NS2 showed that MOCHSAPGAN-AVO outperformed benchmark methods like FL-CHESDA-WSN, DAWSN-MLOA, and IDFA-ASLPPRR in terms of delays of 38.96%, 57.80%, and 41.97%. as well as higher packet delivery ratios of 37.94%, 22.96% and 18.35% compared to the benchmark methods, respectively.

Suganthi et al. [18] showcased the effectiveness of multi-swarm optimization (MSO) combined with TS for improving routing optimization and network longevity by selecting efficient CHs. Results indicated that the MSO-Tabu technique outperformed genetic algorithm, differential evolution, Tabu, and MSO-based clustering with a

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higher number of clusters and lower average packet loss rate. The MSO-Tabu technique also demonstrated significantly increased lifetime computation and average dissipated energy.

Vijayalakshmi and Anandan [19] proposed a strategy that focuses on selecting the best path in routing to enhance network lifespan and energy efficiency. The strategy combines PSO and TS algorithms to increase cluster formation, node survival, and reduce packet loss rate and end-to-end delay. Maleki et al. [20] suggested a fuzzy logic-driven TS model to enhance the lifespan of WSNs by managing energy usage and distance. Their TS method surpasses other algorithms like PSO, LEACH, and hybrid LEACH-PSO by decreasing energy consumption and extending network longevity.

Abdelmorhit and Samuel [21] proposed a centralized clustering approach for WSN. The clustering issue is addressed as hypergraph partitioning and solved with a TS algorithm. Method detects movements based on the largest cliques in a feasibility cluster graph. To reduce cluster cost and execution time TS-based approach is the best solution when compared with other techniques.

3. SYSTEM MODEL

TS networks comprise randomly distributed nodes within a network area, where each node can function as either a CH or a CM. CM gather data and send it to CH, which aggregates and transmits to the base station (BS) or sink node for analysis. The proposed method selects CH after execution at the sink node and builds clusters by connecting neighbouring CH nodes. The network model [22] is depicted in Figure 1.

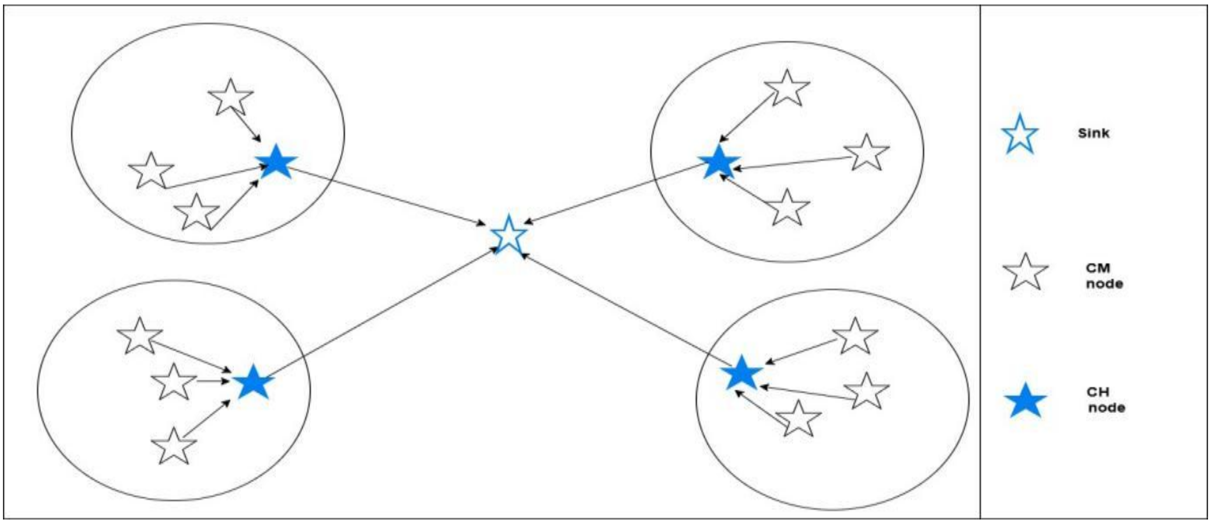

Figure 1. TABU SEARCH network model.

Assumptions for the TABU SEARCH network model include:

- The network's nodes are distributed in a random pattern.
- Each node has equal energy and computational power.
- Nodes have unique identifiers to identify them from others.
- The position of the sink node is at the center of the network.
- The sink node's location is known by all network nodes.
- The sink node collects incoming data packets from cluster's CMs, which are then aggregated by the CH.

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4. TS ALGORITHM:

The metaheuristic TS utilizes a local heuristic search to explore the solution space before optimization [23]. It involves modifying N(x) during the search, replacing it with neighbourhood N*(x). The goal is to find answer x0 ϵ N(x) from solution x ϵ X, respectively moving to the closest neighbour even if the objective function worsens. This differs from traditional hill climbing as it only advances to neighbours' with improved objective functions [18].

The TS technique uses specific memory structures to determine N*(x) and is designed to assist space exploration. To prevent cycling, TS uses recency-based memory through the Tabu list to prevent particular moves from being re-instantiated for a set amount of time. Tabu-active designation allows for the use of recent memory to select attributes. Tabu-tenure is the number of iterations that an attribute is kept as Tabu. TS employs aspiration criteria to override a motion's Tabu status, resulting in more flexible performance. Algorithm 1 [18] shows the pseudocode for the TS protocol.

Algorithm 1: TS Protocol Pseudocode

```
1.  Start
2.  Select an initial solution s ϵ S
3.  Let bestsolution := s {bestSolution denotes the best solution currently found}
4.  Set iterationCount = 0
5.  TList =∅ {TList is a Tabu List}
6.  if Neighborhood(s) – Tlist is empty
7.      Go to step 18
8.  else
9.  iterationCount = iterationCount + 1
10. Select a ϵ Neighborhood(s) – Tlist such that a ϵ Optimum (Neighborhood(s) : s ϵ
    Neighborhood(s) – Tlist)
11. end if
12. s := a
13. if Cost(s) < Cost(bestSolution)
14. bestSolution :=s
15. end if
16. if a chosen number of iterations has elapsed either in total or since bestSolution was last
    improved, or if ϵ Neighborhood(s) – Tlist = ∅
17. Go to step 18
18. else
19.     Update TList ( as subsequently identified)
20. Return to step 6
```

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21. end if

22. end

Efficiency Analysis of the Suggested TS Method

CH is chosen using the T Method in nodes after clusters are established by calculating distances between network nodes. In the simulation 50 random nodes have taken in a 2D space.

These nodes represent positions in a network, which could represent anything from physical locations to logical positions in a network. A pairwise Euclidean distance matrix is computed for these nodes. This matrix assists in determining the distance between each pair of nodes, which is necessary for clustering and optimizing cluster heads. These nodes are divided into four clusters using K-Means clustering algorithm. This process assigns each node to a cluster based on their proximity to the cluster centres.

Calculation of Distance Matrix: Between two points $P(x_1,x_2,\ldots,x_n)$ and $Q(y_1,y_2,..,y_n)$ the Euclidean distance is computed by the given formula :

$$d(P, Q) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$

TS for Selecting CHs:

The purpose is to identify the best cluster heads, or representative nodes, by minimizing the total distance between each node in a cluster and its respective cluster head. The TS algorithm is implemented to achieve this:

Initialization: Several parameters are initialized, including the number of iterations, the Tabu list (to avoid revisiting solutions), and variables to track the best solution and its cost.

Cost Function: The calculate cluster head cost function computes the total distance from a cluster head to all other nodes in its cluster.

Iterative Optimization: The approach systematically explores to identify the most effective group of cluster heads:

1. In each iteration, a random set of nodes is chosen as potential cluster heads.
2. The total cost is calculated for this configuration.
3. If this configuration results in a lower cost than the best-known cost, it is updated as the best solution.
4. The configuration is added to the Tabu list to prevent cycling back to it.

Network Longevity: By choosing the best cluster heads, the average communication distance for nodes is decreased, leading to lower energy consumption during data transmission to the cluster head. Lower energy consumption leads to longer battery life for individual nodes, thus enhancing overall network longevity.

Throughput Improvement: Efficient cluster head selection ensures that data is aggregated and transmitted more effectively, reducing the likelihood of congestion and packet loss. This increases the throughput, meaning that the network can handle more data transmission efficiently. Result of distance matrix with 20 nodes is shown in Table 1.

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Table 1. Distance Table

Nodes	Node 0	Node 1	Node 2	Node 3	Node 4	Node 5	...	Node 19
Node 0	0	0.178	0.143	0.208	0.531	0.306	...	0.396
Node 1	0.179	0	0.205	0.384	0.395	0.189	...	0.367
Node 2	0.143	0.205	0	0.246	0.6	0.386	...	0.521
Node 3	0.209	0.384	0.246	0	0.731	0.507	...	0.547
Node 4	0.531	0.395	0.6	0.731	0	0.225	...	0.299
Node 5	0.306	0.189	0.386	0.507	0.225	0	...	0.215
Node 6	0.211	0.382	0.314	0.134	0.671	0.455	...	0.447
Node 7	0.789	0.701	0.66	0.884	0.94	0.845	...	1.056
Node 8	0.541	0.649	0.444	0.421	1.044	0.829	...	0.935
Node 9	0.276	0.369	0.419	0.341	0.52	0.341	...	0.25
Node 10	0.109	0.453	0.575	0.548	0.415	0.328	...	0.122
Node 11	0.109	0.274	0.139	0.113	0.64	0.415	...	0.492
Node 12	0.437	0.493	0.305	0.406	0.883	0.682	...	0.826
Node 13	0.465	0.609	0.409	0.298	0.993	0.77	...	0.842
Node 14	0.301	0.153	0.251	0.484	0.442	0.293		0.499
Node 15	0.29	0.408	0.204	0.209	0.8	0.581		0.685
Node 16	0.173	0.148	0.084	0.323	0.54	0.337		0.5
Node 17	0.538	0.588	0.405	0.5	0.973	0.778	...	0.927
Node 18	0.116	0.072	0.19	0.325	0.422	0.2	...	0.337
Node 19	0.396	0.367	0.521	0.547	0.299	0.215	...	0

Best Cluster Heads Indices: [0, 8, 19, 13]

Best Cost: 4.040

Likewise, we calculate the distance matrix with 50 nodes Distance Matrix:

```
[[0.000   0.179   0.143   ...   0.592   0.696   0.764]
 [0.179   0.000   0.206   ...   0.479   0.525   0.586]
 [0.143   0.206   0.000   ...   0.482   0.647   0.759]
...
 [0.592   0.479   0.482   ...   0.000   0.339   0.568]
```

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[0.696	0.525	0.646	...	0.339	0.000	0.243]
[0.764	0.586	0.759	...	0.568	0.243	0.000]]

The figure 2 shows the cluster heads with best cost. Best Cluster Heads Indices: [15 25 39 16] Best Cost: 13.804

Cluster Head 15 costs:

[0.204, 0.209, 0.251, 0.197, 0.198, 0.209, 0.000, 0.281, 0.291, 0.216, 0.120, 0.145] Total cost for cluster head 15: 2.323

Cluster Head 25 costs:

[0.397, 0.399, 0.537, 0.203, 0.312, 0.424, 0.435, 0.434, 0.173, 0.347, 0.419, 0.505]

Total cost for cluster head 25: 4.586

Cluster Head 39 costs:

[0.227, 0.372, 0.324, 0.086, 0.246, 0.097, 0.212, 0.137, 0.269, 0.013, 0.000, 0.296, 0.065] Total cost for cluster head 39: 2.346

Cluster Head 16 costs:

[0.174, 0.148, 0.338, 0.374, 0.441, 0.571, 0.163, 0.501, 0.234, 0.172, 0.530, 0.522, 0.381] Total cost for cluster head 16: 4.550

Best Cost Calculation: Within the assigned cluster the sum of distances from each chosen cluster head to all other nodes is the best cost. This is iteratively refined by the TS, which explores different sets of cluster heads, ensuring that already tried suboptimal solutions are not revisited.

Optimization Using Tabu Search: By maintaining a list of recently considered solutions (Tabu list), the algorithm avoids cycling back to them, promoting the exploration of new solutions and potentially finding a better overall configuration of cluster heads.

Visualization: The final output includes a plot showing the clustered nodes and the cluster heads, providing a visual representation of how the TS has optimized the selection of cluster heads.

5.1 Comparing TS approach with SWARAM, HSWO, EECHIGWO, and EECHS-ARO.

A scatter plot is generated to visualize the clusters and the selected cluster heads. CHs are highlighted with red 'x' markers, and the nodes are colored based on their cluster assignments.

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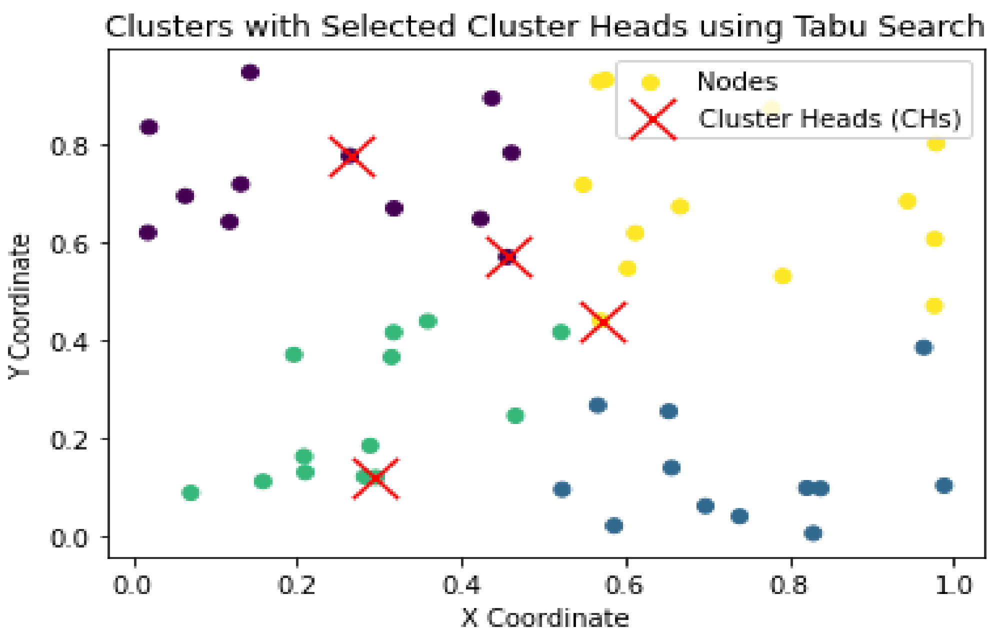

Figure 2. Scatter plot: TABU SEARCH

Tabu Search Best Solution: [15 25 39 16]

Tabu Search Best Cost: 13.804476808297835

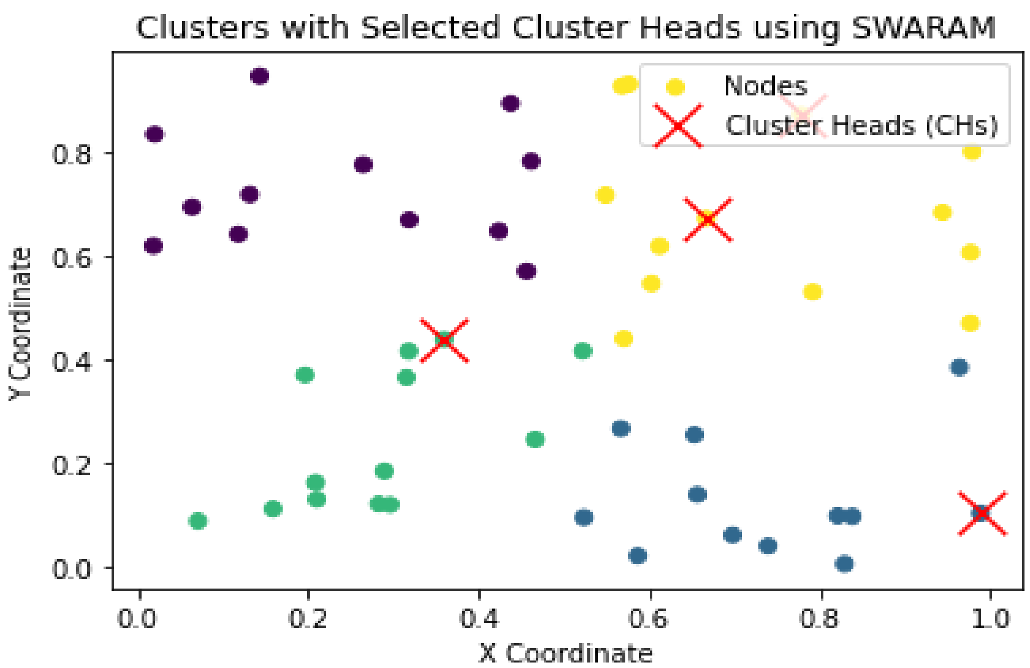

Figure 3. Scatter plot: SWARM ALGORITHM

SWARAM Best Solution: [22 26 20 9]

SWARAM Best Cost: 15.526

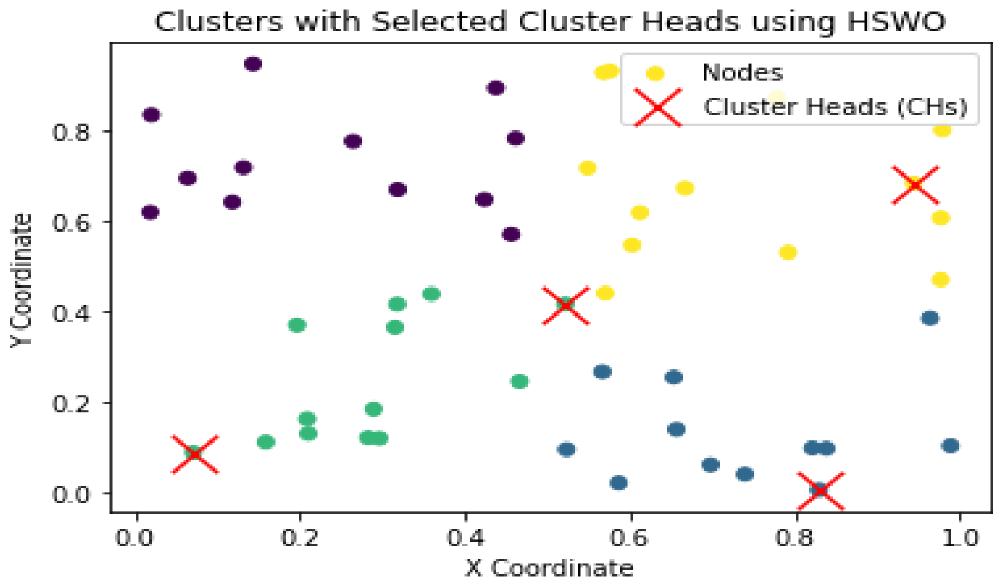

Figure 4. Scatter plot: HSWO Method

HSWO Best Solution: [7 14 49 19]

HSWO Best Cost: 24.441

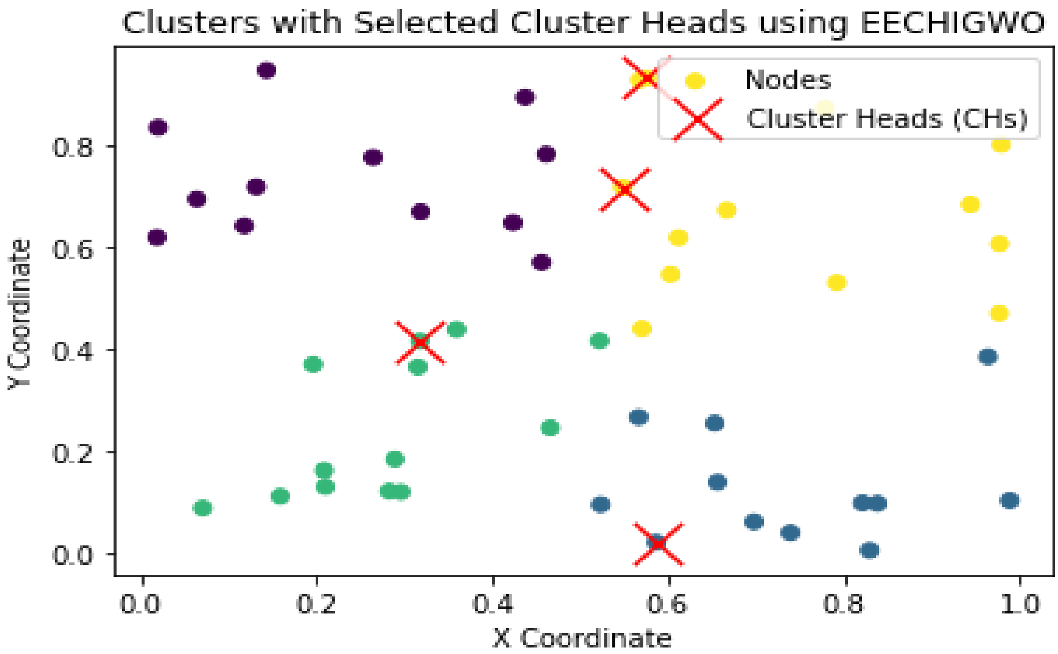

Figure 5. Scatter plot: EECHIGWO

EECHIGWO Best Solution: [48 0 44 40]

EECHIGWO Best Cost: 33.878

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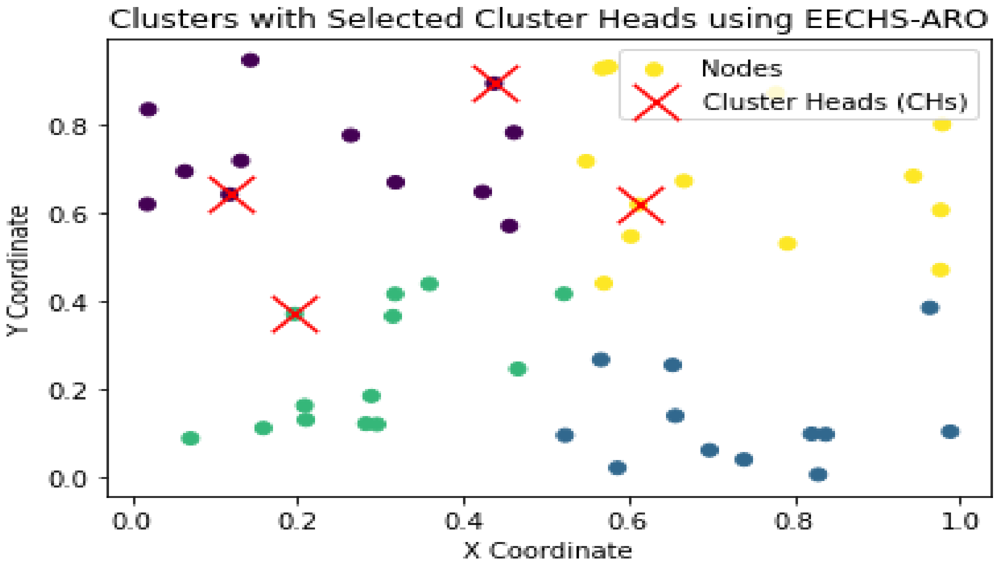

Figure 6. Scatter plot: EECHS-ARO

EECHS-ARO Best Solution: [12 3 32 18]

EECHS-ARO Best Cost: 18.495

The figure 3 shows the cluster heads with best cost of SWARAM.

Best Solution: [22 26 20 9]

Best Cost: 15.526

The figure 4 shows the cluster heads with best cost of HSWO.

Best Solution: [7 14 49 19]

Best Cost: 24.441

The figure 5 shows the cluster heads with best cost of EECHIGWO.

Best Solution: [48 0 44 40]

Best Cost: 33.877

The figure 6 shows the cluster heads with best cost of EECHS-ARO.

Best Solution: [12 3 32 18]

Best Cost: 18.495

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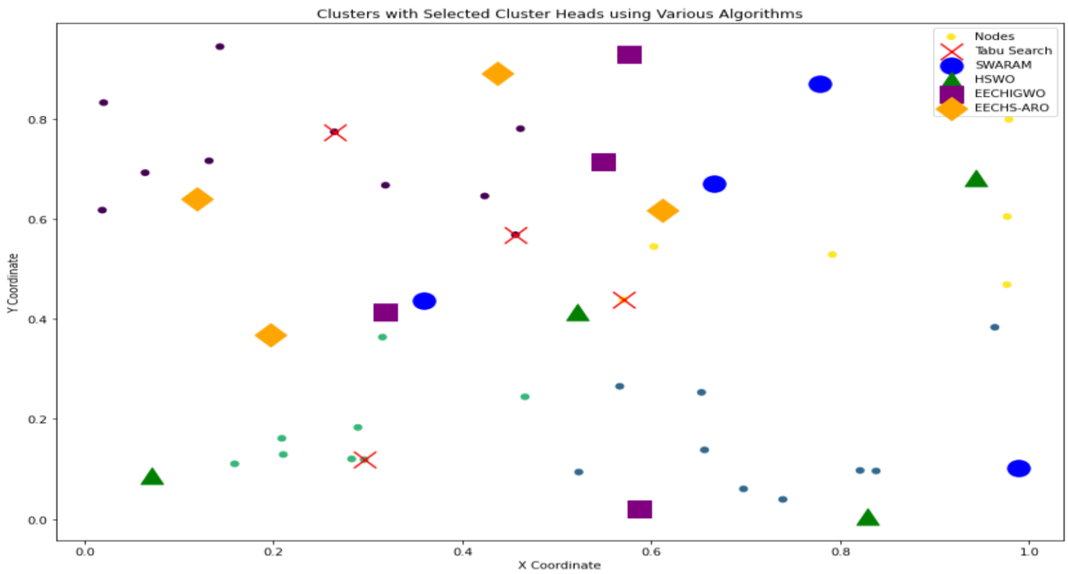

Figure 7. Scatter plot: TABU SEARCH, SWARAM, HSWO, and EECHIGWO, EECHS-ARO.

Table 2:Algorithm and Fitness Value

Algorithm	**Fitness Value**
Best Cost, Tabu Search	13.804
Best Cost, Swaram	15.5264
Best Cost, EECHS-ARO	18.4954
Best Cost, HSWO	24.441
Best Cost, EECHIGWO	33.877

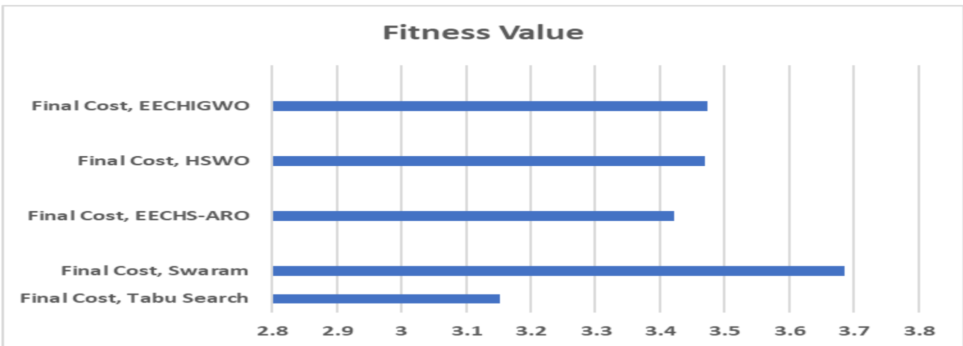

Figure 8. Fitness value with TABU SEARCH, SWARAM, HSWO, EECHIGWO and EECHS-ARO.

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6. CONCLUSIONS AND FUTURE DIRECTIONS

The TS algorithm's performance was compared to existing CH selection techniques such as SWARAM, HSWO, and EECHIGWO, EECHS-ARO. The suggested TS strategy increases the network's overall performance. The best cost for TABU Method, SWARAM, HSWO, EECHIGWO and EECHS-ARO given respectively 13.804, 15.526, 24.441,18.495 and 18.495. In future we can implement mobile chargers path planning with the given CH to increase overall performance of the network.

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