Optimizing Cluster Head Election in IoT Networks Using Reinforcement Learning

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***Abstract*—[Font: IoT's are hot cake in all sectors from daily wearable's to automated industries. They avoid disasters, reduce the manpower, and increase the performance in all fields. But the wireless sensor networks used in IoT are resource constraints and ensuring the security, energy efficiency is a challenging task. This paper addresses the review of the existing routing protocols in IoT. The observed limitations are suboptimal energy usage, resource inefficiency and security threats during communication. To resolve these issues we propose a cluster based WSN, where the clusters emerge and cluster head (CH) is elected based on reinforcement learning algorithm (RL). Initially cluster head is elected using K-Means algorithm and in the second iteration Cluster head is dynamically elected based on important factors like residual energy, distance and delay using RL. The nearby nodes to the CH that doesn't have obstacle around them were taken into consideration in CH election. A MS is used to achieve energy efficiency. In data transmission process cluster members forwards monitored data to cluster heads, from cluster heads mobile sink will collect the data by reaching all cluster heads. Later it forwards data to end user. There are many applications such as e-health, smart home, face recognition, automated industries etc, are working on the basis of IoT. Our proposed algorithm achieves great energy efficiency through the best obstacle free cluster head selection, when compared to GEEC, EADCR, DNN and TTDFP.**

***Index Terms*—IoT, Mobile sink, Obstacle, Reinforcement algorithm, K-Means.**

I. INTRODUCTION

IoT is booming in sectors from smart homes to industries by connecting millions of devices which are useful for multiple applications like industrial internet, smart cities, health care monitoring, smart homes, transportation and logistics etc. [1]. IoT devices consist of sensors to monitor and exchange the data. These devices often operate within a distributed or clustered network topology to manage and process the monitored data of sensors efficiently [2],[3]. IoT devices have constraints in terms of energy resources, security threats and providing mobility due to dynamic topologies. Due to these constraints, durability of the network, routing and security becomes challenging for the communication protocols. Coming to the first challenge durability, it depends on the individual node's energy in the network [4]. To overcome this issue, in our proposed work we are forming clusters and electing a cluster head, so that the nodes can send data to cluster head instead of sending data to base station directly. From there a mobile sink will collect the data. Moving to the second challenge routing. Routing is a crucial process in wsn's of IoT. Sometimes looping may happen in routing or longest path is chosen from source node to base station. This creates the energy scarcity in the network. So an optimized route must be chosen for the transmission of packets. To address this issue, in traditional routing algorithms the authors have used optimization algorithms for finding out the shortest path or optimized path but we are using ML based RL algorithm along with optimization algorithms. The greatest advantage of RL algorithm is, it always gives rewards for each node whenever a packet is forwarded over it to base station. Depending on the reward of the before experience the best optimized route can be found dynamically. So here the current action will always depends on the previous action based reward. During the routing process the security threats will come into picture. A security threat refers to any possible risk that could jeopardize the system's and its data's availability, confidentiality, or integrity. These threats can manifest in various forms like, [5]. Sybil, Denial of service, distributed denial of service, Spoofing and Impersonation, Eavesdropping etc. The proposed approach segments the network into multiple clusters and utilizes a Reinforcement Learning (RL) algorithm to select a Cluster Head (CH). The selection process is based on energy metrics and the distance to efficiently transmit data to the base station[6,7, 8]. I. INTRODUCTION IoT is booming in sectors from smart homes to industries by connecting millions of devices which are useful for multiple applications like industrial internet, smart cities, health care monitoring, smart homes, transportation and logistics etc. [1]. IoT devices consist of sensors to monitor and exchange the data. These devices often operate within a distributed or clustered network topology to manage and process the monitored data of sensors efficiently [2],[3]. IoT devices have constraints in terms of energy resources, security threats and providing mobility due to dynamic topologies. Due to these constraints, durability of the network, routing and security becomes challenging for the communication protocols. Coming to the first challenge durability, it depends on the individual node's energy in the network [4]. To overcome this issue, in our proposed work we are forming clusters and electing a cluster head, so that the nodes can send data to cluster head instead of sending In this proposed scheme we are introducing a mobile sink node to collect the data from all the cluster heads and then the data is forwarded to the base station.. Depending on RL algorithm the best optimized route can be found dynamically for the MS and the energy efficiency is achieved. As well as due to the MS and CH the data is transferred very quickly and the packet delivery ratio will be increased by reducing the delay of packets. The Motivation behind our work is energy scarcity of WSN's in IoT, optimized path for routing. Main objective of our work is to use energy efficiently and forward the data packet with less delay using mobile sink, achieving good performance.

The main Contributions of the proposed work are:

1. Cluster formation and first CH election using K-Means algorithm
2. Next CH's election from neighbor nodes based on metrics such as energy and distance, reward collection using RL algorithm.

There are many applications based on IoT [10]. like agricultural IoT, supply chain management, smart homes, transportation and logistics. The rest of this article is organized as follows. In Section 2, we give a summary of the most current research on WSN routing protocols in IoT. In Section 3, we illustrate proposed work with architecture flow diagram and algorithms. The performance analysis is discussed in section 4. In Section 5, we describe the conclusion part.

II. RELATED WORK

The performance of IoT devices in all sectors plays key role and also the updating and improvement in this area is very important. Many researches are working on IoT based WSN network. This section covered our analysis of recently released papers. Most of the algorithms in these papers have explored optimization algorithms to optimize shortest path for routing.

Bing Fan et al., [11]. developed an algorithm to adopt Fast changes in clustering and routing in the network. This routing algorithm is introduced to overcome the premature death of nodes which are present near the base station, this process of death is called energyhole problem. Here clusters are formed based on cluster radius depending on energy factor and distance factor, along with that the load is shared in between nodes or cluster heads near BS by using inter cluster and intra cluster communication to avoid the energyhole problem.

Elham at el., [12]. focuses mainly on load balancing and distribution of load among base stations for the longevity of the network. The proposal made in this article is a new architecture based on SDN architecture to prolong network lifetime. A new algorithm is proposed and installed in every individual node during deployment to discover the nearby BS, topology and neighbour nodes, so that the traffic and energy consumption both reduces. Here they were trying to separate application, data and control. The controller node is main incharge of controlling the network.

Aditya Pathak at el., [13]. developed a multi objective novel algorithm known as LSR, which addresses security, QOS and energy efficiency. A QOS model is proposed is proposed to select a source node with metrics average routing delay and PDR, and energy efficiency using network lifetime. Trust values are calculated by incorporating trust models to provide the security based on average routing delay and PDR. An adaptive connectivity model is proposed to improve connectivity between nodes and it's measured in terms of performance. A deployment model also proposed to overcome energyhole problem.

Authors in [14]. developed a routing algorithm which extends the lifetime of WSN network. It focuses on energy balancing subject to, the packets must reach base station within predefined probability. To achieve this they have proposed two hop and multi hop routing algorithms, This determines the most efficient route for the nodes to take while communicating with the BS in order to send the monitored data.

Muhammad Usman at el., [15]. implemented a routing algorithm which is based on SDN architecture named as software defined WSN routing algorithm. In this era SDN controller handles routing in the entire network by using RL algorithm. RL have a special function which gives rewards for each action. So depending on each current reward the next action will be taken during routing and the optimized routing path is developed using the previous experiences.

Hassan zeb at el., [16]. sensor-based IoT faces a barrier from limited energy sources, Researchers have presented Energy Harvesting technique, a routing protocol for energy harvesting here, where the protocol consists of two primary components: the distributed neighbour discovery and routing operations. It contains an efficient connection selection based on the closest angle to the destination node to increase network lifetime by utilizing EH approaches. The experimental results show encouraging results in relation to energy and use approaches along with successful routing.

Neetesh Kumar at el., [17]. suggested a green routing method to prolong the life of the sensor network by using fork and join adaptive particle swarm optimization (FJAPSO). FJAPSO functions at two levels for auto optimization: the optimal number of control nodes and the optimal control node clustering. The experiments' findings demonstrated that FJAPSO outperforms other cutting-edge techniques and significantly increases the sensor network's lifespan.
Mahyar at el., [18]. proposed method is CLRP-MMSs, wherein nodes are partitioned into clusters and a CH is chosen through the use of CHCF. A significant amount of data loss could result from disconnecting nodes from CH nodes when clustering is used on networks with moving nodes. Although the energy and data rate received will alter, less energy will be wasted because the position will be predicted and the distance between the sink and CH nodes will be shortened.

Yinghui at el., [19]. recommends utilizing the EEMSR protocol in Internet of Things networks to reduce the substantial communication cost that arises from the scalability of these networks. It also improves intercluster routing, which is assumed to be supported by a multitude of diverse IoT entities and services as well as heterogeneous IoT networks. Multiple trust levels, including data perception trust, data fusion trust, and communication trust, are employed to protect against various threats by calculating the trust factor within the clustering and routing processes.
Sumayah at el., [20]. developed RDEC which choses the best route depends on two metrics related to energy, 1.transmission distance energy and 2.average battery consumption between intermediate nodes. In SDN controller the decision making is centralized, energy wastage is avoided and improves network lifetime.
S. Verma at el., [21]. Proposed Artificial-Intelligence-Based Green Routing (AGRIC) for Industrial Cyber–Physical Systems. It’s a cluster based network where the cluster head is elected based on AI based extended spotted hyena Levy flight optimization (ESHLFO) algorithm using a fitness function along with parameters such as distance from sink node, energy, count of nodes in the cluster. The authors have used 4 sink nodes which are of unlimited energy to avoid multi hop communication as well as to reduce the energy usage of individual nodes.

Qian Wei at el., [22]. developed a routing algorithm with a mobile sink. A dynamic minimum spanning tree is constructed using mobility parameters of mobile sink. In this framework, depending on the motion parameters of mobile sink the rendezvous points were selected and built a rendezvous layer to constraint the hierarchical transmission of DSTMS. In addition to this energy efficient function is proposed based on transmission energy consumption and residual energy distribution, the weight factor, to find the best path within MST. Finally they achieved energy efficiency by updating the frequent location of mobile sink and collision is avoided by constructing dynamic hierarchical transmission.

Greeshma at el., [23]. suggested DBN-based routing algorithm that provides the optimal route for improving the packet delivery ratio. Here, Reinforcement Learning (RL) to cluster the network nodes, optimizing energy usage and path construction. By employing the Modified Red Fox Optimization (MRFO) algorithm, they select Cluster Heads (CHs) based on multiple criteria including energy levels, delay, traffic density, and distance. The DBN then facilitates the determination of the most efficient route from CHs to the sink node. Performance metrics such as energy consumption, packet delivery rate, network longevity, and the number of active nodes indicate that this DBN-based routing protocol surpasses traditional methods in effectiveness.

On the other hand, Vaibhav et al. [24] present an energy-efficient routing strategy that leverages particle swarm optimization to select cluster heads and organize the network into groups. Their Mobile Sink-Based (MSB) intelligent routing scheme involves the mobile sink node traveling to predefined reference points to gather data from the CHs. This approach minimizes energy usage by optimizing the choice of reference points for data transmission to the sink node. The study aims to improve data collection efficiency and network energy management through strategic sink movements and optimal reference point selection.

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III. PROPOSED WORK

In this section we propose a scheme for clustering and path selection using Machine Learning approach for mobile sink and we consider a cluster based network. In distributed network each and every node has to send the monitored data to the base station. This process will ruin the energy of nodes to transfer data in multihop network. To overcome this issue we are using cluster based network. Fig. 1. Indicates the architecture of proposed system. It based on the clustering network topology. Cluster formation and first cluster head election is done using K-Means and next CH’s (from nn)are elected using RL algorithm (Circles indicates nodes and stars indicates cluster heads). A mobile sink will collect the data from all cluster heads and forwards it to end user through internet. This scheme has 3 phases: 1. Clustering phase, 2. CH election phase, 3. Optimized routing phase. The notations used in the algorithms for all these phases are listed below in Table 1. Fig. 2. Indicates the data flow diagram of the proposed work. At first the nodes are deployed in to the preferred area and they were initialized with their work. Later clusters are formed and a cluster head is elected based on RL algorithm by taking the input of some key parameters such as distance, remaining energy and delay. A mobile sink will move in a specific path and collect the data from cluster heads and forwards it to the end user or base station. Moving to the phases of the proposed work the first phase is the clustering phase.

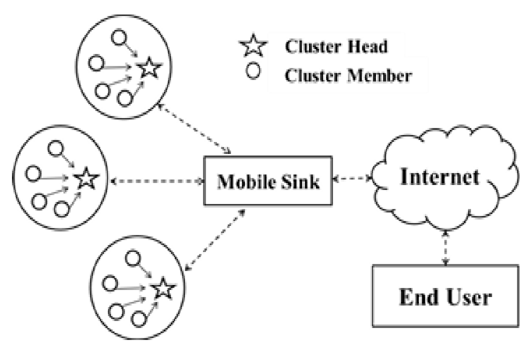

Fig. 1. Architecture of the proposed system

A. Clustering Phase: This phase describes the formation of clusters using K- Means algorithm. The entire network is divided into clusters with equal number of cluster members. In each cluster the cluster members initially have equal energy potentials to compete each other to become CH. Cluster members will exchange the data dynamically so that they will have knowledge of cluster head as well as neighbor nodes. CMs transfer the monitored data individually to the CH instead of base station.

Table – 1 Description of the symbol definition

CH_j	Cluster head where j=1…..k
CM	Cluster member
PDR	Packet delivery ratio
QOF	Quality of service
BS	Base station
N_i	Sensor Nodes where i=1….n
n	number of nodes
A_t	Activity
Ph_t	State
R_t	Reward
T	state transmission
k	number of cluster heads/clusters
sn	number of surrounding/ neighbor nodes
d_{th}	Distance threshold
t	Initialized with number of neighbor nodes

B. Cluster Head Election Phase: This phase depicts the election of cluster head. In traditional approaches after formation of clusters all CMs will compete each other to become a cluster head. Unlike existing approaches, in the proposed system a centroid node of the cluster will become cluster head in the beginning using K Means algorithm. Once the energy of this cluster head ruins the next cluster head election process will happen dynamically on the basis of RL algorithm. In this scenario the nodes which are near to the current CH will be considered to participate in the cluster head election with key parameters such as which node has less distance from the current CH and have more energy. The special feature that included here is electing an obstacle free CH.

No neighbor node to current cluster head, which has obstacle around it is considered as cluster head. So that the mobile sink can easily move towards the cluster heads and collect the information. It makes the mobile sink tour efficient so that the delay gets reduced and also packet loss is reduced. The monitored data that is collected from provided by the members of the cluster to the cluster head. By balancing the energy in the cluster heads the entire network lifetime is increased. Once the CH election process stops the entire network will die, so the election process must be continued. So cluster head election phase is a very crucial process and CH plays a major role in sensor node communication. Algorithm 1 describes the overall flow of the proposed work. Algorithm 2 depicts about CH election process. Where n number of sensors are given as input to algorithm 2 and as output CH's are elected for all clusters. At first n nodes are deployed into the network area and a network topology is formed. Then clusters formation and centroid node as cluster head election takes place based on K-Means algorithm. When the centroid node energy drains the next cluster head has to be elected based on RL algorithm with key parameters such as distance, delay and energy. In the proposed system not all the nodes are eligible to participate in this process but only the neighbour nodes. Nodes within threshold ditanse will compete to become next cluster head. If the nodes are not present in the distance dth then the the distance in incremented by 2 mtrs and the nodes are selected. These neighbor nodes(sn) are given as input to RL algorithm, and it will elect the energy efficient node as cluster head for each cluster. The RL algorithm we are using is Q-learning algorithm. Cluster head formation using Q– learning algorithm in algorithm 3.

Algorithm-3 Reinforcement basedCluster Formation Algorithm

1. The parameters: Phase and action pair (Ph, A)
2. Start
3. Set $Q\ (Ph, A)$'s table entry value to 0. 4: Iterate
4. Do the activity which is chosen
5. Reward the action immediately with R
6. Examine the most recent phase P'
7. Update $Q\ (Ph, A)$ by applying equation 1
   $Q_{t+1}\ (ph_t\ ,\ A_t\ ) = (\ 1\text{-}A)\ Q_t\ (\ ph_t\ ,\ A_t) + A[R\ (Ph_{t+1}, A\ ') - Q_t\ (Ph,A_t)]$
8. $Ph = Ph'$
9. Select action (ph_i)= argmax $Q\ (Ph, A)$
10. Exploration= $\frac{Ph\left(\frac{A_i}{Ph}\right)=kQ(Ph,A)}{\sum kQ(Ph,A)}$
11. End loop

The function of RL is, from existing state, node has to take next action and change its state based on Q-value. Every node in the network incorporate the concept of RL for clustering i.e., node first investigates the cost of route and intimates the same to cluster head. Markov decision process involve the concept of rewards as cost along with different phases (ph) multiple actions and learning algorithm makes the fundamental rule. The learning agent calculates the energy consumed by each cluster based on all phases and the activities of (A) done during the phases. The next phase is to getting reward *R* based on the activity done in that phase. The activities are like Ai+1 , Ai+2 ….and phases p*h*, p*h*i+1…….

The current activity and phase tied up with the Reward R with a transition phase T. The main objective of the learning agent is to creating policy Depending on initial phase p*h*i the Q-values are updated as follows,

Qt+1 (pht , At) = (1-A) Qt (pht , At) + A[R (Pht+1, A') - Qt (Ph,At)] (1)

C. Optimized Routing Phase:

Mobile sink is also a normal node but have some special features like it will have more energy and able to move. In this article the purpose of mobile sink is to collect the data individually from each cluster head by moving itself near the cluster head later it forwards data to base. During the mobility of the mobile sink, MS need to select the best optimized routing path to travel to each cluster head. So that the usage of energy will get reduced and the energy efficiency is achieved. In the future work we are going to explore on routing.

IV. PERFORMANCE ANALYSIS

The performance of proposed system will be compared with existing algorithms TTDFP, EADCR, CLONALG-M, GEEC and DNN. TTDFP is proposed for a multihop WSNs. This is an energy efficient protocol for data aggregation. The cluster heads elected here are based on relative node connectivity, remaining node energy and distance to base station. To achieve energy efficiency we are also including mobile sink. CLONALG-M is proposed to increase the performance of rule-based fuzzy clustering algorithms through which they were to enhance the network's performance. In our proposed work instead of using fuzzy we will be using ML based reinforcement algorithm to improve the performance of the network through Q-learning algorithm. Here we considered the parameters like obstacles, nodes which are near to the current cluster head becoming as next cluster head. Due to near by nodes transmission delay will be less and due to no obstacle consideration the packet loss will be less. we can achieve energy efficiency through mobile sink by collecting the data from cluster heads without any obstacle in between them. The performance of the RL based energy efficient routing protocol will be analyzed through experimental results. The evaluation metrics we are considering are Time complexity, network lifetime, throughput, energy consumption, delay, and transmission speed. As we are considering the nodes which are near to the centroid as cluster heads, the distance between the cluster members and cluster head will be less and also an obstacle free node we will be selecting as cluster head. So that the packet delay ratio will be less and throughput will be high. The energy efficiency is achieved through the key parameters used for cluster head election and a mobile sink is used to collect the data from cluster heads. Table 2 lists the simulating parameters in the proposed work.

The experiment is conducted on 100 nodes and they were clustered using K-Means clustering algorithm into 5 clusters. The first cluster is elected using K-Means. Fig.4 depicts the centroid as first cluster head in all clusters. Fig.3 visualizes the cluster head and near by nodes to cluster head which can be elected as next cluster head when the current head energy ruins. Fig.5 shows the elected second cluster head using Q-Learning which is near to the previous cluster head. The cluster head is elected using K-Means due to Fast convergence and lower computational complexity which is depicted in fig.6. Coming to the second cluster head election as we will be electing cluster head.

Algorithm-1 cluster formation and overall flow of the work

1. Deployment of set of $N_1, N_2, \ldots N_n$ sensors into *MxN* network area.
2. Formation of clusters and initial *CH* election using K-Means algorithm
3. Fixing the threshold values and selecting neighbor nodes, process is done in Algorithm 2
4. *CH* election process using s_n is done
5. Routing the data from cluster members to cluster head
6. Mobile sink visits each *CH* using optimized path and collects the data
7. The collected data is forwarded to the end user

Algorithm-2 Cluster Head Election

1. INPUT: Group of sensors
2. OUTPUT: List of cluster heads $CH_1, CH_2, \ldots, CH_k$
3. Deployment of $N_1, N_2, \ldots N_n$ sensor nodes and forming the topology
4. Cluster formation using K-Meansand head election using RL $CH_1, CH_2 \ldots CH_k$ among the nodes in the cluster
5. If distance< d_{th}
   Elect all nodes within distance d_{th} and add to surrounding nodes list
6. Else increment threshold d_{th} by 2 and repeat the above step 5
7. Applying reinforcement algorithm to surrounding nodes process shown in Algorithm 3

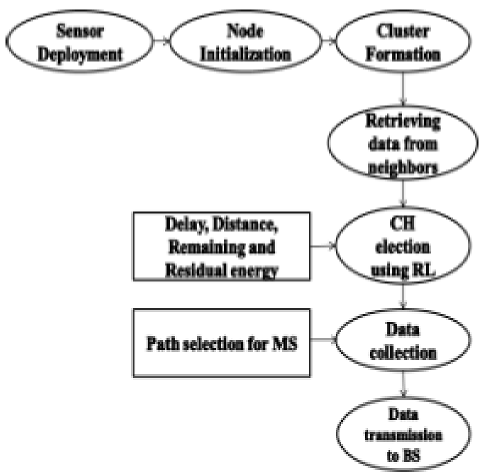

Fig-2. Dataflow Diagram

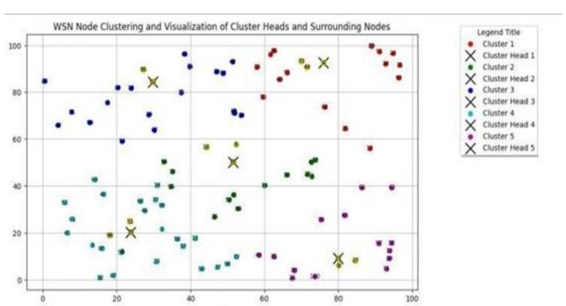

Fig. 3. Visualization of clusters, cluster heads and surrounding nodes

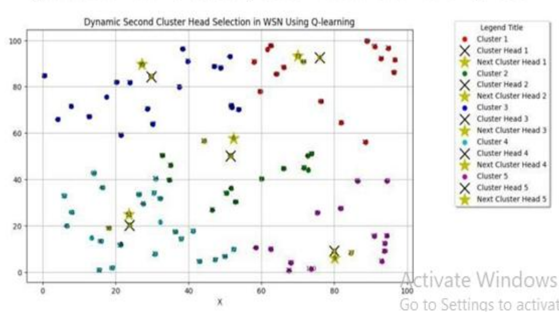

Fig. 5. Second cluster head election using Q-Learning algorithm

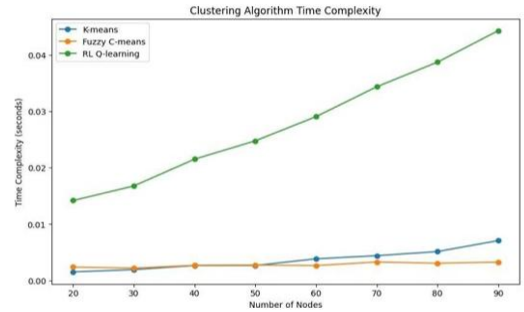

Fig. 6. Time complexity for the first CH election using K-Means

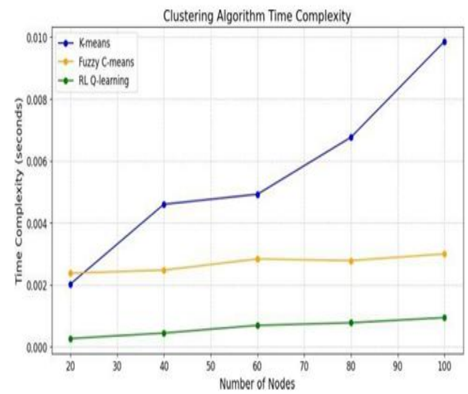

Fig. 7. Time complexity for the second CH election using Q-Learning

complexity, which is depicted in fig.7. Here we will be considering only the near by nodes to first cluster head. The time complexity is very less compare to K Means and Fuzzy C-means clustering algorithms which are used in TTDFP, EADCR, CLONALG-M, GEEC and DNN. So our algorithm gives best time complexity.

V. CONCLUSION

The primary concern of this article is to efficiently utilize the energy resources of an IoT device to achieve energy efficiency as well as to decrease the transmission delay of the packets. This is achieved by using a mobile sink and an efficient obstacle free CH. Initially using K-Means algorithm the centroid node is elected as cluster head irrespective of energy. Later dynamic obstacle free cluster heads are elected using Q-Learning algorithm. Fuzzy C- Means is better suitable for clustering and analyzing static datasets with overlapping clusters. As we were considering RL algorithm for second iteration cluster head election with only near by nodes to first cluster head, energy efficiency is increased by75% and the time complexity is reduced to O(n/2) compared to K-Means and Fuzzy C-Means algorithms. This achieves performance with less delay. An efficient cluster head is elected and the monitored data is collected from all cluster members. In the future a mobile sink is introduced to collect the data from cluster heads and forwarded to the end-user. The limitation is it's suitable for 2D environment. In future it can be implemented in 3D environment.

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