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Dynamic Cluster Head Selection Algorithm for IoT-Based Smart Agriculture: An Energy Efficient Approach

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Abstract – The Internet of Things (IoT) can be deployed over agricultural land to support various processes. Field sensors collect data and forward it to the base station via the Cluster Head (CH), which is responsible for network operations, including data collection, aggregation, and packet forwarding. This extra control overhead can reduce the CH's lifespan. If CH is down, this may cause broken links/network partitioning because sensors cannot communicate directly with the base station. Researchers used various parameters (e.g., residual energy, intermediate distance from base station/field sensors) as criteria to optimize CH selection. However, this process does not ensure the overall network performance and its lifespan. It is still an open issue, and the objective of the current research work is to explore the other parameters that can be used to enhance the CH selection process. In this paper, a dynamic cluster-head selection scheme is presented to address this issue. It performs CH selection using multiple parameters (i.e. sensitivity, distance, residual energy, interference level, collision, congestion, signal-to-noise ratio, packet drop, member threshold, etc.). Its performance will be evaluated using the Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol, the LEACH-centralized (LEACH-C) variant, and the Power-Efficient Gathering in Sensor Information Systems (PEGASIS) under various constraints. Analysis shows that it outperforms other protocols in terms of higher throughput, higher packet delivery ratio, optimal residual energy, minimal Delay/Jitter, and a higher number of alive sensors with minimal collision level. A performance comparison with two-level game theory-based CH selection indicates that it is an energy-efficient approach that can extend the overall network lifespan by optimizing resource consumption using the CH selection metric.

Index Terms – Cluster Head Selection, Energy Efficiency, Internet of Things, LEACH, PEGASIS, LEACH-C, Smart Agriculture.

1. INTRODUCTION

Smart Agriculture uses different technologies and applications to manage the various processes related to irrigation, such as crop health and livestock monitoring. There are several parameters associated with each process, and there may be a little bit of variation in their values. Sensors may monitor constant parameters over a long interval, or, to perform random sampling, may generate a huge volume of redundant data.

This results in processing consuming the excessive network resources unnecessarily [1]. Researchers addressed this issue and introduced the concept of data aggregation, which is used to suppress redundant data. It is essential for smart farming due to the following reasons:

- Farming applications produce large volumes of data as per the crop type and fail to consider the excessive computational load on sensors.
- Bulk transmission of redundant data may reduce the overall lifespan of the sensors.
- IoT networks are designed to forward the data over long distances, and excessive transmission may cause congestion over the network [2].

To perform the data aggregation, the entire network is subdivided into multiple small regions, called clusters, and inside a region, a special node is selected to perform the data aggregation after collecting the data from field sensors, called the cluster head (CH). There are different network models to arrange the clusters in the network, as shown in Figure 1.

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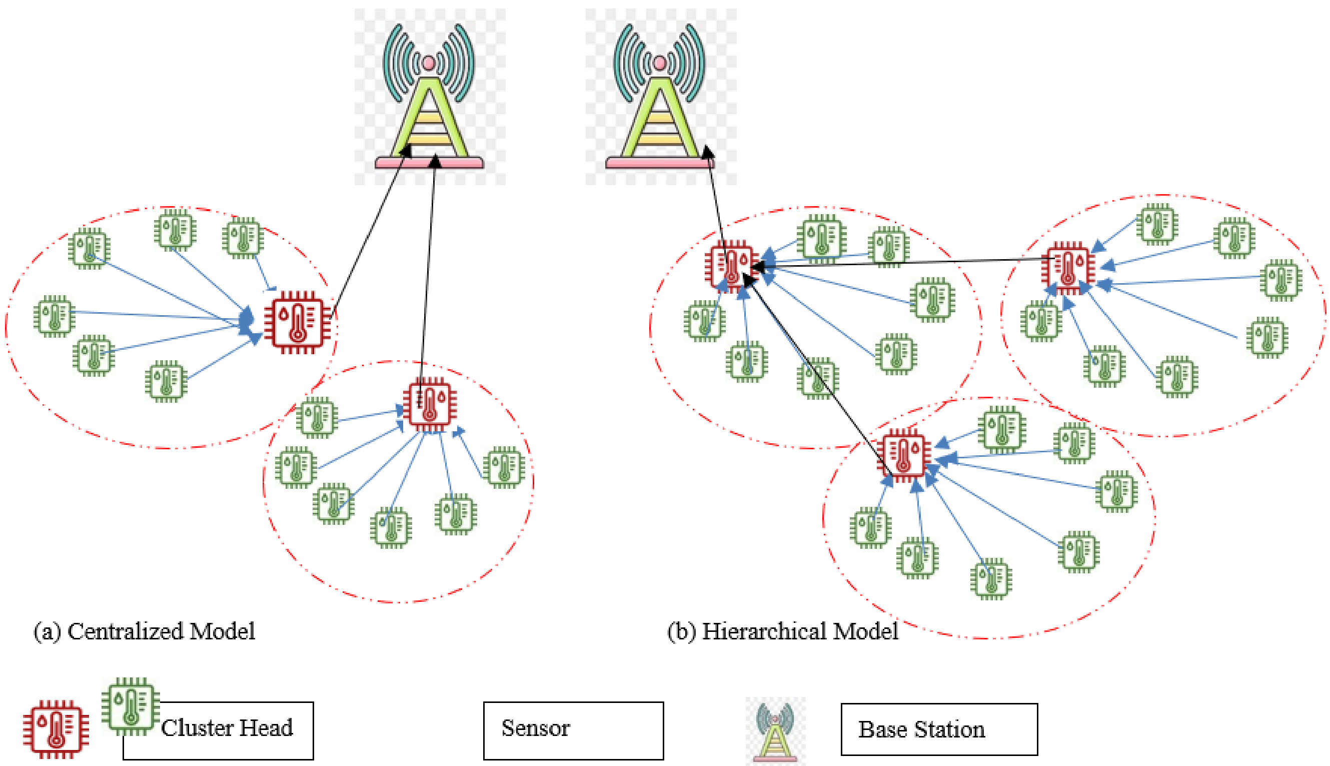

Figure 1 An Overview of Network Clustering Models for IoT-Based Sensor Networks

In the case of a centralized model, data is forwarded to a common CH. In a hierarchical approach, data is forwarded from the lower level to the upper level through CHs towards the base station. By combining these two approaches, a hybrid model can be constructed. With the rapid evolution of the Internet of Things, it has become essential to monitor environmental conditions, automate irrigation, increase crop output, and facilitate data-driven decision-making in the smart agriculture field. A cluster head forwards the sensed data to a base station. The CH uses a lot more energy than standard field sensors because it carries out various network functions. However, one of the most critical issues in IoT-enabled agricultural networks is still choosing the best cluster head. Choosing the best cluster head is not easy, yet it is very important because the cluster as a whole becomes non-functional if the CH runs out of energy too soon, which not only causes data loss and network partitioning, but also broken communication channels [3]. For CH selection, traditional clustering procedures like LEACH, LEACH-C, and PEGASIS mostly rely on factors like residual energy or random chance. These methods make the procedure simpler, but they don't take into account how dynamic and complex agricultural landscapes are. Because of this, the chosen CH might not necessarily be the best choice in terms of network stability, dependability, or energy consumption, which would result in poor performance and a shorter network lifetime. Factors such as uneven sensor deployment, fluctuating channel conditions, large coverage areas, and varying network loads greatly influence communication reliability and energy consumption. Therefore, a range of operational and environmental constraints must be considered during CH selection to avoid premature CH failure, excessive retransmissions, and network partitioning. The following key parameters significantly impact the CH selection process in IoT-based smart farming and must be evaluated to ensure stable, energy-efficient, and long-lasting network operations [4-5]. Figure 2 represents the various constraints for choosing CH, including energy level, distance from the base station to the sensors deployed in the field, congestion and lastly collision at the CH. If these constraints are properly managed and checked, then there are chances that CHs may last longer in the network and consume less energy. Hence, selecting an optimal CH requires evaluating all the parameters given below.

- Energy Level: Smart farming requires continuous field monitoring; thus, it requires efficient data aggregation and packet forwarding. Sensors may select a common CH with a higher energy level. Due to excessive computations, CH's battery may be depleted at earlier stages, thus breaking down the entire network. So, on the basis of energy constraints only, CH should not be selected [6].

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- Distance: There are different deployment techniques to deploy the sensors over large-scale agricultural land. Sensors may forward the data to the nearest CH having minimal distance, but it may be far away from the base station. In this case, the cluster head may use multi-hop packet forwarding, thus producing extra control overhead. So, CH must be within the transmission range of the base station and sensors.
- Congestion: Sensors may collect the farming data dynamically, and it can be forwarded to a single CH, which may cause congestion at the CH side, and due to excessive payload, there may be packet drop, retransmission, etc. Sensors should also consider this constraint for CH selection [7].
- Collision: Smart farming-based IoT networks support long-distance transmission. Simultaneously, packet forwarding towards CH may trigger a collision at the MAC layer. It may also cause excessive packet drop/retransmission.
- Transmission Constraints: Another significant issue is related to transmission quality that may be reduced due to different constraints, i.e. large-scale coverage area of agricultural land, noisy channel, farming landscape, and environmental conditions, which can cause signal loss owing to interference [8].

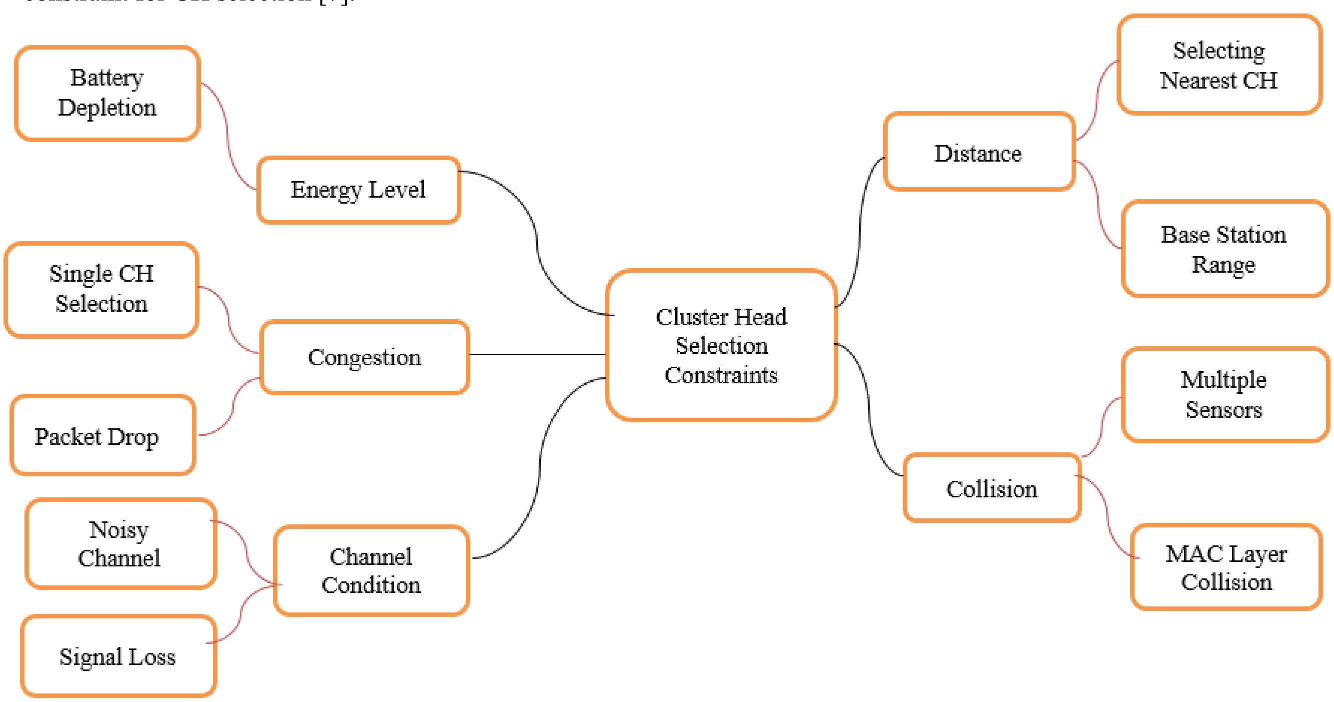

Figure 2 Constraints for Cluster Head Selection

1.1. Problem Statement

There are different types of routing protocols (i.e. LEACH, LEACH-C and PEGASIS) that can be used for smart farming-based IoT networks. These protocols select the CH to perform the network operations, and the following are the two basic phases [9]:

(a) Set Up Phase: In this CH formation process, the process is initiated, and a node with the highest energy is elected as CH, and its advertisement is broadcast over the network, and other nodes receive the incoming advertisement and accept it to become a member of the cluster. At the end of this phase, CH schedules the Time Division Multiple Access (TDMA) slots for the member nodes.

(b) Steady Phase: During the TDMA slot, member nodes can forward the data to their CH, which is responsible for the aggregation, and finally, it is further forwarded to the base station. After expiry of the current slot, the CH formation phase is repeated, followed by the steady phase.

There are a few limitations of the LEACH protocol, i.e. first of all, there is no provision to estimate the exact count of required CH for the entire network. Clusters are formed randomly, and each cluster contains an unequal density of sensors, which may cause variations in energy consumption with respect to the size of each cluster volume. If CH could not survive, then there is no provision to collect the data from an unattended cluster. In the case of a mobile environment, it is quite challenging to synchronize the velocity of each sensor with CH, as sensors may join/leave the network at any time. All the above limitations act as performance barriers for the LEACH protocol, and still, all these are open issues. In the case of LEACH-C, the base station selects the CH on the basis of the location and energy level of the sensors, whereas PEGASIS forms a chain for data forwarding. It may have a single CH as the chain head, and dead nodes in the chain may cause broken links. There is a need to develop an approach to overcome these issues.

1.2. Contribution of the Research

To address the discussed shortcomings, researchers propose a Dynamic Cluster Head Selection Algorithm (DCSA) that optimizes CH selection using a holistic set of parameters rather than a single factor. This includes Sensitivity (Sn), Distance (D), Residual Energy (Re), Interference Level (Il), Collision (Cl), Congestion (Cg), Signal-to-Noise Ratio (SNR), Packet Drop (Pd), and Maximum Member Threshold (MT). It supports the following features.

1. Multi-constraint CH selection: It enhances network performance by simultaneously considering energy, distance, interference, congestion, packet drop, and cluster size.
2. Balanced energy consumption: Ensures that cluster sizes are uniform, reducing energy usage variation across the network.
3. Enhanced fault tolerance: Enables continuous operation and data collection even when a CH fails.
4. Optimized for reliable communication: Increases data transmission reliability by incorporating SNR and packet drop constraints.
5. Reduced congestion and collisions: Reduces delays and retransmissions through optimised cluster design.
6. Scalable design: Suitable for both static and moderately dynamic IoT deployments in smart agriculture.

There are few limitations of proposed scheme as discussed below

1. It does not consider the node's mobility.

2. There is no support for network partitioning recovery.

1.3. Paper Organization

The structure of this paper is organized as follows: Section 1 provides an overview of smart agriculture and IoT-based clustering, explaining how data aggregation reduces redundant transmissions and describing existing clustering models, CH selection constraints, and the limitations of popular protocols such as LEACH, LEACH-C, and PEGASIS. Section 2 conducts a thorough literature review, summarising existing research and highlighting key gaps. Section 3 describes the proposed approach, the Dynamic Cluster Head Selection Algorithm, including its design, working principles, and advantages over current methods. Section 4 presents the results and analysis, with a focus on the performance evaluation and comparative assessment of the proposed scheme. Last but not least, Section 5 concludes the paper by summarising the key findings and suggesting potential directions for future research.

2. LITERATURE SURVEY

In the case of smart agriculture, WSN performs the long interval operations. Its performance depends on the various factors such as routing strategies, intermediate communication and data exchange process between sensors, location and distance between sensors, shared channel allocation and signal propagation methods (underwater/surface level), data computational cost, network dynamics, etc. In [3], the authors present an energy-saving clustering method in which an improved water–cycle algorithm based on an IoT network is developed. In this work, the CH are chosen by considering both the factors that are remaining energy of sensors and their distance, so that the network lasts longer. The developed approach is tested against various existing algorithms, and results show better performance in terms of various parameters such as packet delivery, delay, throughput, and overall lifetime. Additionally, in [10], a genetic algorithm for the CH selection over a heterogeneous network environment on the basis of different parameters, i.e. residual energy/distance/density of intermediate nodes, etc., and finally, a greedy method is applied to select the optimal cluster head. Analysis shows that it can reduce the overall energy consumption, thus increasing the network lifespan.

Further, in [11], the fuzzy logic with a routing protocol for IoT networks is integrated to select CH dynamically. Performance comparison with existing protocols (LEACH/Adaptive LEACH) shows that it outperforms in terms of residual energy/node life time etc. Moreover, in [12], a clustering method for smart farming is presented. It forms a region-based cluster head that forwards the data to the base station using the shortest paths. Analysis indicates that it offers a higher network lifespan as compared to the existing shortest path routing algorithm. Additionally, in [13] a smart irrigation scheme is discussed that offers multiple connectivity options between intermediate nodes and the CH, thus extending the IoT network geographically. Results show that it optimises the overall energy consumption. In [14], the authors developed a clustering algorithm for IoT-based UAV-sensor networks. It uses a vector-based global optimiser for the selection of CH over a large-scale coverage area. UAV forwards the data to the nearest cluster head to minimise the transmission overhead. Analysis shows that it optimises the computation overhead/energy consumption, thus resulting in

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an extended life span. Subsequently, in [15], a routing solution for smart irrigation is developed. It uses multiple optimisers to select the CH based on residual energy/current traffic conditions, etc. Simulation results show that it can redirect the traffic dynamically by selecting optimal paths, thus consuming less network resources as compared to existing solutions. Additionally, in [16], a scheme to ensure the quality of transmission over WSN-IoT networks for smart farming is proposed. It selects the intermediate CH based on link quality and the current value of the signal-to-noise ratio. Experiments show that it enables long-distance transmission by ensuring the quality of services (QoS), and it is suitable for heterogeneous networks. Further, in [17] a fuzzy logic-based CH section method for smart farming is presented. It uses fuzzy interference to calculate the next CH on the basis of residual energy and distance to the intermediate nodes (for data forwarding). Analysis shows that it minimises the overall energy consumption, and it also offers reliable communication over IoT networks. Moreover, in [18], the authors developed an energy-efficient routing solution for smart farming. It supports multiple operations (i.e. data sensing & analysis/optimal CH selection) over IoT networks. It uses fuzzy logic for the CH selection over a distributed coverage area, and after that, region-based routing paths are used to ensure the transmission quality. Experiments indicate that it outperforms in terms of QoS/ resource utilisation/node's life-span, etc. Subsequently, in [19], a routing scheme for smart farming is introduced. It uses a deep learning method for CH selection. Analysis shows that it can update its CH selection process using feedback and it is more efficient and supports optimal energy consumption as compared to existing methods.

In [20], the authors investigated the different issues related to resource utilisation for smart farming, and they found that traditional sensor networks can be upgraded to an IoT platform, to improve crop production, and operating costs can be further optimised using cutting-edge technologies. Moreover, [21] proposed an energy-efficient method for smart forming that forms a group of sensors on the basis of the highest energy level, and it selects CH from this group. Experiments show that this scheme optimises the CH selection process, thus improving the overall network lifespan. Additionally, in [22], an energy-efficient solution for smart farming is proposed. The cluster head is selected on the basis of the resource consumption rate. Intermediate nodes with sharp battery depletion are not selected as Cluster heads, thus increasing the network life span. Analysis indicates that it consumes optimal resources as compared to existing schemes.

In [23], the authors proposed a routing protocol that forms a CH over multi-hop paths. Comparison with chain/grid-based routing solution, it outperforms in terms of extended network lifespan/ optimal resource consumption/minimal routing overhead, etc. In [24], the authors merged the ant colony algorithm with K-means clustering and developed a reliable routing scheme for smart farming. Analysis shows that it utilises minimal energy for the CH selection process and extends the network lifespan as compared to traditional methods. In [25], the authors presented inter-clustering-based routing for smart farming. It selects the cluster head by estimating the current load factor and the residual energy level of intermediate nodes. Analysis shows that it improves the network life with minimal packet loss. Further, in [26], the performance of cluster-based routing over IoT networks is investigated. Study shows that there is a need to optimise the CH selection to minimise the energy consumption, which also affects the overall network performance.

Moreover, in [27] a hybrid clustering method for IoT networks is developed. It uses a meta-heuristic optimisation approach for CH selection. Analysis shows that it outperforms in terms of throughput/residual energy consumption, etc. Subsequently, in [28], the authors used fuzzy logic with k-means clustering to form the cluster head over an IoT network. Furthermore, in [29], a clustering algorithm for a UAV-based IoT network is developed. It uses deep learning to elect the cluster head, and its location is dynamically updated as per the current UAV's trajectory. Analysis shows that deep learning can be used to enhance the cluster head selection process, and it also enhances the network lifespan. In [30], the authors developed a cross-layer routing for WSN-IoT networks. It forms CH by considering the QoS parameters of different layers (i.e. MAC/PHY layers).

Experiments show that it fulfils QoS constraints/optimal energy consumption/minimum routing overhead as compared to existing schemes. However, in [31] a distributed CH selection scheme for IoT networks is presented. It forms CH as per the current traffic load over the network, and intermediate nodes can forward the data using the shortest path to the intermediate CH. Analysis shows that it is highly efficient as compared to existing load balancing algorithms for WSN-IoT networks. Additionally, in [32], the authors proposed a nature-inspired method for smart farming. It uses a fitness function to estimate the next CH. Analysis shows that it consumes minimal energy for the CH selection process as compared to existing methods. On top of that, in [33], a fuzzy logic-based IoT network that uses the MapReduce framework for the CH selection is represented. CH uses a fitness function to forward the data to the base station. Analysis shows that it reduces the routing delay/overhead and enhances the network performance.

Moreover, in [34] a cluster-based routing protocol for smart farming is presented. It forms a centralised CH on the basis of the residual energy level of intermediate nodes and forwards the data by adapting the shortest routes. Analysis shows that it offers reliable transmission with optimal resource consumption. Subsequently, in [35], the authors introduce an intelligent Neutrosophic Clustering-based Routing Protocol (INCRP), which addresses uncertainty and unequal parameter weighting in WSN cluster formation. Using a Self-Adaptive Weighted Neutrosophic C-Means (SWNCM) algorithm and Greylag Goose Optimization (GGO), the model improves CH selection and routing efficiency.

Results show significantly higher packet delivery, lower delay, and reduced energy consumption compared to LEACH, Threshold Sensitive Energy Efficient Sensor Network (TEEN), and Hybrid Energy Efficient Distributed (HEED). Lastly, in [36] authors present an Energy-based Cauchy Mechanism – Pufferfish Optimization Algorithm (ECM-POA) based clustering and routing mechanism through which issues of energy imbalance and early CH depletion in IoT-assisted WSNs are addressed. A Cauchy mutation mechanism is incorporated into the Pufferfish Optimization Algorithm so that global search capability is enhanced and premature convergence is avoided. Experimental analysis demonstrates that network lifetime is extended, with higher residual energy, improved throughput, and reduced delay achieved compared to existing techniques. Table 1 summarizes the overall work done by various researchers in the form of comparative analysis and it can be observed that efficient CH selection is quite critical, thus may fulfil the different constraints associated with network performance, resource consumption, cluster formation, heterogeneous network operations, QoS-enabled routing and reliable transmission, etc.

Table 1 Comparison of the Different Schemes

Issue	Method	Outcomes	Limitations
Inefficient CH selection affecting network lifespan	Improved water-cycle based clustering [3]	Higher throughput, improved PDR, reduced delay	Less effective in dynamic networks
CH selection over a heterogeneous network environment	Constrained-based CH selection [10]	Optimal selection of CH	Extra control overhead
Efficient routing	Fuzzy logic-based route formation [11]	CH selection over reliable routes	Complexity
Cluster localization	Shortest path-based CH selection [12]	Extended network life-span	Computational cost
Multiple locations based cluster formation	Multiple connectivity scheme [13]	Reliable transmission	Topology maintenance
CH selection for UAVs	Global optimizer [14]	Distributed region-based CH selection	Performance dependency on optimizer
Payload-aware routing	Optimal path-based CH selection [15]	Reliable routing	Routing overload
Reliable link formation	Optimal link-based CH selection [16]	Quality of Service (QoS) enabled transmission	Suitable for small networks

Reliable communication over IoT networks	Fuzzy logic-based CH Selection [17]	Reliable routing	Performance may vary due to channel conditions
CH selection using fuzzy logic	Region-based routing [18]	Efficient resource utilization	CH selection accuracy depends on fuzzy logic
Intelligent Routing	Deep learning method-based CH selection [19]	Optimal energy consumption	Dataset validation required
Resource aware routing	Energy aware route selection [20]	Resource-constrained optimal CH selection	Investigation of performance issues only
Network life-span	Resource-based CH selection [21]	Efficient network performance	Computational overhead
resource consumption optimization	Criteria-based CH method [22]	Energy efficiency	Resource consumption rate may vary
Resource utilization	Multi-hop [23] routing	Efficient CH selection	Routing load
Resource-aware routing	K-means clustering [24]	reliable routing	Variations in outcomes
Payload-constrained aware routing	Inter-clustering scheme [25]	Extended network lifespan	Load factor
Cluster-based routing	Cluster-based routing [26]	Efficient energy consumption	CH selection rate
Reliable cluster formation	Meta-heuristic approach for CH selection [27]	Higher network performance	Performance variations due to the meta-heuristic approach
Resource-aware clustering	C-means clustering [28]	Optimal CH selection	Resource allocation
Cluster formation for UAVs	Deep learning method [29]	Location-based clustering	Network dynamics
Crosslayer routing	Optimal CH selection [30]	QoS-constrained clustering	Dependency over multiple layers
Optimization of shortest path routing	Distributed CH selection [31]	Reliable transmission	Computational overhead

Resource aware routing	Nature-inspired routing [32]	Minimal energy consumption	Variations in fitness function outcomes
Delay aware routing	MapReduce-based method [33]	Higher network performance	Computational overhead
Reliable transmission	Cluster-based routing protocol [34]	Reliable transmission	Routing overhead
Uncertainty in CH selection	Neutrosophic clustering (SWNCM) + GGO technique [35]	Higher PDR, lower delay, reduced energy	High computational complexity
Premature CH depletion	ECM-POA with Cauchy mutation [36]	Longer lifetime, higher residual energy, better throughput	Optimization overhead

As per the study, recent solutions focus on optimal Cluster Head (CH) selection, aiming for minimal energy consumption and reliable data transmission. However, each method comes with its own set of limitations related to excessive computational and routing load, resource utilization, network dynamics and payload factor, etc. All these are open issues, and there is a need to develop an optimal solution for the same because these factors may act as constraints for the IoT-based sensor network.

3. DYNAMIC CLUSTER HEAD SELECTION ALGORITHM

IoT networks use multiple CHs to communicate with field sensors, and they also perform various network operations. It is necessary to select an optimal CH for efficient resource utilization and higher network performance. As per the basic concept of the LEACH protocol, only residual energy is used as a constraint for the optimal selection of CH, and the current CH cannot be selected again. So, every time there is a need to select the new CH under the same constraint. Researchers addressed this issue and updated the CH selection phase using different constraints, i.e. payload factor, location of CH, residual energy, resource utilisation and QoS, enabling reliable communication, but still, its optimal selection is an open issue. LEACH is a widely used protocol as compared to LEACH-C and PEGASIS. Current research work investigates its performance issues further and presents a cluster head selection method for IoT networks by optimising the various network operations of the existing LEACH protocol. It modifies the different network operations, i.e. network deployment, that is used to place the sensor over the network. In the cluster formation process, CH is selected, and a cluster is built for data collection. Finally, transmission is initiated and sensors forward the data to the current CH. Algorithm 1 of the proposed scheme is given below, and network operations are represented in Figure 3.

Step 1: Initialize the IoT network.

Step 2: Initiate Cluster.

Step 2.1: Calculate cluster head selection metric (CSM).

Step 2.2: Add sensor(s) to the cluster head list under the constraints of CSM.

Step 2.3: Select Cluster head (CH) w.r.t. CSM.

Step 2.4: Set max. member Threshold (MT) for CH.

Step 2.5: Add sensors in the member list of CH under the constraints of MT.

Step 2.6: Increment the current member capacity for CH.

Step 3: Initiate the transmission towards CH.

Step 4: Finally, CH forwards the data to the base station after aggregation.

Step 5: The Above steps may be repeated if required. The proposed scheme supports the various network operations that are arranged in different steps, and these are discussed in detail below:

Algorithm 1 Dynamic Cluster Head Selection Algorithm

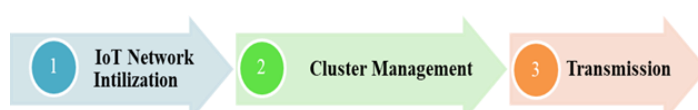

Figure 3 IoT Network Operations

Step 1: IoT Network Initialization: At the initial level, it is used to deploy the sensors over a given coverage area.

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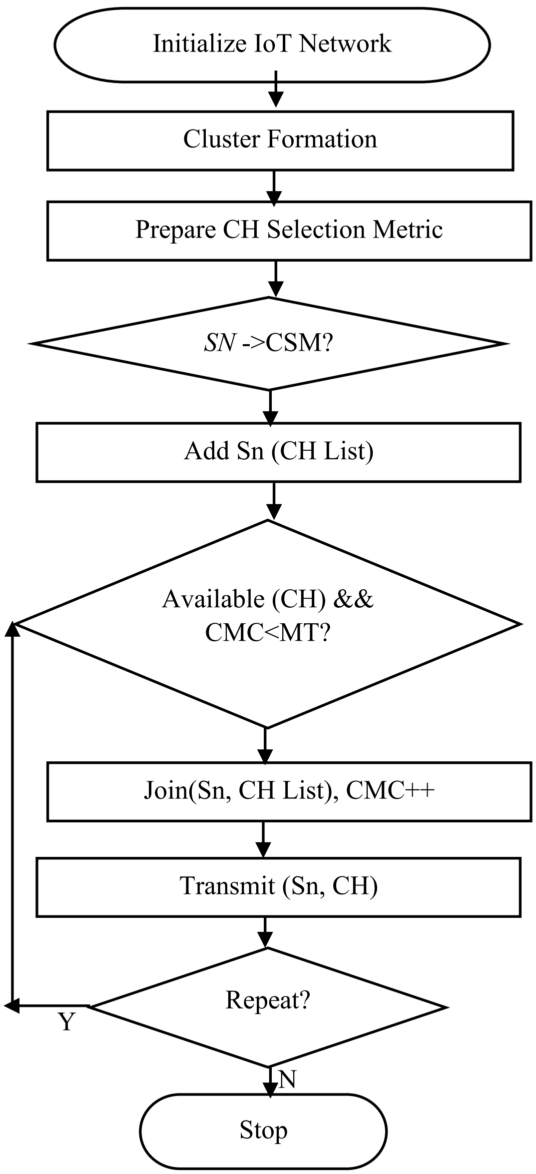
Step 2: Cluster Management: It includes different processes, i.e. cluster formation and cluster head selection.

Step 3: Transmission: In this phase, data is collected from field sensors, and after aggregation, it is forwarded to the base station.

The following section provides a detailed discussion about these steps:

3.1. Step 1: IoT Network Initialization



Flowchart 1 Dynamic Cluster Head Selection for IoT Network

To deploy the IoT network, first of all, set the total agriculture coverage area ∑Ag and initialize the receiving & transmission power *Rx, Tx,* Minimum & Maximum Energy Level: *Emin eMn, Emax eMx,* Packet Drop *Pkt,* Distance *D,* initial energy level Iel. If eR energy is required to transmit a single packet, then the minimum energy k required to transfer p packets over a distance d may be defined as $eMn = k * D$ and total packet to be transferred: $p \leq Iel/(eMn * d)$.

Flowchart 1 provides an overview of dynamic cluster head selection for an IoT Network using different steps. First of all, cluster formation is done over the entire network and as per Table 2. The CH selection metric is prepared, and the sensors' eligibility to become a CH is verified.

Optimal sensors are added to the CH selection list, and using this list, intermediate sensors can select optimal CH and so on. However, the member capacity of a CH is limited using a threshold value to avoid unnecessary congestion, collision, and extra control overhead, etc. The following sections describe the different processes in detail:

Table 2 shows the metrics of the different constraints for CH selection. It indicates that a CH may be selected if its sensitivity is medium (to avoid interference), with minimum distance from intermediate neighbours and lowest collision, congestion, interference, and minimal packet drop and with higher SNR and residual energy level. It also maintains a threshold (that contains total sensors N/4) to keep track of the total number of members of a gateway and ∑members<MT, to avoid the excessive payload over cluster heads.

Table 2 Cluster Head Selection Metric (CSM)

Parameters	Value	Description
Sensitivity *Sn*	Medium	It must be at a medium level to avoid channel interference
Distance *D*	Minimum	The distance between nodes must be minimal for the optimal selection of the CH
Residual energy *Re*	High	CH must have enough energy to support long interval operations
Interference Level *Il*	Low	Minimal interference is required to avoid the channel noise
Collision *Cl*	Low	It must be at a low level to avoid the retransmission due to packet drop
Congestion *Cg*	Low	Congestion must be avoided to prevent

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		delay, packet drop, etc.
SNR *Sn*	High	It must be at an optimal level for reliable transmission
Packet Drop *Pd*	Low	The above constraints may cause packet drop, and it must be at minimal to retain higher network performance.
Max. Member Threshold *MT*	∑N/4	CH should have an optimal number of members for reliable communication

As per Table 2, CSM is prepared, and a CH can self-declare its availability to the sensors.

3.2. Step 2 (a): Cluster Formation and Cluster Head Selection

If a sensor has a range (Rx, Tx) to sense an area, then range (Rx, Tx) * ∑Sn sensors are required to cover ∑Ag. If there are total ∑*Sn* sensors that can be used to cover ∑Ag area, then a Cluster *C* must have at least two sensors, so that one of them can act as CH. To form the multiple Clusters, randomly deploy the sensors, build a Cluster and include N number of sensors, with Cluster capacity. Finally, there will be ∑C Clusters, and it can be defined as per equation no. (1) and equation no. (2):

$$\sum Ci \in \{Si, Sj, Sk,, \dots \dots\ Sn\} < Capacity \quad (1)$$

$$((\sum Ci \in \{Si, Sj, Sk,, \dots \dots\ Sn\}) \in \sum C\ ) \in \sum Ag \quad (2)$$

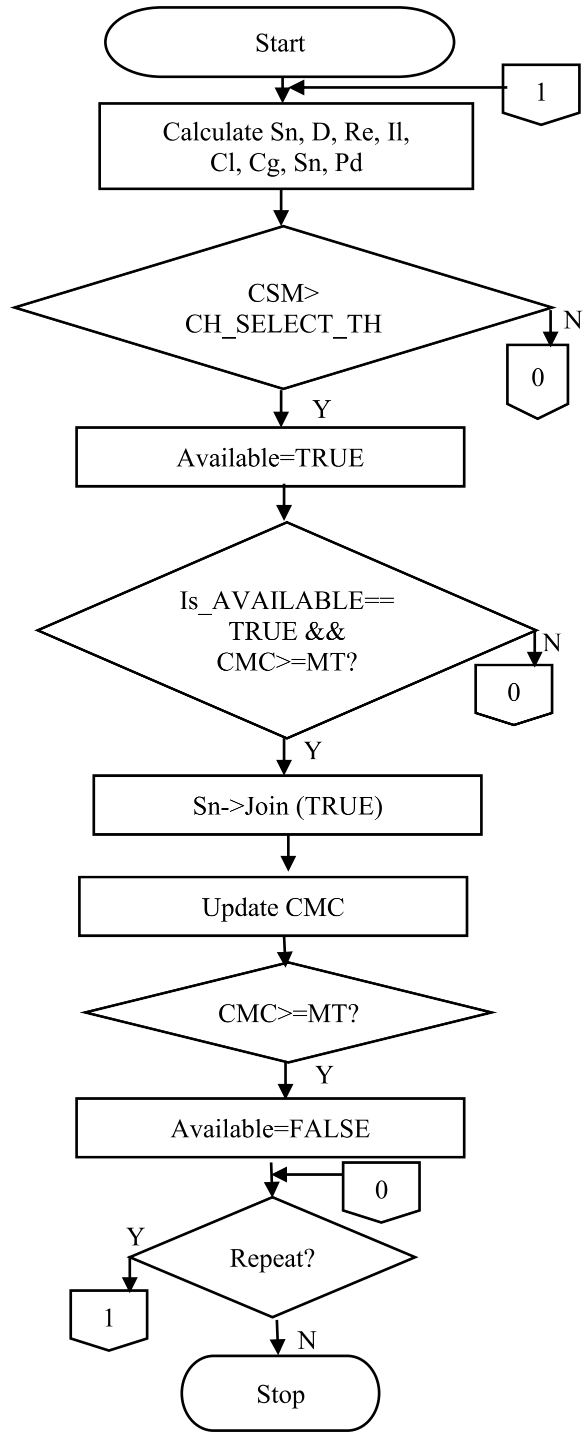
It is necessary to form at least one cluster with a minimum of two sensors so that one of them can act as CH for data processing and so on. After Cluster formation, the Cluster list is shared with the base station. After that, each Cluster builds a Cluster head availability list using the given equation (3):

$$CSM = \sum\{Sy, D, Re, Il, Cl, Cg, Sn, Pd\} \quad (3)$$

And, it evaluates each sensor randomly with respect to ∑CSM and initiates the process to build a Cluster head availability list. Finally, a list is sorted, and the top-most entry is elected as the first CH w.r.t. each Cluster. After this step, all Clusters must have at least one CH.

Current CH broadcasts the join request within the current Cluster only, and all members within its range are allowed to join the current CH only. If all sensors cannot join the current CH due to its member threshold constraints, then the Cluster head availability list is traversed and another CH is selected for the rest of the sensors, and this step is repeated to allocate a CH to all sensors in a Cluster. The following are the various steps performed by CHs and sensors during network operations.

3.2.1. Step 2 (b): Cluster Head Availability Check



Flowchart 2 CH Availability Check

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Flowchart 2 To check the constraints for the availability of CH as explained below:

Step 1 (a): A self-availability check is performed by a CH, and it is available only if ∑CSM value is less than or equal to the CH selection threshold; otherwise, it is not added to the list of available cluster heads, maintained by the base station as per the given equation. (4) and step 1 (b):

$$\sum CSM = \sum\{Sy, D, Re, Il, Cl, Cg, Sn, Pd\} \tag{4}$$

Step 1 (b): Check if ∑CSM <= CH_SELECT_TH and Is AVAILABLE (CH->ID, TRUE) then

update CHList_AVL

Step 2 (a): If CH is available and multiple sensors may join a CH, and its current member capacity (CMC) is managed by a constraint, Member Threshold MT as mentioned below:

Step 2 (b): Check if CH is available and its CMC < MT, then follow step 2 (c); otherwise, follow step 2 (d):

Step 2 (c): If the Sensor can join, then (Sn, CHi, TRUE) and update CMC accordingly

Step 2 (d): Check if CH is available and its CMC >= MT, then CH ->Status==UNAVAILABLE

Step 3 (a): As sensors join the CH, its member count increases, and finally, it reaches its threshold value. After that, the sensor cannot join a CH if the CH's capacity is full. If a sensor leaves the current CH, then the member count is updated accordingly, as mentioned below:

Step 3 (b) If any sensor Sn leaves the CH, then update CMC

The following are the constraints for CHs as mentioned below:

A CH must exist in CHList; otherwise, the sensor should not send a join request to that cluster head as per equation no. (5):

$$\sum CHList \in \{Chi, Chj, Chk, , \dots \dots\ Chn\} \tag{5}$$

If a senor joins a CH, then it is a member of that CH, and it cannot join another CH at the same time. Also, two CHs cannot have the same members at the same time, as per equation no. (6) and equation no. (7):

$$\sum CHi \in \{Si, Sj, Sk, , \dots \dots\ Sn\} \tag{6}$$

$$\sum CHn \in \{Si, Sj, Sk, , \dots \dots\ Sn\}\ Where\ CHi\ \cap\ CHn\ = \emptyset \tag{7}$$

3.3. Step 3: Transmission

Flowchart 3 shows the various steps to select a CH dynamically. First of all, a sensor determines the CH availability by checking the CH list as given below:

Step 1: Check *CH* ->List and if it is not empty, then follow the given step 2; otherwise, follow the step 3:

Step 2: for each CH in the *CH* ->List, follow the steps below:

Step 2.1: Check CH availability, and if CH is available, then follow the steps below:

Step 2.2: Check the current member capacity of CH, and if it is less than MT, then set Sn->CH=CH

Step 2.3: Update CH->CMC

Step 2.4: Repeat the above steps if required.

Step 3: Sn->Wait++

Step 3.1: If (Sn->Wait>wTH), then follow the steps given below:

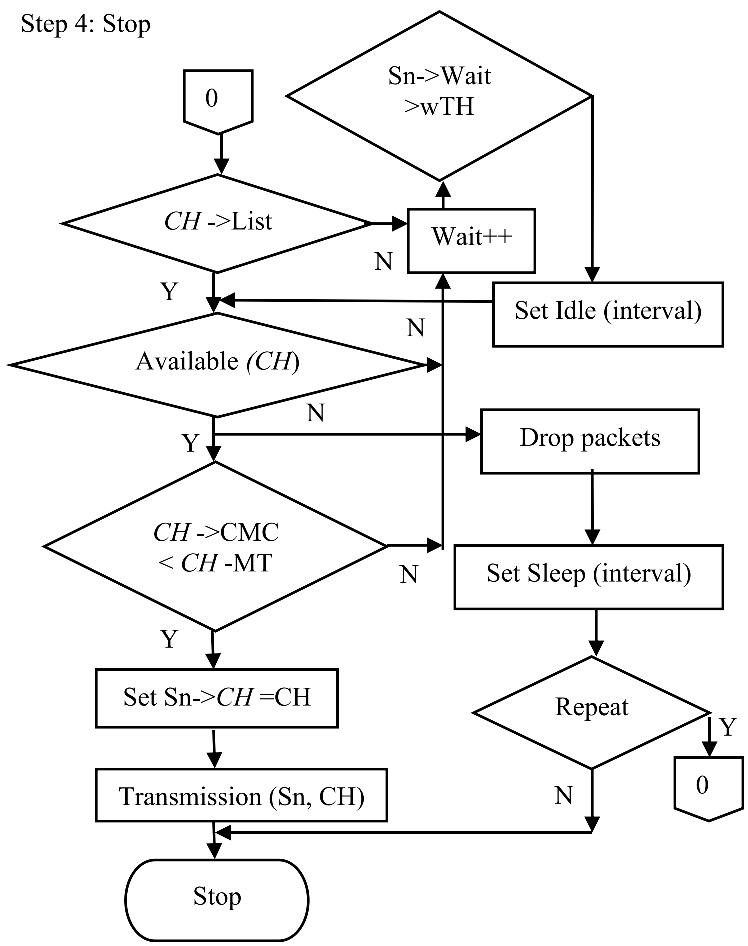
Step 3.2: Set State_Idle (interval),

Step 3.3: Check the CH availability as per step 2; otherwise, drop packets (Sn->Drop_packets),

Step 3.4: Set Sn->State_SLEEP (interval),

Step 3.5: Repeat the above steps if required.

Step 4: Stop



Flowchart 3 CH Selection Process for the Sensor

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3.4. Step 4: Cluster Head Switching

If CH is available and its member list is below the member threshold constraint, only then can the sensor join that CH; otherwise, the entire CH list is traversed, and finally, it selects an optimal CH and starts transmission.

If any sensor failed to select a CH, it sets its idle state for a small interval and after that, it tries again. After the idle interval, it sets the ACTIVE state and follows Step 1, and if CH is still unavailable, then drop packets and so on, and the above steps may be repeated again, if required.

4. RESULTS AND ANALYSIS

4.1. Simulation Configuration

For experiments, NS-2, the network simulator, is used with the configuration as shown in Table 3. It includes simulation scenarios with different parameters i.e protocols (LEACH, LEACH-C and PEGASIS), sensor density 100-300, TwoRay Ground propagation model, terrain size 1000mx1000m, initial energy level 5J, Linux platform and 600s simulation interval.

Table 3 Simulation Configurations

Parameters	Value
Simulator	Network Simulator-Version-2 (NS-2)
Sensors	100/200/300
Propagation Model	TwoRay Ground
Terrain Size	1000mx1000m
Initial Energy Level	5J
Platform	Linux
Simulation Interval	600Seconds
Simulation Scenarios	(a) Comparison with standard energy efficient protocols (that support similar routing behavior like DCSA) supported by NS-2 simulator: LEACH, LEACH-C, PEGASIS [38]. (b) Comparison with other solutions developed by different researchers (that support dissimilar routing behavior in contrast of DCSA).

4.2. Performance Comparison of DCSA with Standard Energy-Efficient Protocols

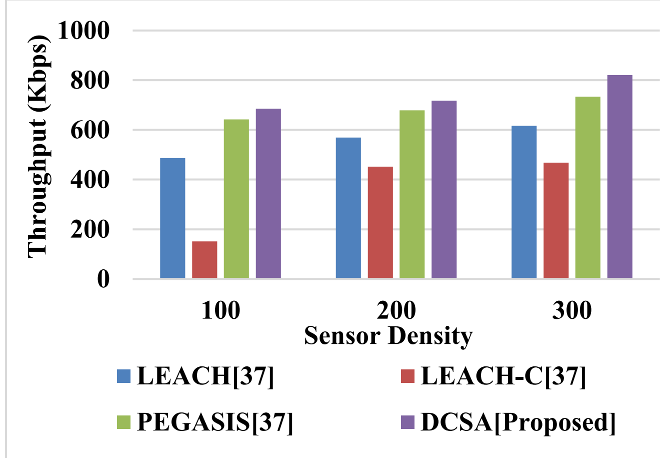

Figure 4 Throughput

CH performs critical operations, redundant data detection, and data forwarding to the base station after its suppression. CH performs excessive network operations, which may exhaust its battery life. Researchers addressed this issue and developed different routing protocols (i.e. LEACH, LEACH-C & PEGASIS) to optimize the CH selection process. During the CH selection process, all these protocols estimate the intermediate distance and residual energy of the nodes, and the CH is selected having a higher battery life with minimal distance from member nodes. There are several other attributes (i.e. SNR, interference, packet drop, collision, congestion level and CH capacity, etc.) that can be used as criteria for CH selection As per survey, it can be observed that existing solutions do not consider all these factors for CH selection and main contribution of the research work is that it enforces the CH selection on the basis of above mentioned attributes and following results show the improvement in the network performance in terms of throughput, packet delivery ratio, residual energy, and extended sensor's life-span under the constraints mentioned in Table 2.

Figure 4 shows the comparison of the Throughput of LEACH, LEACH-C, PEGASIS and DCSA under the constraints of sensor density variations. It can be observed that PDR of LEACH, LEACH-C and PEGASIS is quite less as compared to DCSA; however, it is marginally increased for the highest sensor density. In the case of 100 sensors, using LEACH, it is 486.52Kbps, with LEACH-C, it is 150.71Kbps, for PEGASIS, it is 641.78Kbps, and in the case of DCSA, it is 684.78Kbps. In the case of 200 sensors, using LEACH, it is 569.59Kbps, with LEACH-C, it is 452.06Kbps, for PEGASIS, it is 678.254Kbps, and in the case of DCSA, it is 717.87Kbps. In the case of 300 sensors, using LEACH, it is 616.15Kbps, with LEACH-C, it is 467.74Kbps, for PEGASIS, it is 733.587Kbps, and in the case of DCSA, it is

821.08Kbps. DCSA efficiently regulated the CH selection phase along with the transmission phase, resulting in higher packet transmission and reception, and finally, it enhanced the overall network performance in terms of higher throughput.

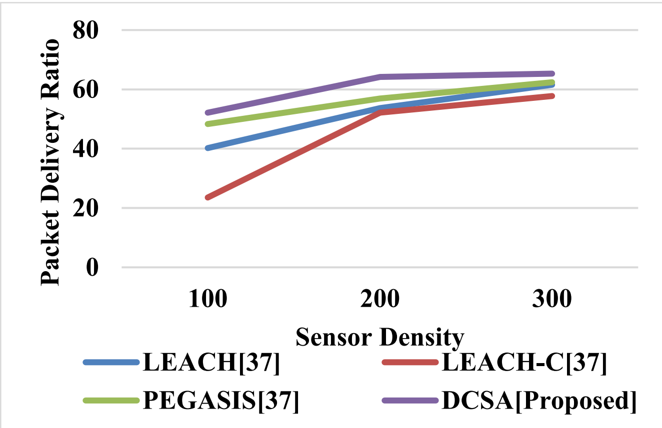

Figure 5 Packet Delivery Ratio

Figure 5 shows the comparison of the Packet delivery ratio (PDR) of LEACH, LEACH-C, PEGASIS and DCSA under the constraints of sensor density variations. It can be observed that PDR of LEACH, LEACH-C and PEGASIS is quite less as compared to DCSA; however, it is marginally increased for the highest sensor density. In the case of 100 sensors, using LEACH, it is 40.21, with LEACH-C, it is 23.54, for PEGASIS, it is 48.3126218, and in the case of DCSA, it is 52.14. In the case of 200 sensors, using LEACH, it is 53.6426, with LEACH-C, it is 52.1672, for PEGASIS, it is 56.87542, and in the case of DCSA, it is 64.1692. In the case of 300 sensors, using LEACH, it is 61.55, with LEACH-C, it is 57.75522, for PEGASIS, it is 62.39231, and in the case of DCSA, it is 65.31. DCSA also managed the packet drop by avoiding congestion and collisions over the network, and it ensured the maximum packet transmission over the network, resulting in improved PDR.

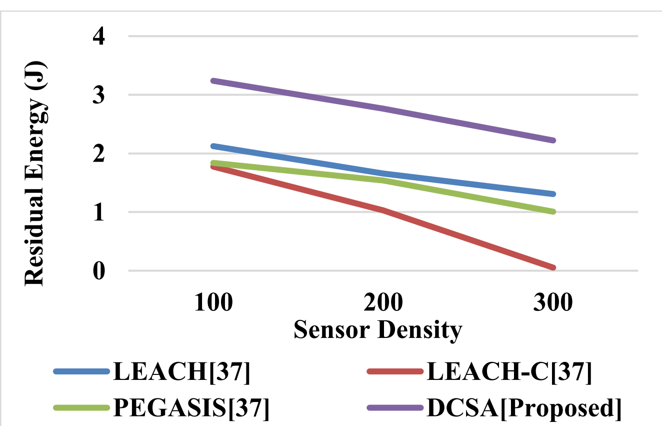

Figure 6 Residual Energy

Figure 6 shows the comparison of the Residual Energy of LEACH and DCSA schemes using LEACH under the constraints of sensor density variations. It can be observed that LEACH could not retain the energy level under the constraints of a scalable network, and there is a sharp decline in its value. With the highest sensor density, it reached up to its minimal value, whereas DCSA retained its efficient level as the sensor density varied. In the case of 100 sensors, using LEACH, it is 2.1239J, with LEACH-C, it is 1.775J, for PEGASIS, it is 1.8379638J, and in the case of DCSA, it is 3.23885J. In the case of 200 sensors, using LEACH, it is 1.6568J, with LEACH-C, it is 1.029J, for PEGASIS, it is 1.540635J, and in the case of DCSA, it is 2.764706J. In the case of 300 sensors, using LEACH, it is 1.306812J, with LEACH-C, it is 0.0523J, for PEGASIS, it is 1.00631J, and in the case of DCSA, it is 2.221269312J. DCSA prevented the unnecessary engagement of sensors in the CH selection and transmission phase by enforcing CSM. It finally conserved the residual energy at the sensor level.

Figure 7 shows the comparison of the average delay of LEACH and DCSA schemes using LEACH under the constraints of sensor density variations. It can be observed that LEACH has a higher delay as compared to DCSA. In the case of 100 sensors, using LEACH, it is 647.831ms, with LEACH-C, it is 709.15.53ms, for PEGASIS, it is 384.069ms, and in the case of DCSA, it is 385.009ms. In the case of 200 sensors, using LEACH, it is 749.315ms, with LEACH-C, it is 864.8111ms, for PEGASIS, it is 741.638ms, and in the case of DCSA, it is 1477.68ms. In the case of 300 sensors, using LEACH, it is 2784.32ms, with LEACH-C, it is 2625.33ms, for PEGASIS, it is 1024.25ms, and in the case of DCSA, it is 2175.33ms. DCSA checks the CH availability for the transmission, and meanwhile, sensors are not allowed to transmit, which results in an extended delay interval over the network. It also caused a packet drop due to the expiry of the waiting interval.

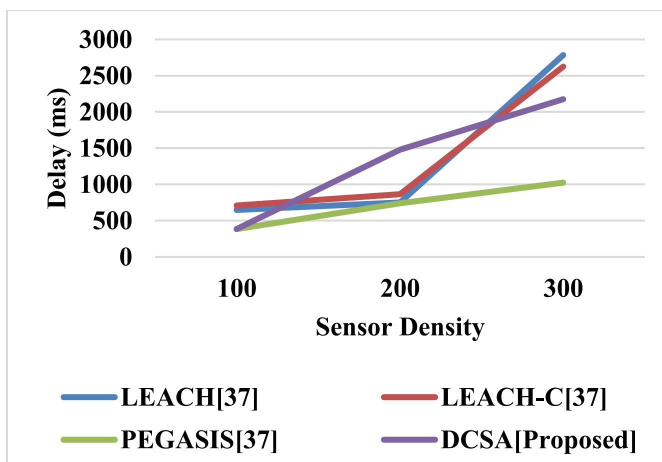

Figure 7 Delay

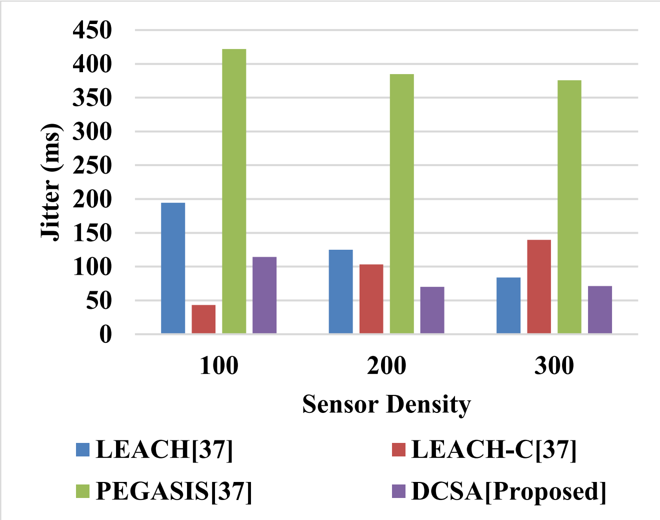

Figure 8 Jitter

Figure 8 shows the comparison of Jitter of LEACH and DCSA schemes using LEACH under the constraints of sensor density variations. It can be observed that LEACH has higher jitter as compared to DCSA. In the case of 100 sensors, using LEACH, it is 194.33ms, with LEACH-C, it is 43.14ms, for PEGASIS, it is 421.98ms, and in the case of DCSA, it is 114.46ms. In the case of 200 sensors, using LEACH, it is 125.07ms, with LEACH-C, it is 103.4ms, for PEGASIS, it is 384.81ms, and in the case of DCSA, it is 70.16ms. In the case of 300 sensors, using LEACH, it is 83.98ms, with LEACH-C, it is 139.71ms, for PEGASIS, it is 375.71ms, and in the case of DCSA, it is 71.15ms. DCSA has minimal jitter because sensors just wait for the transmission slots, and once it is available, the entire data is forwarded to the base station through the CH without any intermediate delay.

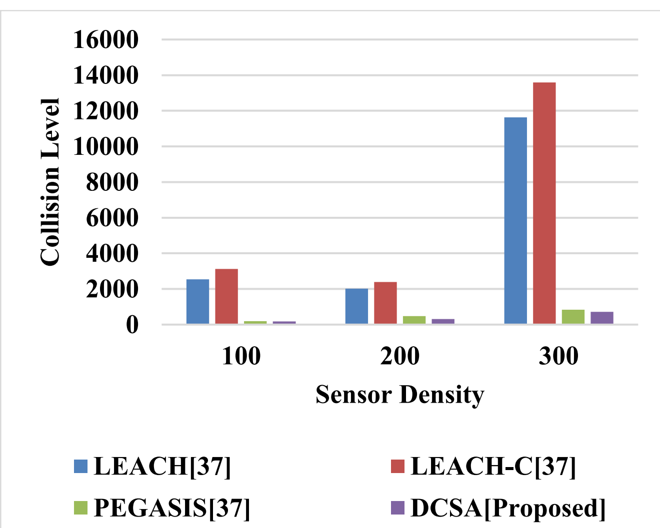

Figure 9 Collision

Figure 9 shows the comparison of the Collision level of LEACH and DCSA schemes using LEACH under the constraints of sensor density variations. It can be observed that LEACH has a higher collision level as compared to DCSA. In the case of 100 sensors, using LEACH, it is 2539, with LEACH-C, it is 3119, for PEGASIS, it is 192, and in the case of DCSA, it is 173. In the case of 200 sensors, using LEACH, it is 2015, with LEACH-C, it is 2396, for PEGASIS, it is 478, and in the case of DCSA, it is 310. In the case of 300 sensors, using LEACH, it is 11626, with LEACH-C, it is 13584, for PEGASIS, it is 829, and in the case of DCSA, it is 710. Sensors are attempted for transmission, only if CH is available under the constraints of CSM, thus minimizing the number of transmission attempts. It also ensured the efficient utilization of the shared channel. Due to low collision levels over the network, higher packets are sent and received over the network with minimal packet drop. Finally, it improves the Throughput and PDR. It also preserves the residual energy of sensors by avoiding unnecessary packet re-transmission, thus extending the overall lifespan of sensors.

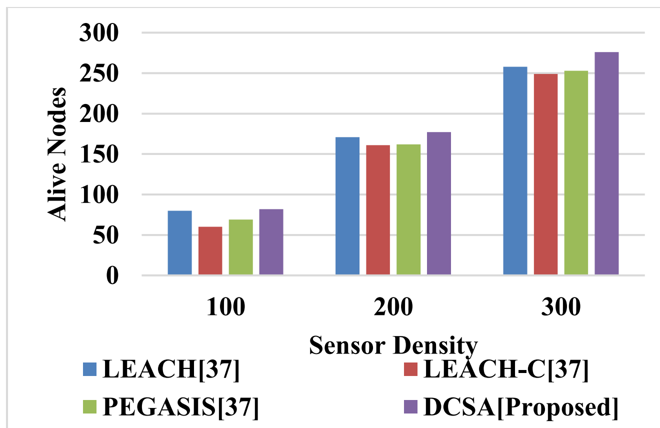

Figure 10 Alive Sensors

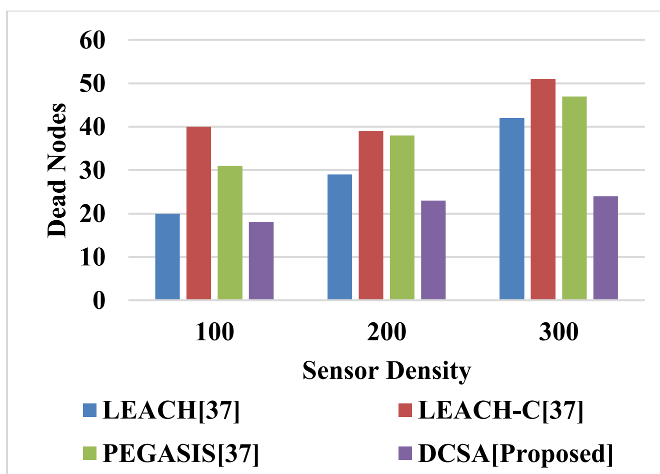

Figure 11 Dead Sensors

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Figure 10 shows the comparison of Alive sensors of LEACH, LEACH-C, PEGASIS and DCSA under the constraints of sensor density variations. It can be observed that DCSA has a higher number of alive sensors as compared to others. Out of 100 sensors, in the case of LEACH, the number of alive sensors is 80, for LEACH-C, 60, for PEGASIS, 69, and it is highest for DCSA (82). With 200 sensors, it is 171 for LEACH, 161 for LEACH-C, 162 for PEGASIS and 177 for DCSA. With 300 sensors, it is 258 for LEACH, 249 for LEACH-C, 253 for PEGASIS and 276 for DCSA.

Figure 11 shows the comparison of dead sensors for LEACH, LEACH-C, PEGASIS, and DCSA under varying sensor density. It can be observed that DCSA has the least number of dead sensors as compared to others. Out of 100 sensors, in the case of LEACH, the number of dead sensors is 20, for LEACH-C, 40, for PEGASIS, 31, and it is lowest for DCSA (18). With 200 sensors, it is 29 for LEACH, 39 for LEACH-C, 38 for PEGASIS and 23 for DCSA. With 300 sensors, it is 42 for LEACH, 51 for LEACH-C, 47 for PEGASIS and 24 for DCSA. As per the analysis, it can be observed that the proposed scheme regulated the various network operations under the various constraints (congestion and collision, etc.), thus decreasing the overall energy depletion and finally resulting in a minimal amount of exhausted sensors.

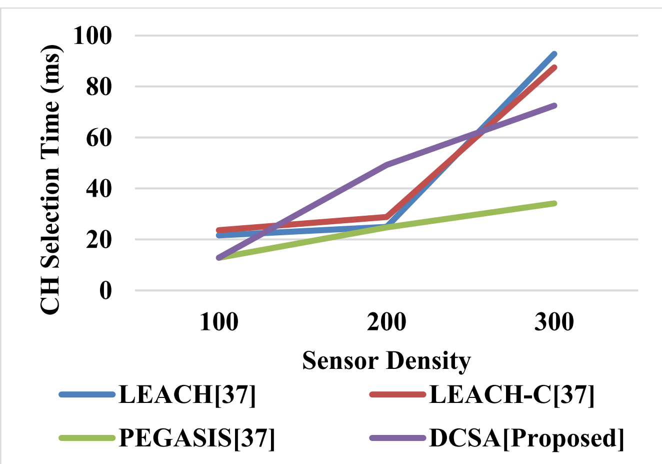

Figure 12 CH Selection Time

Figure 12 shows the time interval of CH selection. It can be observed that it is increasing with respect to sensor density variations. In the case of 100 sensors, using LEACH, it is 21.59436667ms, with LEACH-C, it is 23.63851ms, for PEGASIS, it is 12.8023ms, and in the case of DCSA, it is 12.83363333ms. In the case of 200 sensors, using LEACH, it is 24.97716667ms, with LEACH-C, it is 28.82703667ms, for PEGASIS, it is 24.72126667ms, and in the case of DCSA, it is 49.256ms. In the case of 300 sensors, using LEACH, it is 92.81066667ms, with LEACH-C, it is 87.511ms, for PEGASIS, it is 34.14166667ms, and in the case of DCSA, it is 72.511ms.

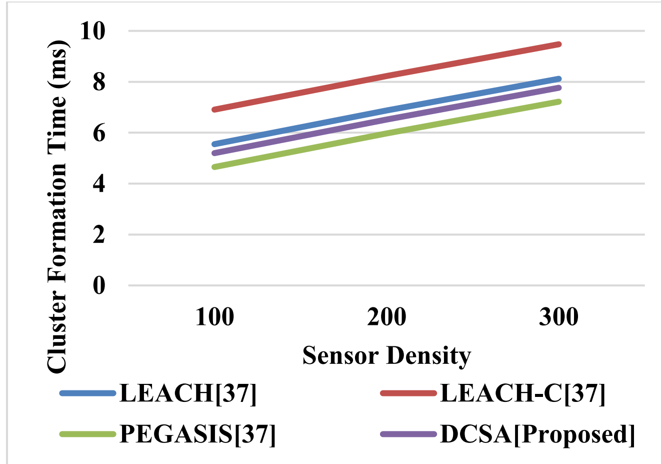

Figure 13 Cluster Formation Time

Figure 13 shows the time interval of cluster formation. It can be observed that it is increasing with respect to sensor density variations. In the case of 100 sensors, using LEACH, it is 5.55ms, with LEACH-C, it is 6.90681ms, for PEGASIS, it is 4.65202ms, and in the case of DCSA, it is 5.19782ms. In the case of 200 sensors, using LEACH, it is 6.875ms, with LEACH-C, it is 8.2318ms, for PEGASIS, it is 5.97702ms, and in the case of DCSA, it is 6.52282ms. In the case of 300 sensors, using LEACH, it is 8.116666667ms, with LEACH-C, it is 9.473466667ms, for PEGASIS, it is 7.218686667ms, and in the case of DCSA, it is 7.764486667ms.

4.3. Performance Comparison with Other Solutions

The performance of the proposed Dynamic Cluster Head Selection Algorithm (DCSA) has been evaluated with two existing energy efficient schemes having different routing behavior (developed by other researchers): the Duty-Cycled Ant Colony Optimisation with Priority (DC-ACOP) approach [38] and the Joint Topology Control and Routing (JTCR) protocol [39].

This comprehensive comparison demonstrates the significant advantages of DCSA in terms of throughput, residual energy retention, and overall network energy efficiency for IoT-based smart agriculture environments.

4.3.1. Comparative Analysis

The comparison is conducted across three fundamental performance metrics that are critical for IoT-based agricultural sensor networks: throughput (measured as the percentage of successfully delivered data packets relative to total transmitted packets), residual energy (measured as the percentage of remaining energy in the network nodes relative to initial energy capacity), and energy consumption (measured

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as the percentage of total energy expended during network operations). These metrics are selected because they directly impact the network's ability to sustain long-term monitoring operations in remote agricultural settings where sensor battery replacement is challenging and costly.

- DC-ACOP Scheme: This scheme employs a priority-based energy-efficient metaheuristic routing approach specifically designed for smart healthcare systems. It incorporates duty-cycled sensor nodes with Ant Colony Optimization (ACO) to determine optimal routing paths while managing data packets based on their criticality levels. The scheme uses on-demand activation of communication units in sensor nodes and prioritizes critical data packets to reach the destination first. However, its design is optimized for healthcare applications with relatively smaller network scales and lower density deployments.
- JTCR Scheme: This protocol implements joint topology control and routing in UAV swarms through three integrated modules: virtual force-based mobility control (VFMC), energy-efficient mobility-aware fuzzy clustering (EMFC), and topology-aware Q-routing (TAQR). While JTCR is designed for UAV-assisted IoT networks with dynamic topology management, it introduces substantial computational overhead due to its multi-module architecture and reinforcement learning-based routing decisions.
- DCSA Scheme: The proposed scheme addresses the specific challenges of static IoT-based smart agriculture networks by implementing a holistic cluster head selection strategy that simultaneously considers nine critical parameters: sensitivity, distance, residual energy, interference level, collision, congestion, signal-to-noise ratio, packet drop, and member threshold.

The DCSA scheme significantly outperforms both DC-ACOP and JTCR across all three critical performance metrics, achieving 91% throughput (24 percentage points above JTCR), maintaining 60% residual energy (15 percentage points above JTCR), and consuming only 40% of total network energy (15 percentage points less than JTCR). This superior performance stems from DCSA's comprehensive nine-parameter cluster head selection strategy that proactively prevents network problems rather than reactively managing them.

Unlike DC-ACOP, which manages issues through priority queuing after they occur, and JTCR, which introduces computational overhead through multi-module architecture, DCSA eliminates suboptimal cluster heads before deployment by considering sensitivity, distance, residual energy, interference level, collision probability, congestion, SNR, packet drop rate, and member threshold.

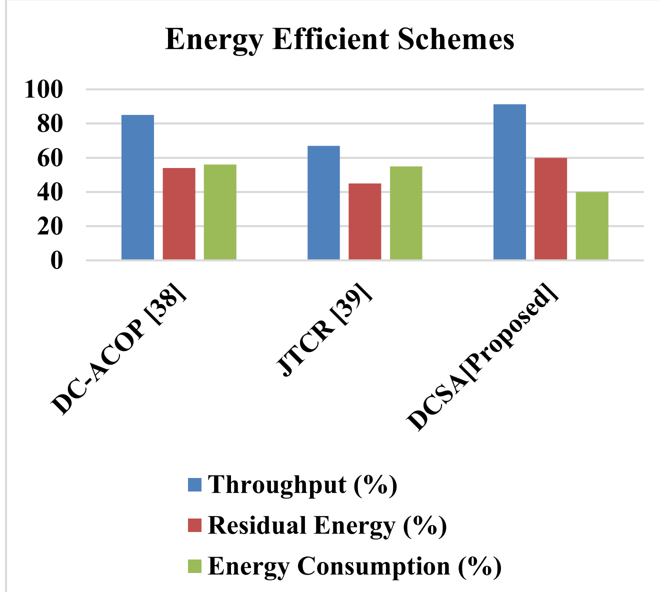

Figure 14 Comparison of Energy Efficient Schemes

The distance optimization constraint directly reduces transmission energy consumption (which scales quadratically with distance), while collision and congestion prevention eliminate wasted energy from failed retransmissions. Critically, DCSA’s uniform member threshold distribution ($MT = N/4$) prevents energy-depleting hotspots that plague competing schemes. Through this prevention-based design philosophy specifically tailored for agricultural IoT deployments, DCSA achieves 6-24 percentage point improvements across all metrics, making it the superior choice for long-term, maintenance-free smart agriculture applications.

5. CONCLUSION

In this paper, a Cluster head selection scheme is presented for smart agriculture, and its performance was compared with LEACH, LEACH-C and PEGASIS under various constraints, i.e. sensor density, residual energy, delay, jitter and sensor’s life-span, etc. As per the results, it can be observed that the performance of each protocol varied under the constraints of sensor density. LEACH-C delivered the least Throughput and PDR, followed by LEACH and PEGASIS, as compared to DCSA. LEACH and LEACH-C both have higher collision levels, which also result in congestion level variations due to excessive re-transmissions. It is higher for LEACH-C and PEGASIS, whereas it is average for LEACH and minimal for DCSA. In case of residual energy, DCSA retained a higher level of residual energy, thus also improved the overall life-span of the network (in terms of a higher number of alive sensors) in contrast to others. With a medium range of sensor density (up to 200 sensors), DCSA has a higher delay factor due to the waiting threshold for the transmission cycle;

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however, with the highest sensor density (300), delay is marginally declined due to a higher rate of packet forwarding. On the other hand, jitter also varied, but DCSA maintained its level due to the dedicated transmission slots. It is higher for PEGASIS, LEACH-C and LEACH because these routing schemes just assign the transmission slots and ignore the capacity of CH as well as the current channel conditions. Finally, it can be concluded that LEACH-C could not perform at a significant level, and LEACH delivered the average performance as compared to PEGASIS. DCSA outperformed in terms of higher throughput, PDR, and it also retained the acceptable level of residual energy during network operations, thus increasing the network life span and decreasing the dead sensor density. The advantage of the proposed scheme is that it can manage the delay and jitter as compared to others, and it is suitable for scalable networks. It can be easily integrated with any protocol. The main drawback of the proposed scheme is that it keeps the sensors in a waiting state, and there is a need to optimize the waiting threshold Interval (In order to minimize the delay factor). Compared to the existing schemes, DC-ACOP and JTCR, DCSA outperformed in terms of higher residual energy, higher throughput, and lower energy consumption. In current research work, a dynamic cluster head selection scheme is presented for IoT-based smart farming. A similar concept can be implemented for the different types of networks in which intermediate nodes or access points can act as sinks, gateways, data collectors or aggregators, etc., e.g. in the case of IoT networks, LoRAWAN and SigFox both protocols support long-distance packet forwarding using gateways. These gateways are predefined for the entire network, and in case of gateway breakdown, network partitioning may occur, as there is no standard provision to select the gateways dynamically. Similarly, in the case of Vehicular Ad Hoc Networks (VANETs), where Roadside Units (RSUs) are used to support long-distance transmission and are also fixed in nature, there is no standard provision to select an alternative RSU. To achieve reliable communication, the proposed scheme can be integrated with these networks.

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