Sidra Khan, 2026, 14:3
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology
An Open Access Journal

Teacher Learning Based IOT Wireless Network Optimization Models and Techniques

Sidra Khan, Mtech S.S Scholar, Sujeet Gautam, Assistant Professor
Department of Computer Sciences and Engineering,
Patel College of Science and Technology Bhopal

Abstract- Wireless Sensor Networks (WSNs) and Internet of Things (IoT) systems play a crucial role in modern smart applications such as smart cities, healthcare, industrial automation, and precision agriculture. Despite rapid advances in communication, cloud, and edge computing technologies, energy efficiency remains a fundamental challenge due to the limited power resources of sensor nodes. This work has proposed a IOT network optimization model that cluster nodes into cluster and further transfer packets from sensing ITO device to the base station. Clustering of model was done by teacher learning model as without prior knowledge algorithm cluster nodes in dynamic situations of WSN. Use of linear routing algorithm energy utilization was highly dropped. Experiment was done on various virtual environment of nodes and region. Result shows that Teacher Learning based Optimize Cluster Center (TLOCC) algorithm work has improves the life span of the ITO network.

Keywords: IOT network, WSN, Genetic algorithm, clustering, energy optimization.

I. INTRODUCTION

The Internet of Things (IoT) has transformed the way devices communicate and interact with one another. It enables a large number of smart devices to connect and exchange information for various applications. The rapid growth of IoT has led to the deployment of extensive networks consisting of heterogeneous and resource-constrained devices. These devices are widely used in applications such as smart cities, industrial automation, healthcare systems, and environmental monitoring. Since most IoT devices operate with limited battery power, energy efficiency has become one of the most important challenges. Therefore, the development of energy-aware routing protocols is essential to prolong network lifetime and ensure reliable data transmission within IoT environments [1].

In Industrial Wireless Sensor Networks (IWSNs), sensor nodes are responsible for collecting and transmitting data to a base station. When nodes communicate directly with the base station, especially those located at greater distances, a significant amount of energy is consumed during data transmission [2]. This excessive energy usage can quickly drain the battery resources of sensor nodes and reduce the overall network lifespan. To overcome this limitation, hierarchical multi-hop routing techniques are commonly employed. In such approaches, data is forwarded through intermediate nodes before reaching the base station, thereby reducing transmission distance and energy consumption [3].

During the implementation of hierarchical multi-hop routing, the network is organized into clusters. Each cluster consists of ordinary sensor nodes, known as cluster members, and a special node called the Cluster Head (CH) [4]. The cluster head is typically selected based on factors such as residual energy, network location, and communication capability. Compared with regular sensor nodes, cluster heads usually possess higher energy resources and are strategically positioned to efficiently collect data from cluster members, aggregate the received information, and forward it toward the base station. This clustering mechanism helps balance energy consumption across the network and improves overall communication efficiency.

Traditional routing protocols such as LEACH (Low-Energy Adaptive Clustering Hierarchy) and HEED employ clustering mechanisms to reduce the energy consumption of sensor nodes during data transmission to the base station [5]. In these approaches, cluster heads collect and aggregate data from member nodes before forwarding it to the base station, thereby minimizing communication overhead and conserving energy. Although these protocols improve network efficiency and extend network lifetime to some extent, they face significant challenges in dynamic IoT environments where network topology and traffic conditions frequently change.

In addition, single-level clustering approaches often fail to distribute energy consumption evenly among all network nodes. As a result, certain nodes, particularly cluster heads, may deplete their energy resources much faster than others. This uneven energy utilization can lead to early node failures, reduced network coverage, and a gradual decline in overall network performance.

The remainder of this paper is organized as follows. Section 2 reviews existing clustering and routing techniques used in wireless sensor networks. Section 3 describes the proposed Teacher Learning-Based Optimized Cluster Center (TLOCC) methodology in detail. Section 4 presents the performance evaluation of the proposed approach and compares its results with the conventional DPSO method and the advanced EBPT-CRA technique. Finally, Section 5 summarizes the major findings of the study and discusses potential application areas and future research directions.

II. RELATED WORK

Yousra Mahmoudi et al. [6] investigated energy optimization in IoT networks by addressing the clustering problem through a quantum-inspired metaheuristic algorithm that combines the Firefly Algorithm and Particle Swarm Optimization (PSO). In their approach, the cluster head selection process is represented using n-Qbits. The algorithm explores the search space by adjusting the rotation angles of Qbits associated with less effective solutions, thereby generating improved candidate solutions. This strategy enhances the ability of the network to select energy-efficient cluster heads and reduce overall energy consumption.

Shi et al. [7] proposed a routing protocol based on Ant Colony Optimization (ACO) and evaluated its performance through simulation. The proposed method performs clustering and routing by considering several factors, including node energy levels, collision avoidance, distance between cluster heads and the destination, and the energy status of neighboring nodes. Cluster heads are selected according to maximum residual energy, minimum communication distance, and lower energy consumption. To further improve routing efficiency, nodes with energy levels above a predefined threshold are chosen as new cluster heads. The routing process follows multiple criteria, including shortest path selection, optimal forwarding path, minimum distance between source and destination nodes, and efficient route maintenance.

Almudayni et al. [8] focused on identifying the major causes of energy wastage in IoT systems and proposed a framework to improve energy efficiency and overall system performance. Their study reviewed research published since 2010 and identified eleven important factors contributing to energy inefficiency, including task offloading, scheduling, latency, topology changes, load balancing, node deployment, resource management, congestion, clustering, routing, and bandwidth limitations. Based on these findings, they developed a framework that integrates optimized communication protocols such as CoAP and MQTT, adaptive fuzzy logic techniques, and bio-inspired optimization algorithms. The proposed framework aims to improve resource utilization, increase network stability, extend device lifetime, and reduce operational costs.

M. Haris et al. [9] introduced a Particle Swarm Optimization-based clustering approach that employs a double-exponential adaptive inertia weight mechanism. This adaptive strategy effectively balances global exploration and local exploitation during the optimization process, reducing the likelihood of premature convergence. The proposed method improves cluster head selection accuracy and enhances network energy efficiency. Sensor nodes are categorized as cluster members, cluster heads, and free nodes. The residual energy of each node is used to determine the optimal number of clusters dynamically, while location information is utilized to form balanced clusters and assign high-energy nodes as cluster heads.

Amutha et al. [10] developed a hybrid cluster-based optimization method called Energy-Efficient Chimp Optimization Algorithm (EE-CHOA) for wireless sensor networks with both static and mobile sink nodes. The objective of the proposed approach is to extend network lifetime by selecting the most suitable sink node and optimizing data transmission routes within a clustered communication structure. Experimental results indicate that EE-CHOA improves energy efficiency by approximately 20% and increases network lifetime by nearly 35% compared to existing approaches.

Rawat et al. [11] proposed a clustering and sleep scheduling technique based on Particle Swarm Optimization for wireless sensor networks. Their method enhances energy conservation by intelligently controlling the active and sleep states of sensor nodes while simultaneously forming efficient clusters. Simulation outcomes show that the proposed scheme significantly reduces overall energy consumption by nearly 50% and extends network lifetime by approximately 60%, demonstrating its effectiveness for energy-aware wireless sensor network applications.

III. PROPOSED METHODOLOGY

The proposed Teacher Learning-based Optimized Cluster Center (TLOCC) algorithm is explained in this section to provide a comprehensive understanding of the entire methodology. The proposed approach focuses on identifying the optimal set of cluster centers by incorporating a genetic optimization strategy during the cluster formation process. The effectiveness of the algorithm depends on the dynamic energy conditions of sensor nodes deployed within the network. Heterogeneous sensor nodes with varying energy capacities are considered in this work, making residual energy a crucial parameter for cluster center selection.

Develop Heterogeneous Node Environment
An M × M sensing region is created in which N sensor nodes are randomly deployed, as illustrated in Figure 1. Each sensor node possesses a different initial battery energy level, resulting in a heterogeneous wireless sensor network [12]. Before any data transmission or reception takes place, the initial energy of every node is assigned and monitored. The energy consumption of each node must be evaluated to determine its suitability for cluster head selection. The energy consumed during data transmission and reception can be calculated using the following equations:

$$ETx(L,d) = Eelec \times L + a \times L \times db$$

$$ERx(L,d) = Eelec \times L$$

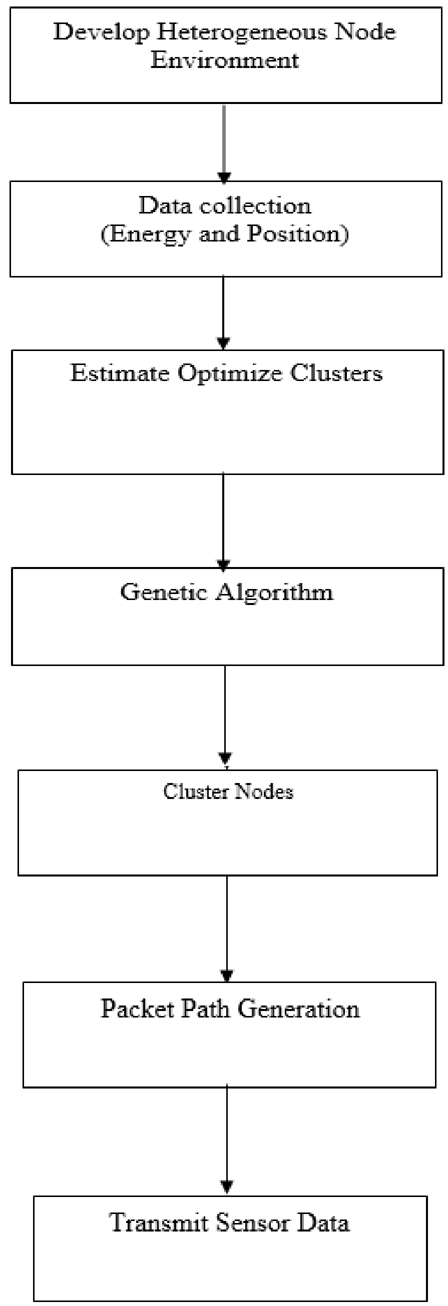

Fig. 1 Block diagram of TLOCC.

where: L represents the length of the transmitted data packet in bits. d denotes the distance between the source and destination nodes. Eelec is the energy consumed per bit by the communication circuitry. a and b are parameters that depend on the transmission distance. When the transmission distance satisfies $d \leq d_0$, the values of a and b are assigned as afs and 2, respectively. Otherwise, for $d > d_0$, the values become aamp and 4. Here, afs and aamp represent the amplifier energy consumption factors. Nodes communicating over longer distances require significantly higher transmission energy because the amplifier must compensate for increased signal attenuation. Therefore, the primary objective of the clustering problem in a wireless sensor network is to maximize the number of active sensor nodes while preserving the residual energy of the entire network. Efficient cluster formation can significantly reduce energy consumption and extend network lifetime.

Estimate Optimize Cluster

To determine the optimal number of clusters that minimizes the overall energy consumption of the wireless sensor network, the total energy consumption function (Etotal) is analyzed with respect to the number of clusters (k). The derivative of Etotal with respect to k is computed and equated to zero. Solving this condition yields the optimal cluster count, denoted as kopt, which minimizes the total energy expenditure of the network. The calculated optimal cluster value serves as the basis for forming energy-efficient clusters and selecting suitable cluster centers within the proposed TLOCC framework.

$$K_{opt} = \sqrt{\frac{N \times \varepsilon_{fs} \times M^2}{2\pi(2E_{elec} + E_A)}}$$

Where ε_fsis amplifier power consumption of the free-space, EA is energy consumption required for nodes to fuse k-length data.

Genetic Algorithm

The proposed work employs a Teacher Learning-Based Optimization (TLBO) assisted Genetic Algorithm for cluster center selection in wireless sensor networks. This optimization technique performs population updates through two distinct phases within a single iteration, namely the teacher phase and the learner phase. The dual-stage learning mechanism enhances the exploration and exploitation capabilities of the algorithm, thereby improving the efficiency of dynamic node clustering and cluster head selection [13].

Generate Population: The optimization process begins by generating an initial population consisting of candidate cluster center sets. Each candidate solution represents a possible arrangement of cluster heads within the network. Population initialization is performed using a Gaussian randomization function, as expressed in Equation (7), to ensure diversity among the generated solutions.
Assume that the network is partitioned into K clusters and the initial population size is IP. A candidate solution can be represented as: Cc = $\{N_1, N_5, N_7, \ldots, N_m\}$ where each selected node acts as a cluster center. A collection of such candidate solutions forms the population:

P = $[Cc_1, Cc_2, \ldots, Cc_n]$ where n denotes the total number of chromosomes in the population and m represents the number of cluster centers within a chromosome. Only sensor nodes having residual energy greater than a predefined threshold energy (TE) are eligible to participate in the cluster center selection process. The population matrix is generated as:

$$P \leftarrow \mathrm{Rand}(m, n)$$

This initialization strategy ensures that the search process starts with feasible and energy-efficient cluster center candidates.
Fitness Function

For finding difference two chromosomes function are use first is total energy consumption required to while transmiting and receiving packets in region under selected cluster set.

The objective function is a variant of that described in [22], which can be divided into two parts. The first part is the normalized energy consumption. The energy consumption for non-CHs is defined as

$$E_{non\text{-}CH} = \sum_{i=1}\sum_{j=1} (E_{Tx} (L, d(CH_i, N_j)) \times Xij$$

where k is the number of CHs; N the number of nodes; l the packet size; and d(CHi;Nj) the distance between the ith CH and the jth node. The value of xij will be set to 1:0 if Nj belong to CHi; otherwise, it will be set 0:0.

For finding difference between two nodes Eludician Distance formula was used. The Euclidean distance d between two nodes X and Y feature vector distance was used in this calculated by
d = [SUM((X-Y).^2)]^0.5

The energy consumption for CHs is defined as

$$E_{CH} = \sum_{i=1}(Lx|Cij|x(E_{DA}+E_{Rx})+E_{Tx}(L, d(CH_i, BS))$$

where jCij is the number of members belonging to the ith CH, and EDA is the energy consumption for data aggregation. In this study, we assume that data from different nodes can be compressed and aggregated into l bits.

$$D = E_{CH} + Enon\text{-}_{CH}$$

So the matrix D contain all the values of the centriod distance from the nodes present in one cluster then find the minimum distance which will evaluate specify best possible solution.

Teacher Phase
In the teacher phase, the best solution in the population is selected as the teacher after sorting all candidate solutions according to their fitness values. The teacher guides the other solutions by sharing some of its cluster center positions. A fixed number of cluster centers from the teacher solution are used to update the student solutions. As a result, the student solutions move closer to the best solution and have a higher chance of achieving better fitness values.

The population P is updated according to the teacher chromosome. The updated solution is calculated as:

$$Xnew,i = Xold, i + \text{Replacing Cluster value}$$

where Xold,i is the current solution and Xnew,i is the updated solution. The new solution is accepted only if it produces a better fitness value than the previous solution.

Student Phase
After the teacher phase, all solutions enter the student phase. In this stage, solutions learn from each other. The population is divided into small groups, and the better solution in each group acts as a teacher for the weaker solution. The learning process is similar to the teacher phase, where a fixed number of cluster centers from the better student are used to update the other student. This interaction improves the quality of the population and increases the possibility of finding better cluster centers.

After completing the student phase, the algorithm checks whether the maximum number of iterations has been reached. If the stopping condition is not satisfied, the process returns to the teacher phase. Otherwise, the learning process stops, and the best solution in the population is selected as the final set of cluster centers. The nodes are then grouped according to these cluster centers.

Final Solution
After several iterations, the algorithm obtains the optimal cluster centers. Each sensor node is assigned to the nearest cluster center, resulting in the final cluster structure of the network.

Cluster Nodea
In this step, the selected cluster center acts as the representative node of its cluster. The location of each sensor node is used to determine its cluster membership. Nodes belonging to the same cluster are grouped together, while cluster centers are highlighted separately for easy visualization.

Linear Routing
Wireless Sensor Networks require energy-efficient communication methods. The proposed approach consists of two main stages: cluster formation and packet routing. Cluster centers are selected using the optimization process, while routing is performed through a linear path toward the base station.

The objective of linear routing is to reduce packet collisions and energy consumption. A logical path is created from the source node to the base station. First, the distance of every node from the base station is calculated and stored.

The node farthest from the base station is selected as the starting point of the route. The algorithm then searches for a nearby cluster center whose distance to the base station is smaller than that of the current node. This process continues until the path reaches the base station. In this way, data packets move through a linear route, reducing communication overhead and improving network performance.

IV. EXPERIMENT AND RESULTS

So as to lead test and measure assessment results MATLAB 2012a platform was used. This area of paper show experimental arrangement and results. The tests were performed on a machine having configuration of Intel Core i3 machine, outfitted with 4 GB of RAM, and running under Windows 7 Professional. Four sets of environment were utilized to assess the working of the TLOCC. The main benchmark is 100 sensor nodes in a region of 100m x100m, the subsequent environment have 150 nodes in 100 x 100m area. While third setup have 100 nodes having 150x150m region, finally fourth have 200x200m region with 150 nodes.

Evaluation Parameters

Number of Rounds: One cycle of sending packet from non cluster center node to Base station is considered as Round. Here numbers of round are count for each comparing methods.

Packet Transfer: This is the number of packet transfer done in the WSN while all the node get discharge, so wireless arrangement having maximum number of packet transfer is good solution.

Results

Here proposed methodology was compared with existing methods in [9]. Results of the TLOCC were evaluate on above parameters.

Table 1 Comparison of First Node Loss Different Area and Nodes.

Region size	Nodes	LEACH-FC	TLOCC
100x100	70	21846	26387
100x100	100	14529	26061
150x150	100	3596	26939

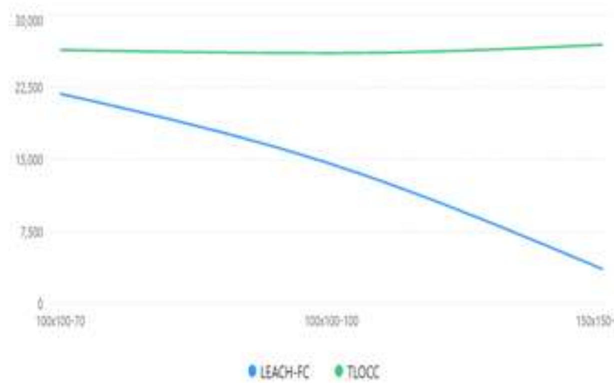

Fig. 2 Block diagram of first node discharge.

Fig. Average first node discharge rounds of the models.

Table 1 shows that TLOCC has improved the number of rounds for first node loss in the network. Here it was obtained that TLOCC efficiently select the cluster center so losses will be reduced and node survive for long duration.

Table 2 Total number of packet transfer count based comparison.

Region size	Nodes	LEACH-FC	TLOCC
100x100	70	1115267	1834173
100x100	100	1614627	2586599
150x150	100	533961	2634932

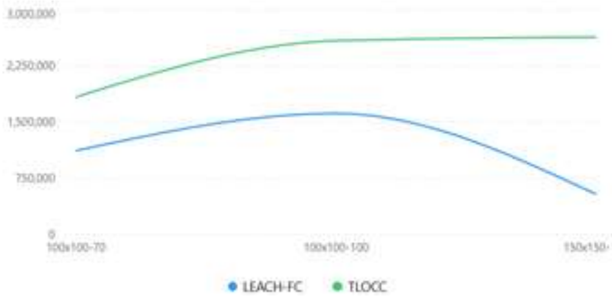

Fig. 4 Packet count based model comparisons.

Fig. 5 Average Packet count based model comparison.

Table 2 shows that TLOCC has improved the number of packets in all set of situations of area and nodes. Here MST based algorithm reduce number of iteration for the efficient cluster center selection. Here large experimental area increment separation between nodes which builds energy requirement for moving same packet size.

Table 3 Number of rounds count based comparison of TLOCC.

Region size	Nodes	LEACH-FC	TLOCC
100x100	70	21389	27918
100x100	100	22558	27502
150x150	100	13595	28518

Fig. 6 Average number of rounds count based model comparison.

Table 3 shows that TLOCC has improved the quantity of rounds in various set of experimental setup and number of nodes. As shown that in small region either number of nodes are less or more number of packets are high. Here huge experimental area increment separation between nodes which builds energy prerequisite for moving same packet size.

VI. CONCLUSION

This paper presented the Teacher Learning-based Optimized Cluster Center (TLOCC) approach for improving energy efficiency and network lifetime in Wireless Sensor Networks (WSNs) and IoT environments. The proposed method combines teacher-learning optimization with a genetic algorithm to identify optimal cluster centers based on residual node energy and network conditions. In addition, a linear routing mechanism was introduced to reduce packet collisions and communication overhead during data transmission.

The performance of TLOCC was evaluated under different network sizes and deployment scenarios. Experimental results demonstrated significant improvements in network lifetime, packet delivery, and node survivability compared with the conventional protocol. The proposed approach achieved a higher number of communication rounds before node failure and increased the total number of successfully transmitted packets. These improvements were obtained through efficient cluster formation and balanced energy consumption among sensor nodes. Therefore, TLOCC provides an effective and scalable solution for energy-aware routing and clustering in resource-constrained IoT and wireless sensor networks.

REFERENCES

1. Vashishth, V., Chhabra, A., Khanna, A., Sharma, D.K., Singh, J. (2018). An energy efficient routing protocol for wireless internet-of-things sensor networks.
2. Sun, X. et al. How To Securely Outsource the Multiple Kernel Fuzzy Clustering Task in Edge Computing (IEEE Internet of Things Journal, 2025.

3. Xu, J. et al. How to characterize imprecision in multi-view clustering? In IEEE Transactions on Emerging Topics in Computational Intelligence. 1–12 (2025).
4. Rahmani, A. M. et al. A routing approach based on combination of Gray Wolf clustering and fuzzy clustering and using multi-criteria decision making approaches for WSN-IoT. Comput. Electr. Eng.122, 109946 (2025).
5. Liang, W., Ma, C., Zheng, M., & Luo, L. (2019). Relay node placement in wireless sensor networks: From theory to practice. IEEE Transactions on Mobile Computing, 20(4).
6. Yousra Mahmoudi, Nadjet Zioui, Hacene Belbachir, A new quantum-inspired clustering method for reducing energy consumption in IOT networks, Internet of Things, Volume 20, 2022.
7. Shi, B.; Zhang, Y. A Novel Algorithm to Optimize the Energy Consumption Using IoT and Based on Ant Colony Algorithm. Energies 2021, 14, 1709.
8. Almudayni, Z.; Soh, B.; Samra, H.; Li, A. Energy Inefficiency in IoT Networks: Causes, Impact, and a Strategic Framework for Sustainable Optimisation. Electronics 2025, 14, 159.
9. M. Haris and H. Nam, "Enhancing Energy Efficiency in IoT-WSNs Through Optimized PSO Cluster Head Selection," in IEEE Access, vol. 13, pp. 126496-126512, 2025.
10. Latha Tamilselvan, Dr. V Sankaranarayanan, "Prevention of Blackhole Attack in MANET", In Proceedings of IEEE 2nd International Conference on Communications, IEEE 2007.
11. A.D. Wood and J.A. Stankovic, “Denial of service in sensor networks”, IEEE Computer, Vol. 35, No. 10, pp. 54-62, 2002.
12. Shahraki, A. Taherkordi, Ø. Haugen, and F. Eliassen, “A survey and future directions on clustering: From WSNs to IoT and modern networking paradigms,” IEEE Trans. Netw. Service Manage., vol. 18, no. 2, pp. 2242–2274, Jun. 2021.
13. Sahoo, A.J., Kumar, Y. (2014). Modified Teacher Learning Based Optimization Method for Data Clustering. In: Thampi, S., Gelbukh, A., Mukhopadhyay, J. (eds) Advances in Signal Processing and Intelligent Recognition Systems. Advances in Intelligent Systems and Computing, vol 264. Springer, Cham.
14. Sushanta Kumar Panigrahi, Sabyasachi Pattnaik, Empirical Study on Clustering Based on Modified Teaching Learning Based Optimization, Procedia Computer Science, Volume 92, 2016.