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Towards Energy Load Balancing in Clustered IoT Network through Unsupervised and Nature Inspired Learning

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Abstract: Balanced Energy Consumption followed by Improved Network lifetime is one of the critical challenges in the design of Internet of Things Network. In IoT, the sensor nodes are energy constrained and depletes quickly if used in an unorganized fashion. Clustering is found to be one of the efficient mechanisms which balances the energy and improves the network lifetime. This paper proposes a new clustering mechanism based on Adaptive Soft *k*-Means (ASKM) and Backtracking Search Optimization Algorithm (BSOA). To balance the nodes in each cluster, ASKM reassigns the member nodes present at the boundaries of multiple clusters into optimal clusters based on their membership degrees. Further, to balance the energy consumption within the cluster, the proposed approach introduced a new concept of multiple Cluster Heads selection for each cluster. In addition, the BSOA is utilized at the determination of optimal membership degree parameter which creates ambiguity about the belongingness of members and resolves in an iterative fashion. Numerous simulation experiments are carries out and the performance is assessed through Residual energy, First Node Death, Half Node Death and Last Node Death. Two set of case studies are carried out by locating the BS at different locations in the Network. In the first case, the BS is located at center of network while in the second case it is located at the corner of network. In the first case, the average residual energy experienced by proposed method is observed as 0.4967j while the k-means and soft k-means experienced 0.3433j and 0.4200j respectively. Further, the case 2 has experienced 0.3347j, 0.2240j and 0.1607j by proposed adaptive soft k-means, soft k-means and k-means algorithms respectively. The comparison proves that the proposed approach can postpone nodes death on an average when compared with three recent existing methods namely Energy Efficient Cluster Head Selection Using Particle Swarm Optimization (EECHS - PSO), Cluster Head Selection using Whale Optimization Algorithm (CHS - WOA) and Energy-Aware Clustering using Artificial Fish Swarm Optimization Algorithm (EAC - AFSA).

Keywords: Internet of things, Energy load balancing, Clustering, Adaptive soft *k*-means, Backtracking search optimization, Residual energy and lifetime.

1. Introduction

Recently, Internet of Things (IoT) has been evolved and attained huge research interest due to its widespread applicability in different applications [1-3] including Smart Cities, Digital Healthcare, Smart Agriculture, retail, Gas leakage detection, smart home etc. In simple words, the IoT is expressed as the sensor based automatic data collection and propagation strategy. The sensor nodes can be mobile and/or static and are enabled with internet facility [4]. The flexible connectivity of IoT devices in wireless communication has increased the interactions between human and machine in different applications like Smart transportation, Environmental monitoring, military, and education [5, 6]. In addition, the advanced communication paradigms in wireless networks have led to the IoT penetration into the medical sensor where the mobile sensor nodes are used to collect the data [7]. Further, the IoT sensor nodes are self-configured, distributed in nature and energy constrained [8]. IoT nodes are accompanied with data analysis capabilities which can provide an interface with real world for the exchange of information through the internet. After sensing the physical environment, IoT sensor nodes processes and transfers the data between nodes and cloud severe to deliver the real time data to users. During these processes, the IoT sensor node suffers from quick depletion of resources (ex. energy and memory) due to their continuous sensing and transmitting of information. Hence, there is a need to preserve the energy of sensor nodes in such a way they can sustain for longer time in the network.

Extensive research has been carried out over energy efficient routing for IoT networks [9, 10]. Among such methods, clustering is found to be one of best solution which makes the IoT network to communicate in a sophisticated manner. Compared to the non-clustering based routing, the cluster associated routing ensures a better sustainability for sensor nodes and makes them withstand for longer times in the network. In the cluster-based routing in IoT, the Cluster heads take the major responsibility for data aggregation and transportation, even for longer distances. Due to such flexibility, the energy of Cluster members will be preserved and makes them to work for longer times. However, most of existing methods employed a common energy or residual energy-based clustering strategies. Recently, M. E. Al-Sadoon et al. [11] proposed a Dual Tier Cluster-Based Routing (DTC-BR) which partitions the entire network into virtual zones in two sets named as Main Connectivity Zone and Candidate Cluster Zone. For clustering purpose, they used Distance, energy, and residual energy of IoT nodes and for each MCZ zone, one node with larger residual energy and larger connectivity is selected as CH. However, the IoT has heterogeneous nodes which have different energy capabilities, and a uniform clustering strategy makes them to deplete quickly. Particularly, the sensor nodes which lie very close to sink node will get seriously affected due to their better connectivity with larger number of sensor nodes as well as with sink node.

Hence, this paper proposes an intelligent driven non-uniform clustering mechanism which clusters the entire sensor nodes into several unequal and non-uniform clusters. The major contribution of this work is outlined as follows.

- To reduce the energy consumption burden on the nodes located nearer to the BS, this work proposed a Hybrid Clustering in which the entire nodes are clustered into two types of clusters; they are proximate cluster and remote clusters. The proximate cluster is only one and lies around the base station while the remote clusters are more in number and lies at minimum one hop distance from BS.
- To ensure the balanced clustering at remote clusters, this work proposes a new clustering mechanism based on Adaptive Soft *k*-means clustering (ASKMC) algorithm which selects the initial cluster centers based on Kernel density estimation and forms clusters based on Density Peaks and Fast Search.
- To optimize the membership parameter, this work uses Backtracking Search Optimization Algorithm which determines the optimal membership parameter at where the ambiguity arises between the members lies on the boundaries of multiple clusters.
- To ensure balanced energy consumption, this work proposes Multiple Clusters Heads Selection in which makes the network to switch for next candidate CHs when the current CHs are founds t have energy levels below the threshold.

The rest of the paper is organized as follows; Section 2 illustrates the particulars about the literature survey. Section 3 illustrates the particulars of proposed hybrid clustering methodology as proximate clustering and remote clustering. The particulars of experimental analysis are illustrated in section 4 and conclusions are elaborated in section 5.

2. Literature survey

In the past, several methods have been proposed to attain a better network lifetime in IoT through different clustering strategies. S. K. Chaurasiya *et al*. [12] proposed an Energy Efficient Hybrid Clustering Technique (EECHT) for IoT based Multilevel Heterogeneous Wireless Sensor Network (HWSN). Based on the static and dynamic configurations of sensor in IoT, EECHT divided the entire nodes as Ultra Super node, extra super node, Super node, advanced node, and normal node. For the cluster head selection, they employed the widely adopted Radio Energy Dissipation Model [13, 14]. Although EECHT classifies nodes into different categories to optimize energy consumption, it relies heavily on static configurations which may not adapt well to dynamic changes in the network topology. Our approach incorporates dynamic reconfiguration capabilities, enabling better adaptation to real-time network changes, thus enhancing overall network resilience and lifetime.

Similarly, A. S. Nandan et al. [15] employed the Genetic Algorithm for Cluster Head Selection in an optimal manner and named it OpiGACHS. The OptiGACHS considers four parameters namely

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capability of heterogeneous sensor node, energy, density, and distance at the formulation of a fitness function for CH selection. In addition, OptiGACHs suggested a movable sink to lessen the communication distance between CH and the sink node. Further, the deployment strategies are also suggested to optimize the distance and energy during communication process. The genetic algorithm used in OptiGACHS, while optimizing cluster head selection, can be computationally intensive and may result in slower adaptation to changing network conditions. Our method utilizes a less computationally demanding optimization algorithm, providing quicker adaptation and maintaining energy efficiency

C. Premkumar *et al.* [16] focused on the network lifetime improvisation through balanced energy consumption and proposed an Improved-Adaptive Ranking based Energy-efficient Opportunistic Routing protocol (I-AREOR). Mainly they concentrated on prolonging the time period of First Node Death (FND) by considering three measures at clustering; they are Residual energy, Relative Distance and Regional Density. In addition, Half Node Death (HND), and Last Node Death (LND) are also used to analyze the impact of energy consumption. I-AREOR focuses primarily on prolonging the time to the first node death (FND), potentially neglecting other important factors like communication overhead and load balancing. Our strategy balances energy consumption more effectively across the network, addressing both communication overhead and load distribution.

Divya Sharma *et al.* [17] proposed an energy efficient cluster based lightweight on-demand AdHoc Distance Vector (AODV) Routing Protocol for IoT Networks. For clustering purposes, they employed the most popular K-means clustering algorithm and for CH selection, Seagull Optimization Algorithm (SOA) is used. While effective in some scenarios, AODV routing may suffer from higher latency and increased control message overhead in dense IoT networks. We reduce latency and control overhead by integrating more efficient clustering and routing algorithms.

Vida D *et al.* [18] proposed an Energy Efficient Minimum Spanning Tree Algorithm (EEMST) based on Graph theory for an efficient data transmission in multi-hop clustered IoT network. The optimal CH selection is done based on the weighted minimum spanning tree calculated through Euclidean distance. The path with minimum weight is considered as the shortest path to transfer data between CH and CMs. This approach ensured a single hop inter clustering and multi-hop intra cluster routing. EEMST relies on the minimum spanning tree approach which may not always be optimal for dynamic IoT environments, particularly in terms of handling node mobility and varying energy levels. Our approach employs a more flexible tree-building algorithm that better accommodates node mobility and energy variations.

Ali. M. K. A., *et al.* [19] proposed an energy efficient Fuzzy Based unequal clustering with Sleep Scheduling (EFUCSS) for IoT-WSNs. Fuzzy C-Means (FCM) is used to form the clusters and fuzzy logic is used to select the CH in each cluster. Three measures namely Centrality, Remaining energy and Distance from gateway are used to form the fuzzy inference based on Mamdani Rules. Further, a sleep scheduling mechanism is induced to lessen the number of transmitted node. The use of fuzzy logic and sleep scheduling, while reducing energy consumption, may lead to increased complexity and difficulty in managing cluster heads in highly dynamic networks. Our method simplifies cluster head management while maintaining energy efficiency through adaptive clustering techniques.

Similarly, S. Suresh et al. [20] also used fuzzy logic and proposed a data routing protocol called as Fuzzy Logic Node Distributed Clustering for Energy Efficient Fault Tolerance (F-NDC-EEFT). They considered energy efficiency, communication delay, withstand node aliveness, and delivery rate for the selection of optimal path.

F-NDC-EEFT may struggle with scalability issues in larger networks due to the inherent complexity of fuzzy logic-based decisions. Our solution scales more efficiently by employing a less complex yet effective decision-making process for cluster head selection.

Mohana Bakshi *et al.* [21] proposed a Modified Glow Worm Swarm Optimization based clustering algorithm to minimize the overhead and to optimize the network lifetime. This method adapts for repeated CH selection such that the load is uniformly distributed among the nodes. This method may suffer from slow convergence rates, leading to suboptimal cluster head selection in real-time applications. We achieve faster convergence and more reliable cluster head selection through a refined optimization process.

Madhyar S *et al.* [22] proposed energy-aware clustering method in the IoT using Artificial Fish Swarm Optimization Algorithm (AFSA). The fitness function is formulated through degree of each node, sum of the distances, and energy. AFSA may not adequately address the balance between energy consumption and communication overhead. Our approach more effectively balances energy usage and minimizes communication overhead through enhanced algorithmic adjustment.

Rao, P. S., et al. [23] used Particle Swarm Optimization (PSO) algorithm for Energy Efficient Cluster Head Selection (EECHS) and Reddy, M. P. K., & Babu, M. R [24] used Self adaptive Whale Optimization Algorithm (WOA) for Cluster head selection in IoT network. PSO can sometimes converge prematurely to suboptimal solutions, particularly in complex IoT environments While WOA adapts well to changing conditions; it may still face challenges in maintaining long-term energy efficiency across all network nodes. Our method incorporates mechanisms to avoid premature convergence, ensuring more optimal solution and also offers improved long-term energy efficiency through continuous optimization and adaptive clustering strategies.

3. Proposed approach

3.1 Overview

The proposed clustering is an adaptive in nature which is executed in two phases; set up phase and steady phase. At the initial phase, each IoT nod broadcasts HELLO packets by including node ID and location. Due to such broadcasting, each and every node can acquire the information of remaining nodes in the network. Next, each node sends its information to the Base station through multi-hop routing algorithm [23]. Then the BS runs proposed approach based on information received from all nodes. Based on the proposed methodology, the BS forms two types of clusters namely proximate cluster and remote clusters. Proximate cluster is located nearer to the base station while the remote clusters locate far away from the base station. The formation of nearby clusters is done based on the closeness of nodes and for distant clustering; we use an improved k-means clustering algorithm. In addition, the proposed approach employs a node reassigning scheme to balance the node count in each cluster. Further, to balance the energy consumption of cluster heads, the proposed approach suggests multi-CH selection mechanism. After the completion of clusters formation and CHs selection, the BS broadcasts the information to all nodes based on the restricted flooding method [25]. Based on the obtained information, the nodes can distinguish themselves as either CH or cluster member. Next, the steady state phase comprises of so many communication rounds and in each round, the member nodes collect the information and transmit it to the CH within the specified timeslots, and the CHs aggregate the information and send to Base station. When the energy of CH is observed as less than the threshold, a SWITCH message is broadcasted to activate the next CH as well to cluster members indicating to send the data to new CH. After enabling all the CHs sequentially, the last CH sends a restart message to the BD to reinitiate the clustering process.

3.2 Proximity cluster

The proximate cluster is the one which locates nearer to the BS. In this cluster, the cluster members occasionally seek the help of CH to transmit their data to BS. Since they lie within the communication range of BS, they can communicate with BS directly. The formulation of proximate cluster is done based on three parameters; they are (1) distance between SNs and BS, (2) maximum number of SNs (N_m) that can be included in the proximity cluster and (3) optimal distance (d_0) for proximity cluster. In the process of proximity clustering, the base station computes distance from every SN and compares it with the optimal distance. The node which satisfies the condition, $d_{n_i}^{BS} \leq d_0$ is clustered into the proximity cluster as a cluster member. Here, the optimal distance is mathematically expressed as

$$d_0 = \begin{cases} \max\limits_{n_i}\left(d_{n_i}^{BS}\right), s.t.\, N_m, & if \max\limits_{n_i}\left(d_{n_i}^{BS}\right) \leq d_t \\ d_t, & Otherwise \end{cases} \quad (1)$$

Here, $\max\limits_{n_i}\left(d_{n_i}^{BS}\right)$ denotes the maximum distance value of the node n_i that lies in maximum distance from BS. The optimal distance d_0 is calculated with respect to N_m limit and it is mathematically expressed as

$$N_m = p_n \times N \quad (2)$$

Where p_n is the percentage of total nodes N and it is measured based on performance metrics like lifetime, and energy consumption in network. Since the total number of nodes in proximity cluster varies with p_n , we varied it for different values and analyzed the performance.

3.3 Remote clustering

Among the all N nodes present in network, after grouping some nodes in proximity cluster, the remaining nodes are distributed into optimal number of clusters which are called as remote clusters. For this purpose, the nodes have to satisfy the condition $d_{n_i}^{BS} > d_0$, means those are beyond the optimal distance are called as distant nodes and they are clustered into remote clusters. To perform remote clustering, we propose an Adaptive Soft k-means

(ASKM) clustering algorithm. Before applying k-means for remote clustering, the total number of clusters needs to be calculated [26], as

$$RC_{opt} = \frac{(L-d_0)*(W-d_0)*R}{d_0 \times d_{PCH}} \tag{3}$$

Where RC_{opt} is the optimal number of clusters needed to group the distant sensor nodes. N_R is the total number of remaining nodes present in the network after proximity clustering and it is simply obtained by subtracting the nodes present in proximity cluster from total number of nodes in the network, i.e., $R = N - N_{pc}$, where N_{pc} represent the total number of nodes present in proximity cluster. Next, $L * W$ is the area of network, L is the length and W is the width of the network, $(L - d_0)$ is the length of network after excluding the length covered by proximity cluster and $(W - d_0)$ is the width of network after excluding the width covered by proximity cluster. Next, d_{PCH} is the average Euclidean distance from remaining nodes to the CH of proximity cluster.

3.3.1. Soft *k*-means (SKM) clustering

Once the number of clusters are calculated through Eq. (3), we apply the proposed ASKM to cluster the remaining nodes into an optimal number of remote clusters. Here the ASKM is an extension of traditional soft k-means clustering algorithm [27]. SKM is a FCM kind of algorithm which considers the centers to represent the clusters. The traditional k-means clustering algorithms are hard in nature and hence they fail in separating the overlapping clusters when the data is noisy [28]. Hence, SKM is derived to address these issues in which each node can be characterized as belongs to more than one cluster with different memberships degrees [29]. The nodes present at the boundaries of clusters cannot be forced to completely belong to a single cluster; rather they can be a member of multiple clusters, based on different probabilities or membership degrees in the range of 0 and 1 [30]. In general, the membership degree is larger for the nodes those lies closer to the center than the nodes lies at the boundary of cluster. This flexibility makes SKM more advantageous than the traditional k-means clustering (KMC).

Consider the locations of nodes is represented as $P = \{p_1, p_2, \dots, p_R\}$, the main aim of KMC is to cluster the network into k sets $C = \{c_1, c_2, \dots, c_k\}$, with more distance between inter and smaller distance between intra cluster. Towards such aim, the objective function of KCM is defined as

$$J(P; M, T) = \sum_{v=1}^{k} \sum_{l=1}^{R} m_{vl} \left\| p_j - c_v \right\|^2 \tag{4}$$

Where $T(c_v; v = 1, \dots, k)$ is the cluster centers matrix, and $M(m_{vl}; v = 1, \dots, k; l = 1, \dots, R)$ is the membership degree matrix of P. m_{vl} is defined as the membership degree of l_{th} node with v_{th} cluster, computed as

$$m_{vl} = e^{-\beta \left\| p_j - c_v \right\|^2} / \sum_{m=1}^{k} e^{-\beta \left\| p_j - c_l \right\|^2} \tag{5}$$

Where β is signified as a softness parameter which has major role in impacting the node's membership. To derive the optimal value of β, we use a most popular nature inspired algorithm called as Backtracking Search Optimization Algorithm (BSOA) [39]. Compared to the KMC, the SKM gives a better clustering solution because the SKM used weighted squared errors while the KMC used only squared errors. The clustering solution is derived based on the minimization of Eq. (4) and the membership degree needs to follows several rules to do minimization; they are (1) $m_{vl} \in [0\ 1]$, (2) $\sum_{v=1}^{k} m_{vl} = 1, l = 1, \dots, R$ and (3) $\sum_{l=1}^{R} m_{vl} > 0, v = 1, \dots, k$. Based on the minimization of Eq. (4), the cluster centers are calculated as

$$c_v = \frac{\sum_{l=1}^{R} m_{vl} p_j}{\sum_{l=1}^{R} m_{vl}} \tag{6}$$

In summary, the SKM functionality is summarized as follows; in each round of iteration, the SKM computes the cluster centers and membership values with the help of Eq. (6) and Eq. (5) respectively. The process of clustering ends u when the values of cluster centers and membership degrees are found to be less than the threshold. Otherwise, new membership degrees and new cluster centers are measured. This process continues until the convergence occurs, if not occurred until the mentioned iterations, the entire process is reinitiated.

3.3.2. Kernel density estimation

KDE is a non-parametric estimator which determines the distribution characteristics from data points without assuming any assumptions over the data statistics. For the given data points, KDE ensures a better smooth Probability Distribution Function (PDF). In KDE, each data point is centered and being determined a peak PDF value while decreasing the intensity with an increase in the distance from location. According to the KDE, for a given node set, the PDF of locations $P = \{p_1, p_2, \dots, p_R\}$, is determined as the weighted sum of kernel functions [30] as

$$\hat{d}_h(p_i) = \frac{\sum_{t=1}^{R} \mathfrak{K}\left(\frac{p_t - p_i}{s}\right)}{R\, h^{\mathfrak{b}}} \tag{7}$$

Where $\mathfrak{K}(.)$ Denotes the kernel function, h is called as a smoothing parameter of $\mathfrak{b}$ dimensions which regulates the neighborhood size round the position $p_i, i \in 1,2, \dots R$. Based on the proximity of a position p_i, the kernel function regulates the weight to P at every position p_i. To get the smooth PDF for every position, we use a multivariate kernel function which can be regarded as a product of multiple univariate kernel functions as $\mathfrak{K}(\boldsymbol{u}) = \varphi(u_1) \times \varphi(u_2) \times \varphi(u_3) \times \dots \times \varphi(u_{\mathfrak{b}})$ where $u_j, j \in 1,2, \dots, R$ denotes the j_{th} component of $\mathfrak{b}$ dimensions vector $\boldsymbol{u}$. Due the most familiar properties of popular Gaussian kernel, it is used at kernel function.

3.3.3. Initial cluster centers selection

In the proposed ASKM algorithm, we use KDE and Density Peaks and Fast Search [33] for the selection of initial clusters. The major assumption behind the density peaks and Fast Search is that the lower density neighbors persist in the surrounding of cluster centers and they present consistently at larger distance from the nodes with higher density. Hence, the proposed method calculates two metrics for every node, they are distance e_i and local density ω_i. Initially, the compute each node's local density and searches for the node set (P') from P which has consistently lager density. Then we compute distances between the nodes in the node set P'. Next, based on the obtained distances and local densities, we choose initial cluster centers by multiplying the density and distances values together as

$$\vartheta_i = e_i \times \omega_i, i \in \{1,2, \dots, r\} \tag{8}$$

Where r denotes the number of nodes with larger local density. For a given set of node's locations $P = \{p_1, p_2, \dots, p_R\}$ and label set $L = \{1,2, \dots, R\}$, the mathematical expression for local density ω_i computation is expressed as follows.

$$\omega_i = \sum_{i \neq j} \chi(d_{ij} - d_c) \tag{9}$$

Where

$$\chi(x) = \begin{cases} 1, x < 0 \\ 0, \ \ x \geq 0 \end{cases} \tag{10}$$

Where d_{ij} is the Euclidean distance between two nodes p_i and p_j and d_c is called as threshold distance which is computed as an average of distance between i_{th} node and remaining nodes in the network. In simple words, the ω_i can be regarded as the nodes number those lies below threshold distance from i_{th} node.

Next, the distance is computed for each node which involves two cases; in the first case, for a node with higher density, the distance is the maximum value from i_{th} node to all the remaining nodes in the network. In the 2nd case, for a node with other than higher density, the distance is calculated as a value of its nearest neighbor node with higher density [32]. The mathematical expression for the distance computation is given as

$$e_i = \begin{cases} \max(d_{ij}), j \in L, \quad if\ \omega_i\ is\ maximum \\ \quad \max(d_{ij}), j \in L^i, \quad otherwise \end{cases} \tag{11}$$

Where $L^i = (t \in L: \omega_t > \omega_i)$ is the label set of nodes with node densities more than the node density of i_{th} node ω_i. The cluster centers are computed from the nodes that have both larger density and distance. Next, the Density Peaks and Fast Search algorithm assigns the remaining points to the closest cluster center to formulate the clusters. Particularly, the node with larger density and smaller distance denotes that it is not center, but it locates close to the center. Unlike, the node with smaller density and larger distance denotes that it is located very far to the center. Finally, based on Eq. (8), the initial cluster centers are chosen which have higher ϑ value.

3.3.4. Custer formation and CH selection

Some past researchers have applied the traditional KMC algorithms like Distributed KMC [35] and Improved KMC [36] for forming the clusters. They used the generalized distance between Cluster heads and Normal nodes. However, they lead to a non-uniform number of nodes in different clusters which in turn results in an unbalanced energy consumption of Cluster heads. So, our approach used the SKM algorithm to address these problems. In the SKM, a node can belong to more than one cluster, due to its different membership degrees with other nodes. But the member node needs to join only to one cluster, and it is based on its larger membership degree. Some nodes may lies on the boundary of different clusters due to their similar membership degrees with more than one cluster. At such instance, the proposed method reassigns the member nodes to different clusters such that the balance is maintained. Consider

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a member node is located at the boundary of two clusters X and Y. In this case, before processing for reassigning, the proposed approach checks for the node count in each cluster. Let the cluster X have 10 nodes and Cluster Y have only 5 nodes. In this case, the nodes present in A sends their information to CH which experiences more energy consumption than the CH in cluster Y. So, for balancing the energy consumption, the node is being clustered into Y. The Reassigning of nodes from one cluster to another cluster slightly increases the energy consumption due to the transmission of messages between nodes and CHs. But it is negligible when compared with the energy consumption of CH. A node will join to the cluster with low density if it found the difference between the probabilities of two clusters in smaller than particular threshold. Further, if a node lies on the boundaries of more than two clusters, then the proposed approach picks the first two maximum values and follows the same above process to cluster it.

In general, the nodes present in different clusters are different n nature and number. For a cluster with larger density, if only one node is selected as CH, it will consume the amount of energy and deletes quickly. So, the proposed approach suggests a Multi CH mechanism where the clusters with larger node density have more than one cluster. The number of CHs required is totally dependent on the total node count in that corresponding cluster. Here, the proposed method uses residual energy and distance between cluster center and nodes to do the CH selection. A node is being elected as CH if it has more residual energy and is close to the cluster center. Consider H $H = \{CH_1, CH_2, \ldots, CH_k\}$ be a set which consist of all the CHs of k clusters and $CH_b, < b \leq k$ be the set of CHs in cluster b, the total amount of average residual energy of cluster b is computed according to the following expression,

$$E_b = \frac{1}{l(b)} \sum_{i=11}^{l(b)} E_r(i) \tag{12}$$

Where $l(b)$ denotes the size of cluster b, $E_R(i)$ denotes the residual energy of i_{th} node in current round r. Here we use the first order radio model [37], [38] to compute the energy consumption of network. Consider Fig. 1 where the types of clusters are present in which the cluster X has only one CH while Cluster Y has two CHs they are CH1 and CH2. As the number of cluster members is more in the cluster, the number of CHs is also more.

After the determination of CHs, the nodes those are closer to center and having lager residual energy is selected as CHs. Such kind of multi-CH selection scheme balances the energy consumption of each node in the cluster and improves the overall network lifetime. After the finalization of CHs in each cluster, BS sends a notification message to all the nodes stating to join into the corresponding clusters. To ensure a collision free data transmission between nodes in the cluster, CHs broadcasts time schedules based on Time Division Multiple Access (TDMA) to the cluster members. Then the steady state of the network begins and data exchanging state between cluster members and the corresponding CHs. towards balancing the energy consumption in network, if the residual energy of any CH is found as below the threshold, then the next candidate CH is enabled. After the completion of all CHs, the re-clustering process gets initiated.

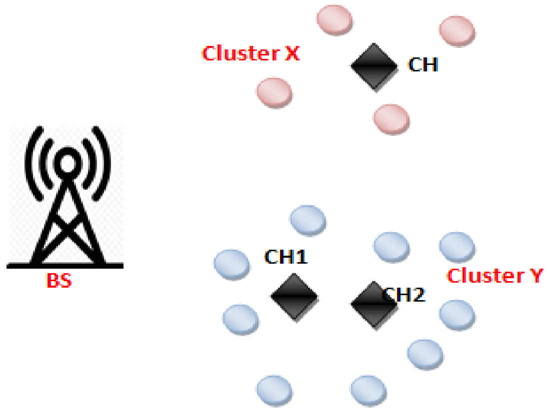

Figure. 1 Multiple CHs scenario

4. Simulation results

This section elaborates the effectiveness of the proposed approach through extensive simulation experiments. Herein the current simulation, we consider two cases; the first case considers BS at center of network while the 2nd case considers the BS at any corner of network. The total number of nodes are 30 and the network area is fixed as 300×300. In the first case, the BS is located at the position of $[150, 150]$ whereas in 2nd case, the BS is located at the position of $[300, 300]$. The network with 30 nodes in case 1 and case 2 are shown in Figs. 2(a) and 2(b) respectively. Table 1 shows the simulation parameters. For every node, the initial energy is given as 1J, transmission and receiving energy for each bit is set 50nJ/bit. Further, the energy required for the amplification in free space and multipath propagation environments is considered as 10pJ/bit/m^2 and 0.0013 pJ/bit/m^4 respectively. Further, the maximum communication rage of each node is assumed as 20% of network length, i.e., 60 m.

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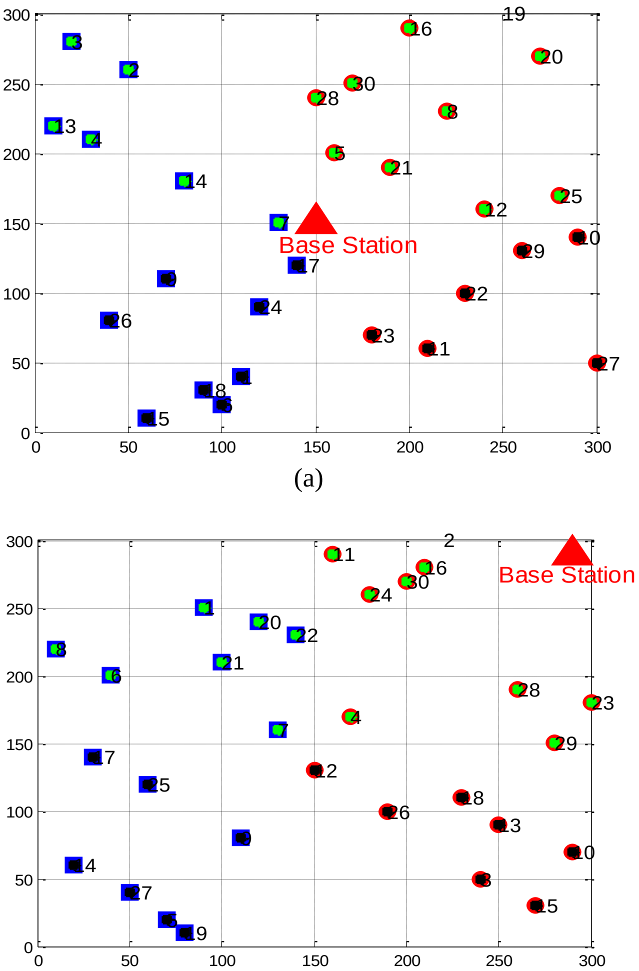
Table 1. Simulation setup

Parameter	**Value**
Number of Nodes	30
Area of Network	$300m \times 300m$
Communication range	60m
BS location	$[150,150]$ and $[300,300]$
Length of Data packet	4000 bits
Length of Control packet	100 bits
Transmission energy per bit	50 nJ
Receiving energy per bit	50 nJ
Free space Energy coefficient	10pJ/bit/m^2
Multipath propagation Energy coefficient	0.0013pJ/bit/m^4



(a)

(b)

Figure. 2 (a) Case 1 – Base station at the center of Network and (b) Case 2 – Base station at the corner of Network

As shown in Fig. 2(a), the node 12, node 10, node 5, and node 28 are present on the boundaries of clusters. Similarly, in Fig. 2(b), the node 29, node 7, node 11 and node 22 are present on the boundaries of clusters. These nodes create an ambiguity about their belongingness, and it is resolved with the help of β from Eq. (5). Towards such analysis, initially we vary the β value as 0 to 1 and applied the proposed clustering mechanism on the network. The β value is varied in the range of 0.2 from 0 to 1 and the better performance is observed at $\beta = 0.2$. The obtained probabilities for different clusters of Case 1 and case 2 are shown in Tables 2 and 3 respectively. Based on the values, it can be seen that for $\beta = 1$, the nodes shown strong belongingness when compared with $\beta = 0.2$. On the other side, the probability scores derived at $\beta = 0.4$ are more than the values obtained at $\beta = 0.2$ and less than the probability values obtained at $\beta = 1$. Such ambiguity is effectively resolved by the proposed approach. In case 1, as node 12 creates ambiguity between Cluster 2 and cluster 4, then its probability is undefined for remaining clusters. Similarly, in case 2, node 7 creates ambiguity between Cluster 1 and cluster 3, then its probability is undefined for remaining clusters. Hence, we kept dash marks at the corresponding clusters which don't have any ambiguity with the above mentioned nodes.

Table 2. Probabilities Comparison for Case - 1

		Node 12	**Node 10**	**Node 5**	**Node 28**
$\boldsymbol{\beta = 0.4}$	**Cluster 1**	-	-	-	-
	Cluster 2	0.3977	0.5896	-	-
	Cluster 3	-	-	0.3790	0.4037
	Cluster 4	0.6023	0.4104	0.6210	0.5963
$\boldsymbol{\beta = 0.2}$	**Cluster 1**	-	-	-	-
	Cluster 2	0.4015	0.5523	-	-
	Cluster 3	-	-	0.4159	0.4896
	Cluster 4	0.5985	0.4477	0.5841	0.5104
$\boldsymbol{\beta = 1}$	**Cluster 1**	-	-	-	-
	Cluster 2	0.1144	0.8974	-	-
	Cluster 3	-	-	0.0855	0.2044
	Cluster 4	0.8856	0.1026	0.9145	0.7956

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Table 3. Probabilities Comparison for Case - 2

		Node 29	Node 7	Node 22	Node 11
$\beta = 0.4$	Cluster 1	-	0.6523	-	-
	Cluster 2	0.4477	-	-	-
	Cluster 3	-	0.3477	0.6012	0.4002
	Cluster 4	0.5523	-	0.3988	0.5998
$\beta = 0.2$	Cluster 1	-	0.5896	-	-
	Cluster 2	0.4952	-	-	-
	Cluster 3	-	0.4104	0.5623	0.4345
	Cluster 4	0.5048	-	0.4377	0.5655
$\beta = 1$	Cluster 1	-	0.9212	-	-
	Cluster 2	0.0477	-	-	-
	Cluster 3	-	0.0788	0.9585	0.0434
	Cluster 4	0.9523	-	0.0415	0.9566

Fig. 3 shows the Residual energy comparison between different CHs in Case 1 after 600 rounds at different clustering methods like K-means, Soft K-means and proposed adaptive soft k-means algorithms. In this case, the maximum residual energy is found at CH2 and CH3 which has only 6 nodes while the CH4 is observed to have 10 nodes. Hence, CH4 consumed more energy and resulted in less residual energy. On the other side, the maximum residual energy is observed when the clustering is carried out through the proposed method, i.e., adaptive soft *k*-means clustering algorithm. Similar observations can be seen at case 2 (see Fig. 4) where the CH 4 experienced less residual energy because it has more cluster embers, i.e., 9. The remaining CHs like CH1, CH2 and CH3 have same member count and hence the approximate equal residual energy is observed. Among these three CHs, CH1 has observed less residual energy than CH2 and CH3 because the BS is present at very far. Due to the presence of far located BS, the CH1 needs to spend more amount of energy to transmit the information to BS. Hence, its residual energy is observed as less than the remaining CHs. Further, the case 2 CHs are observed to have less residual energy than the CHs in case because the BS is located at one corner of the network. Such kind of deployment creates non-uniform connectivity and hence they consumed more energy for data transmission. In case 1, the proposed method has experienced 0.4967J average residual energy while the earlier methods like KMC and SKMC experienced only 0.3433J and 0.4200J average residual energy respectively. In case 2, the proposed method has experienced 0.3317J average residual energy while the earlier methods like KMC and SKMC experienced only 0.1667J and 0.2240J average residual energy respectively.

As the number of rounds increases, sensor node's energy consumption increases and results in the death.

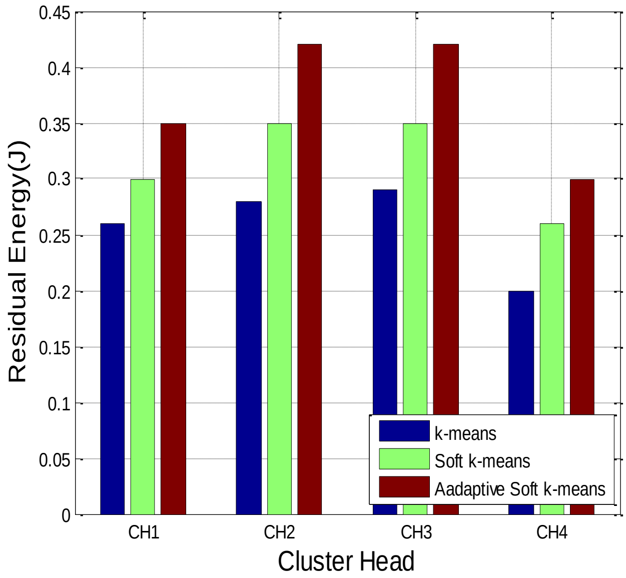

Figure. 3 Residual energy comparison between CHs in Case 1 after 600 rounds at different clustering methods

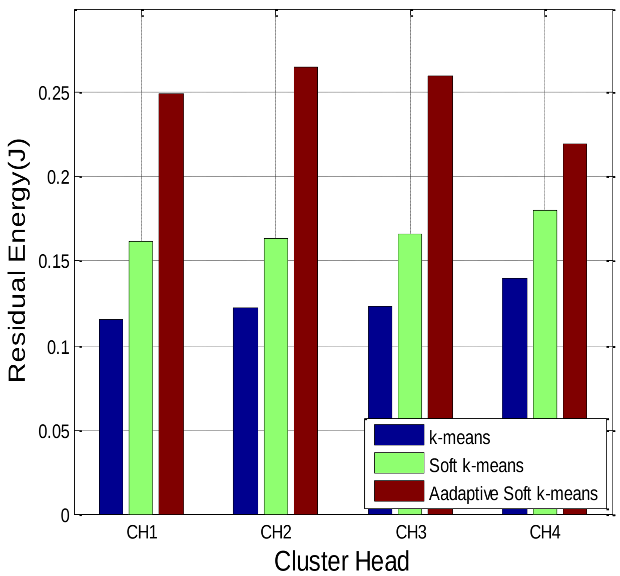

Figure. 4 Residual energy comparison between CHs in Case 2 after 600 rounds at different clustering methods

Here the First Node Death (FND) is defined based on the round at where the death of first node has been incurred. Next the Half Node Death (HND) is defined as the round at where the death of 50% of nodes has been incurred. Finally, the Last Node Death (LND is defined as the round at where the last node in the network was dead. Fig. 5 shows the Number of Rounds comparison between different clustering methods in case 1 through three node death metrics, they are FND, HND and LND. From the observations, it can be seen that the proposed method experienced FND at 455th round while the KMC and SKMC experienced at 248th round and 322nd round respectively. These values denote that the proposed ASKMC can balance the energy of nodes in such a way they can persist for longer time in the network. Almost all the proposed method made the network to exists until 852nd round where KMC and SKMC have only 530th round and 661st round respectively. Similar observations for case 2 is shown in Fig. 6 where the FND of ASKMC is observed at 356th round while FND of KMC and SKMC is observed at 105th round and 182nd round respectively. Compared to the lifetime of network in case 1, the lifetime of network is observed as less in the case 2, because the BS is located in a non-uniform manner. For case 1, the average network lifetime of proposed ASKMC is observe$_d$ as 658 rounds while for KMC and SKMC, it is observed as 392 rounds and 498 rounds respectively. Similarly for case 2, the average network lifetime of propose$_d$ ASKMC is observed as 552 rounds while for KMC and SKMC, it is observed as 225 rounds and 320 rounds respectively.

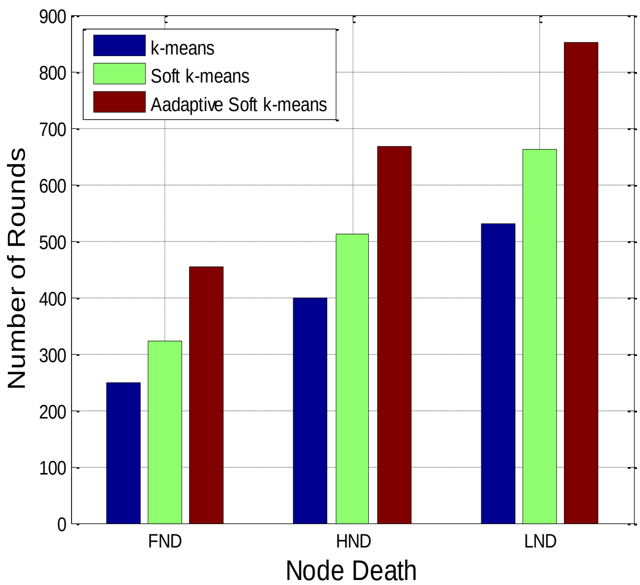

Figure. 5 Number of Rounds comparison between different clustering methods in case 1

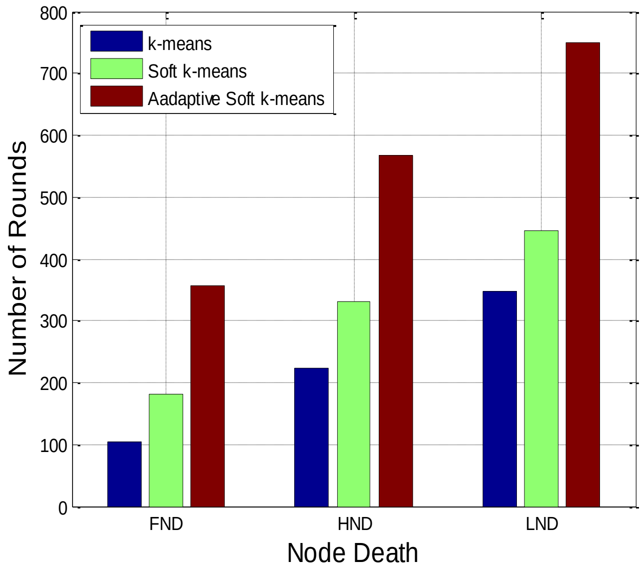

Figure. 6 Number of Rounds comparison between different clustering methods in case 2

Fig. 7 shows the Network lifetime comparison of proposed method with several existing methods through three lifetime metrics they are FND, HND and LND. The major commonality between proposed and existing methods is the accomplishment of nature inspired algorithms for the optimization of network parameters. However, the proposed approach mostly concentrated on the energy balancing through network partitioning in a uniform manner which has major impact in the improvisation of network lifetime. Even though the existing methods attempted to improve network lifetime, they are majorly dependent on nature inspired algorithms which don't have much significance. The methods in [23] used PSO for CH selection and the method in [24] used WOA. Compared to PSO and WOA, the proposed BSOA is simple and effective in the optimization of membership parameter. Hence, from the comparison, it can be seen that the proposed approach has gained better network lifetime than all the existing methods. The proposed well balanced the energy of all nodes in the network and hence it experienced the FND at 356th round which is very far away from the FND of existing methods. This scenario indicates that the proposed approach effectiveness in the selection of multiple CHs and uniform clustering. Alongside, the HND and LND of proposed approach are also incurred at larger rounds which indicate that the better network lifetime.

Fig. 8 compares the residual energy of four clustering algorithms namely Proposed, EAC - AFSA [22], CHS - WOA [24], and EECHS - PSO [23]) over 100, 100, and 1000 rounds in an IoT-based Heterogeneous Wireless Sensor Network (HWSN).

The Proposed method consistently shows the highest residual energy across all rounds, indicating superior energy efficiency. EAC - AFSA also performs well but is consistently outperformed by the proposed method. CHS - WOA and EECHS - PSO demonstrate lower residual energy, with EECHS - PSO having the least residual energy among the four methods. The chart highlights the long-term energy efficiency advantages of the proposed method compared to the others.

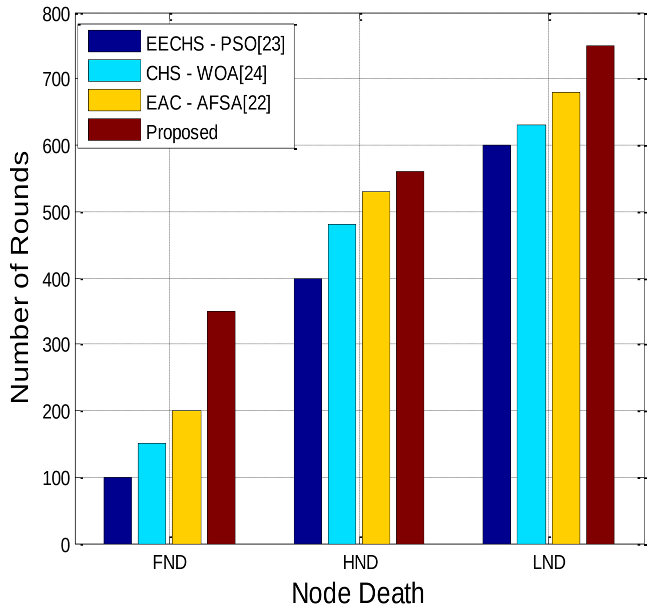

Figure. 7 Network lifetime comparison of proposed method with several existing methods

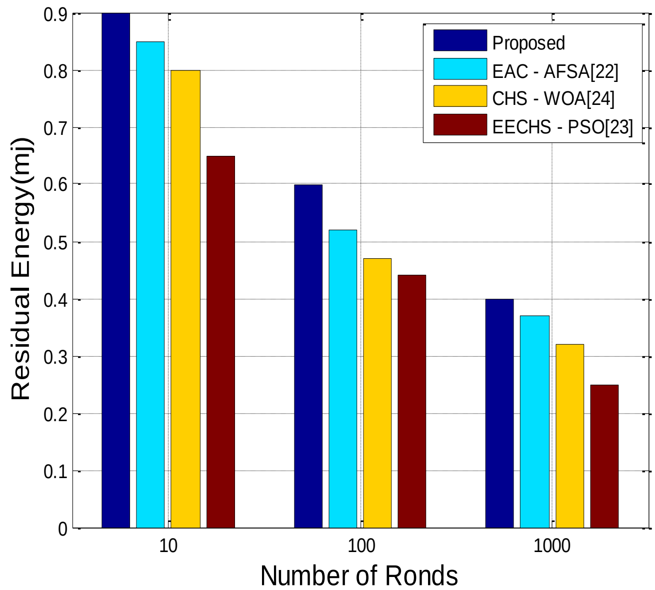

Figure. 8 Residual energy (mj) comparison of proposed method with several existing methods

5. Conclusion

This paper proposed a Hybrid Clustering mechanism for IoT Networks based on Adaptive Soft *k*-means clustering (ASKMC) and Backtracking Search Optimization Algorithm (BSOA). Two types of clusters are formulated based on the node's distance from BS; they are proximate cluster and remote clusters. To balance the nodes in each cluster, the ASKMC utilizes KDE and Density Peaks Fast Search for the selection of initial clusters and reassigns the member nodes with ambiguous membership probabilities into optimal cluster. BSOA is utilized to optimize the membership parameter in an iterative fashion. Next, to balance the energy consumption, the proposed approach selects multiple CHs in the clusters that have larger member nodes. Further, to explore the effectiveness of proposed approach, it was simulated in two network scenarios; they are BS located at center of network and BS located at the corner of network. In both cases, the proposed approach had shown better network lifetime and residual energy. Finally, the comparative analysis between proposed and existing methods proves the superiority in terms of Network lifetime. On an average, the proposed method experienced 553 rounds while the existing methods experienced 47, 420 and 366 rounds by EAC - AFSA, CHS - WOA, and EECHS - PSO) respectively.

Conflicts of Interest

The authors have no material competing interests, either financial or otherwise. Moreover, the authors have no declared conflicting interests that are pertinent to the subject matter of this study.

Author Contributions

The simulation and main manuscript were written by the first author, Prasad Nagelli. Ramana Nagavelli, the second author, assists with the simulation and creates the figures and tables.

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