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Universal and Dynamic Clustering Scheme for Energy Constrained Cooperative Wireless Sensor Networks

MUHAMMAD KAMRAN NAEEM[1], (Student Member, IEEE), MOHAMMAD PATWARY[2], (Senior Member, IEEE) AND MOHAMED ABDEL-MAGUID[3], (Senior Member, IEEE)

[1]Faculty of Computing, Engineering and Sciences, Staffordshire University, Stoke-on-Trent ST4 2DE, U.K.
[2]Faculty of Computing, Engineering and the Built Environment, Birmingham City University, Birmingham B5 5JU, U.K.
[3]Department of Science and Technology, University of Suffolk, Ipswitch IP4 1QJ, U.K.

Corresponding author: Muhammad Kamran Naeem (kamran.naeem@ieee.org)

ABSTRACT Energy conservation is considered to be one of the key design challenges within resource constrained wireless sensor networks that leads the researchers to investigate energy efficient protocols with some application specific challenges. Dynamic clustering is generally considered as one of the energy conservation techniques; but unbalanced distribution of cluster heads, highly variable number of sensor nodes in the clusters and high number of sensor nodes involved in event reporting tend to drain out the network energy quickly resulting premature decrease in network lifetime. In this paper, a dynamic and cooperative clustering and neighborhood formation scheme is proposed that is expected to evenly distribute energy demand from the cluster heads and optimize the number of sensor nodes involved in event reporting. Assuming multiple sensors will form a cluster, while responding to an event to report to the fusion center. However, all the sensor nodes are assuming to report the sensing parameters to a cluster-head; which are to be summarized and then report it to fusion center. The transmission of the same event data from multiple sensors within the cluster at different distances with single or multiple antennas to the cluster-head with similar antenna characteristics can be realized as multiple-input multiple-output (MIMO) channel set up as found in the literature. Such realization among clusters of MIMO channel and existence of a feedback channel between the clusters and fusion center is the key of the proposed framework. The dynamic behavior has been adopted within the framework with a proposed index derived from the received measure of the channel quality, which has been attained through the feedback channel from the fusion center. The dynamic property of the proposed framework makes it robust against time-varying behavior of the propagation environment. The proposed framework is independent of the nature of the sensing application, providing with universal behavior. From simulation results, it is observed that the proposed clustering scheme enhances network lifetime by 24.5% and 36% as compared to existing schemes e.g. DDEEC and EDDEEC respectively. Furthermore, it is validated by simulation results that the proposed framework provides a trade-off model between network lifetime and transmission reliability.

INDEX TERMS Adaptive resource selection, collaborative sensing, cooperative transmission, channel quality index (CQI), dynamic clustering, quality of service (QoS), virtual MIMO, wireless sensor networks.

I. INTRODUCTION

Wireless Sensor Networks (WSNs) are commonly deployed to serve wide range of potential applications e.g. environmental monitoring, health monitoring, battlefield monitoring etc. Regardless of the nature of sensing application requirements WSNs are usually formed with spatially dispersed and dedicated sensor nodes which collectively monitor and distribute information to the desired destinations. Sensor nodes are inexpensive resource constrained devices that consist of a sensor, embedded processors, limited memory, low power radio, and normally powered by battery. WSNs usually suffers from inevitable problems because of resource constrained sensor nodes deployed randomly in hostile environments which make it difficult to change or replace their batteries as discussed in [1]. Consequently, lifetime enhancement is one of the key issue while designing the WSNs regardless of the type of application, without compromising the required quality of service.

To achieve scalability and energy efficiency within WSNs, clustering is defined that virtually divides the sensor nodes of the whole network into logical groups. It also enhances load balancing, fault tolerance and network connectivity within the network as described in [2]. Generally, cluster heads are elected within WSNs to perform special tasks for its sensor nodes e.g. coordination among sensor nodes, data aggregation, communication with other cluster heads and fusion center receiver etc. The cluster heads election criterion is usually based on certain parameters i.e. residual energy, distance from fusion center receiver etc. As a result of aforementioned tasks, the energy of cluster heads drains out at much faster rate than the other sensor nodes within the network. Therefore, the self-organization of the WSNs is a desirable feature as no centralized or external entity is required. Dynamic clustering is introduced within WSNs which is expected to balance the energy consumption among the sensor nodes by re-electing the cluster heads and redefining the cluster boundaries throughout the network; hence enhance the lifetime of the WSN as discussed in [3]. Most of the dynamic clustering schemes presented in the literature as described in [4] are based on random selection of cluster heads which results in uneven distribution of cluster heads that leads to low network coverage and uneven energy consumption. As a result, it also increases the chance of selecting sensor nodes with low energy level as cluster heads which will force frequent re-clustering. Subsequently, controlled size clustering is one of the solutions to overcome the aforementioned challenges that is expected to conserve energy by evenly distributing the energy demand among sensor nodes throughout the network.

Within WSNs, most of the energy consumed while communication, especially data transmission to fusion center receiver which is denoted as long-haul transmission. Generally, conventional single node transmission techniques are used for long-haul communication. But, such high dependency on a single node while long-haul transmissions may lead to reliability risk in severe network conditions such as least amount of available energy at a sensor node or deep channel fading etc. Hence, energy efficient communication schemes are needed to be defined to focus on minimizing the energy consumption during communication. Cooperation among sensor nodes while data transmission allows resource saving within WSNs by implementing virtual MIMO[‡] concepts for energy efficient communication to increase reliability and enhance energy efficiency [5].

The power consumption of a sensor node is directly proportional to the uncertainty of channel propagation conditions. So, one of the design challenges of WSNs is to make them adaptive with the dynamic propagation environmental conditions of radio frequency to guarantee the quality of service based on application requirements. The required quality of service is generally defined in terms of error rate that can be guaranteed by adopting dynamic behavior according to the time-varying conditions of propagation environment. It is also expected to obtain maximum transmit-receive reliability with optimum usage of radio resources such as power and bandwidth. To obtain maximum optimization performance, knowledge of the channel quality features at the transmitter is required. Hence, classification of such channel quality features as estimated at the receiver can be fed back to the transmitter with negligible spectral resources as required.

As discussed earlier, wireless communication is the most energy consuming task within WSNs. A new approach for an improved lifetime of wireless sensor nodes is required that is expected to process the sensing data locally. Each sensor node is expected to decide locally whether to transmit the sensed data to cluster head based on the predefined application specific threshold value provided by fusion center receiver. To reduce the unnecessary communication between sensor nodes and cluster heads for time-driven reporting mode, cluster heads are expected to aggregate the data in order to remove redundant information. All the cluster heads are also expected to collaborate with each other. In some applications, sensor measurements are sent directly to the fusion center receiver from the sensor nodes e.g. traffic surveillance system to monitor traffic on congested roads, watches to monitor health (e.g. blood pressure, pulse rate etc.), wireless motion sensor for the monitoring of stroke patients, etc. In most of the applications, sensor nodes are densely deployed in harsh environments to monitor large scale areas e.g. environmental monitoring, infrastructure protection, agriculture, water management, military surveillance, etc. The energy and sensing range of a sensor node is limited in such scenarios. So, sensor nodes can be organized in a multi-hop fashion that is expected to achieve long distance communication and lifetime improvement of the network. Within WSNs, the fusion center receivers are responsible to collect the information from the network, process and analyze the information and send instructions to the sensor nodes within the network. They are usually connected with internet through wireless or wired communication such that the sensing data can be requested at any time by an end user.

The aim of this paper is to propose a universal framework that enhances the operation efficiency of WSNs by defining dynamic clustering, optimizing number of sensor nodes in event reporting and cooperative communication techniques. It is expected that the proposed framework can support applications that require WSNs to perform sensing for a predefined time referred to as time-driven sensing or to perform sensing based on events referred to as event-driven sensing. Moreover, the proposed framework is also expected to support those applications that required time driven sensing as well as event triggered sensing referred to as hybrid sensing. The dynamic behavior of the proposed framework is expected

[‡]The basic concept of virtual MIMO is the cooperation among multiple devices into virtual antenna array to attain the advantages of MIMO communication.

to provide a trade-off model between energy conservation and detection reliability. The main contributions of this paper are as follows:

1) A dynamic clustering as well as neighborhood formation framework for WSNs is proposed where collaborative sensing is permitted. The proposed framework provides an energy efficient solution by uniformly distributing the network load among sensor nodes and carefully selecting the candidate sensor nodes for event reporting.
2) The proposed framework is universal in nature for its functionality requirement within a WSN, i.e. independent of the sensing parameters. This provides the system design engineer with a tool for lifetime approximation modelling to configure the network for a diverse range of applications by fine-tuning the following parameters i.e. cluster head selection threshold and neighborhood selection criterion.
3) The dynamic behavior of the proposed framework is adopted with a proposed channel quality indexing (CQI) scheme in the context of WSNs. This scheme provides a trade-off model for transmission reliability and network lifetime by dynamically reconfiguring the network according to radio frequency propagation environment conditions while maintaining required quality of service.

In this paper, it is assumed that the fusion center is equipped with multiple antennas, has unlimited energy and its coordinates are known. It is also assumed that the dimensions of the sensing field are known and the coordinates of all the sensor nodes are implicitly deterministic. The rest of the paper is organized as follows: The literature review is elaborated in section II; the system model is described in section III; the proposed frameworks for time-driven and event-driven are presented in section IV; network lifetime models are defined in section V; performance analysis of the proposed frameworks have been presented in section VI along with the comparison of existing frameworks to evaluate the performance of the proposed framework followed by conclusion in section VII.

II. RELATED WORK

The state of the art research studies that provide solutions to resolve the issues within WSNs are elaborated in this section such as uniform energy consumption among sensor nodes within the network by performing network segmentations, and reliable transmission by introducing cooperation between the sensor nodes. Existing network segmentation and lifetime approximation techniques in the literature can be grouped into two categories: time-driven sensing and event-driven sensing.

A significant amount of research has been conducted in the literature for lifetime approximation of time-driven sensing scenarios. Low Energy Adaptive Clustering Hierarchy (LEACH) scheme is proposed in [6] and [7] that designate cluster heads with a predetermined random probabilistic approach which can lead to early energy depletion because the sensor nodes with low residual energy can be elected as cluster heads. A residual energy and communication cost based hybrid energy efficient distributed clustering algorithm scheme is proposed in [8]. In this scheme, cluster heads are elected through iteration process by constant communication between the candidate cluster heads and their neighboring sensor nodes which results in extra communication cost. Authors in [9] proposed a distributed energy efficient clustering algorithm that considers the ratio of residual energy of candidate cluster heads and average network energy for the election of cluster heads that results extra load on the network by calculating the average energy of the network.

The aforementioned schemes perform cluster heads selection randomly that can lead to unbalanced energy consumption throughout the network. To address this issue authors in [10]–[14] proposed that fewer number of nodes should be allocated to the clusters which are near to the sink in order to reduce the cost of inter-cluster communication. However, this approach of clustering can result significant amount of traffic load on the cluster heads near to the sink as discussed in [15]. Authors in [16] discussed the significance of uniform size clustering in order to balance the communication overhead and energy consumption in the network.

Considering WSNs for detection and reporting of events is another attractive approach for significant amount of applications. Authors in [17] discussed that the occurrence of events are generally considered as random and transient which involves the handling of large amount of sensing data that can lead to uneven energy consumption. To overcome this issue, clustering algorithms are proposed in [18] and [19], that consider the residual energy and distance of sensor nodes as cluster head election criteria. Local and global decision based event detection protocols are presented in [20] and [21]. The authors claimed that the proposed schemes conserve energy by reducing transmissions and minimize error probability through local and global decisions respectively. But in order to ensure the detection reliability of an event, it must be detected by a group of sensor nodes. The spatiotemporal correlation of the sensed data can achieve higher energy efficiency and detection reliability as discussed in [22].

It is claimed by the authors in [23] and [24] that cooperation among sensor nodes while data transmission can achieve energy conservation and transmission reliability as well as it is not affected by same fading effects as of the direct link. Therefore, less transmission power is required for communication. In order to achieve the required quality of service, link adaptation schemes are required to be exploited which can select appropriate degree of cooperation and processing intelligence scheme that are best suited to channel conditions. Channel link quality based channel selection schemes are proposed in [25] and [26]. It is claimed that the proposed schemes achieve energy efficient and reliable data transmission within WSNs. Furthermore, WSNs are also expected to achieve transmission reliability with optimum utilization of resources. This can be achieved by attaining implicit or explicit knowledge of channel quality information at the transmitter side. Such channel quality information can be estimated and classified at the receiver and fed back to the transmitter with negligible spectral resources as discussed in [27] and [28].

The research studies in the literature consider time-driven and event-driven scenarios separately and do not provide a unified solution. In this paper, a dynamic clustering and neighborhood formation scheme is proposed that provides a universal framework which is independent of the nature of sensing application. It is expected that the proposed framework will provide an energy efficient solution by rotating the role of cluster head among all the sensor nodes while trying to keep the size of the clusters uniform and minimizing the frequency of re-clustering. Furthermore, considering the residual energy threshold in cluster heads selection process and their location in the network, the proposed framework is expected to avoid unbalanced energy consumption and energy holes in the network. In order to attain transmission reliability, the dynamic behavior is adopted to minimize the effect of variable channel conditions on data transmission. Such adaptation can be achieved by deriving an index from the received measure of channel quality that is attained at the transmitter through a feedback link from the fusion center. The dynamic behavior of the proposed framework is expected to provide a robust solution against variable conditions of propagation environment. The system model of the proposed framework is presented in the following section.

III. SYSTEM MODEL

In this section, a WSN model is described, which assumes a random distribution of n number of sensor nodes within the sensing field of dimensions $(A \times B)$. Each sensor node is assumed to be capable of measuring homogeneous and heterogeneous data sets based on the application requirements. It is assumed that the locations of the sensor nodes are implicitly deterministic and all the sensor nodes within the network are homogenous in terms of processing and computational capability at initial deployment. Let $\mathbf{S}$ is a set of all the sensor nodes in the network which is defined as:

$$\mathbf{S} = \{S_1, S_2, \ldots, S_n\} \tag{1}$$

where $S_{(.)}$ represents the indexing of the sensor nodes. To limit the communications overhead within large scale WSNs, several segmentation schemes have been proposed in the literature. Network segmentation is expected to achieve high energy efficiency, hence contribute to prolong the lifetime of WSNs [29]. In this Paper, the whole network is divided into non-overlapping uniform grids of dimensions $a_c \times b_c$.

Let $\mathbf{Q}$ is a set of all the grids within the network which is defined as:

$$\mathbf{Q} = \{Q_j \mid j = 1, 2, \ldots, q\} \tag{2}$$

where q is the number of grids in the network and each grid consists of p_j number of sensor nodes. The set of sensor nodes within each grid can be defined as $\{S_i \mid i = 1, 2, \ldots, p_j\}$. The sensor nodes within the network can be defined as:

$$n = q \times \sum_{j=1}^{q} p_j \tag{3}$$

Consider $Q_{(\cdot)}$ represent a set of sensor nodes within a grid, then j^{th} grid is represented as Q_j and defined as:

$$Q_j = \{S_i^j \mid i = 1, 2, \ldots, p_j\} \tag{4}$$

where S_i^q denotes i^{th} sensor node of the q^{th} grid. In each grid, a sensor node is selected as cluster head to coordinate with other sensor nodes within the cluster based on certain criteria. Cluster heads act as coordinators between the member sensor nodes and fusion center receiver e.g. collect data from the sensor nodes, perform data aggregation, forward it to the fusion center, take instructions from the fusion center, etc. Dynamic cluster architectures are expected to gain energy efficiencies by selecting cluster heads in order to effectively react and adjust appropriately on network topology.

A typical system model proposed within the scope of this study is shown in Fig. 1. The transmitted data vector from n_t

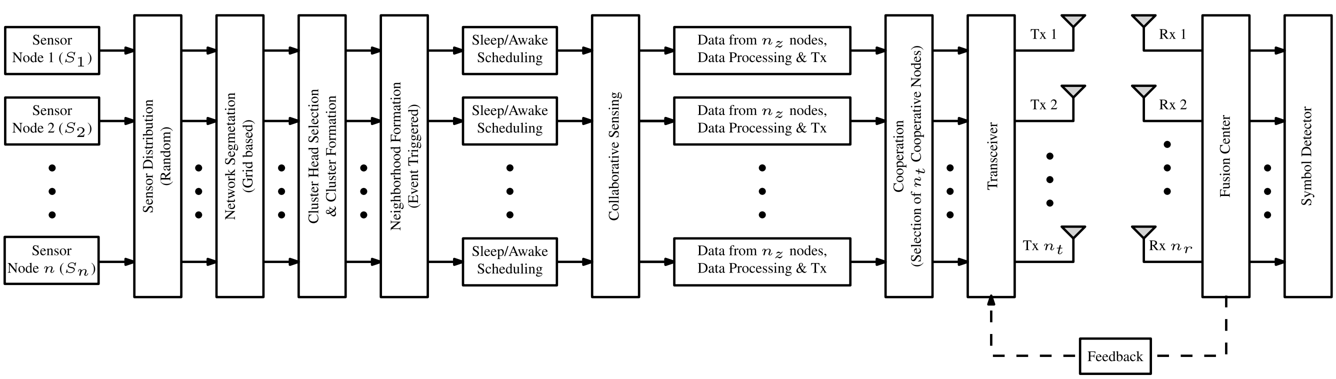

FIGURE 1. Block diagram summarizing the methodological steps of the proposed universal dynamic clustering framework.

number of transmitting sensor nodes is denoted as $\mathbf{x}$ and expressed as:

$$\mathbf{x} = [x_1, x_2, \ldots, x_{n_t}]^T \tag{5}$$

The received signal vector at fusion center can be expressed as:

$$\mathbf{y} = \mathbf{Hx} + \mathbf{n} \tag{6}$$

where $\mathbf{y}$ is the received signal vector with dimensions $(n_r \times 1)$, $\mathbf{H}$ is the Rayleigh fading channel matrix of size $(n_r \times n_t)$ and $\mathbf{n}$ is the noise vector with dimensions $(n_r \times 1)$. The noise is considered to be additive white Gaussian noise with zero mean and unity variance σ^2. The Rayleigh fading channel matrix is defined as:

$$\mathbf{H} = \begin{bmatrix} h_{(1,1)} & h_{(1,2)} & \ldots & h_{(1,n_t)} \\ h_{(2,1)} & h_{(2,2)} & \ldots & h_{(2,n_t)} \\ \vdots & \vdots & \ddots & \vdots \\ h_{(n_r,1)} & h_{(n_r,2)} & \ldots & h_{(n_r,n_t)} \end{bmatrix} \tag{7}$$

where $h_{\hat{j},\hat{i}}$ denotes the channel coefficients from $\hat{i}^{th}$ transmitter sensor node to $\hat{j}^{th}$ receiving antenna at the fusion center with $\hat{i} \in \{1, 2, \ldots, n_t\}$ and $\hat{j} \in \{1, 2, \ldots, n_r\}$ respectively. It is also assumed that there is a feedback link between the sensor nodes and fusion center receiver which is expected to enable the sensor nodes to exploit channel conditions and adapt accordingly. Employment of the feedback channel requires cooperation between the sensor nodes and fusion center receiver. Fusion center receiver is expected to estimate the channel coefficients and fed-back channel state information to the network that can use this information to adapt the transmit signal to the channel.

IV. PROPOSED UNIVERSAL AND DYNAMIC CLUSTERING SCHEME (UDCS)

In order to conserve energy of sensor nodes within WSNs, it is expected to distribute the load of performing tasks among the sensor nodes to balance the energy consumption within the network, select optimum number of sensor nodes to report significant occurrences and to perform reliable communication to relay sensing data to fusion center receiver. Generally, sensing within WSNs can be realized into time-driven and event-driven scenario. In time-driven sensing, the sensor nodes relay acquired data to fusion center receiver on a periodic basis. While in event-driven sensing the sensor nodes are responsible to detect significant occurrences and report it to fusion center receiver. In this paper, a dynamic clustering and neighborhood formation scheme is proposed for time-driven and event-driven applications. Moreover, a universal framework is proposed for adaptive utilization of both the aforementioned sensing scenario to enhance its feasibility of implementation for a diverse range of applications. Moreover, the dynamic allocation of degree of cooperation based on channel propagation conditions is also considered. Within the proposed UDCS framework, all the decisions such as the selection of cluster heads, formation of clusters as well as neighborhoods and the selection of cooperative sensor nodes for reporting to fusion center are made locally within the respective clusters throughout the network. Such distributive decision making ability facilitate the proposed UDCS framework to be energy efficient, as this reduces the amount of information to be broadcasted or transmitted wirelessly to represent an event. The list of key symbols used in this paper along with their definition is given in Table 1.

TABLE 1. Symbols and their definitions.

Symbols	Definitions
n	Number of sensor nodes within the network
q	Number of clusters within the network
n_b	Number of sensor nodes within neighborhood
$\hat{q}$	Number of non-cooperative CHs
$\hat{n}_t$	Number of cooperative CHs
$d_{1(n,q)}$	Distance of n^{th} sensor node from q^{th} grid center
$d_{2(n,q)}$	Distance of n^{th} sensor node from q^{th} CH
d_3^q	Distance of q^{th} CH from fusion center receiver
$d_{4(\hat{q})}^{\hat{n}_t}$	Distance of $\hat{q}^{th}$ CHs to $\hat{n}_t$ cooperative CH
d_5	Distance between cooperative cluster heads (CCH)
$d_6^{\hat{n}_t}$	Distance of $\hat{n}_t^{th}$ CCHs to fusion center receiver
$d_{7(n_b,q)}$	Distance of n_b^{th} sensor node from q^{th} CH
δ_{ch}	Energy threshold for cluster head election
$\hat{p}$	Number of sensing nodes within a cluster
k	Number of neighborhoods within the network

A. TIME-DRIVEN SENSING

A distributed cluster head selection scheme is proposed such that all the sensor nodes that can serve the role with minimum energy consumption have a chance to become cluster heads. It is expected that all the sensor nodes will broadcast their location to their respective cluster heads and cluster heads will broadcast this information within the network. Initially all the sensor nodes are expected to calculate their distance from the center of their grids. Then each sensor node is expected to be ranked based on its respective distance from the center of the cluster. The sensor node which is nearest to the center of the grid has the highest priority to become cluster head. A threshold energy δ_{ch} is carefully defined such that if the energy of a cluster head falls below δ_{ch}, the role of cluster head is expected to be transferred to the second highest rank node. Once all the cluster heads are elected, the remaining sensor nodes find the nearest cluster heads and join them irrespective of their initial cluster assignment. The election of cluster heads and the formation of new clusters is explained below.

Let $\mathcal{F}(\lambda_x^1, \lambda_y^1, \lambda_x^2, \lambda_y^2)$ represents the Euclidean distance function which is defined as:

$$\mathcal{F}(\lambda_x^1, \lambda_y^1, \lambda_x^2, \lambda_y^2) = \sqrt{(\lambda_x^1 - \lambda_x^2)^2 + (\lambda_y^1 - \lambda_y^2)^2} \tag{8}$$

One all the sensor nodes are deployed in the network, sensor nodes are expected to calculate their distances from the center of their respective grids by using the function presented in (8) and expressed as:

$$d_1 = \mathcal{F}(c_x, c_y, s_x, s_y) \tag{9}$$

where

$$\mathcal{F}(c_x, c_y, s_x, s_y) = \mathcal{F}(\lambda_x^1 = c_x, \lambda_y^1 = c_y, \lambda_x^2 = s_x, \lambda_y^2 = s_y) \tag{10}$$

(c_x^j, c_y^j) are the coordinates of center of grids while $j = \{1, 2, \ldots, q\}$ and (s_x^i, s_y^i) are the coordinates of the sensor nodes where $i = \{1, 2, \ldots, p_j\}$. Consider $S_{(j,i)}$ denotes a sensor node and p denotes the maximum number of sensor nodes belonging to a particular grid given by $p = \max\{p_j \mid j = 1, 2, \ldots, q\}$. Let $\mathbf{Q}$ is a matrix of all the sensor nodes in the network which is defined as:

$$\mathbf{Q} = \begin{bmatrix} S_{(1,1)} & S_{(1,2)} & \ldots & S_{(1,p)} \\ S_{(2,1)} & S_{(2,2)} & \ldots & S_{(2,p)} \\ \vdots & \vdots & \ddots & \vdots \\ S_{(q,1)} & S_{(q,2)} & \ldots & S_{(q,p)} \end{bmatrix} \tag{11}$$

where each row of matrix $\mathbf{Q}$ represents the sensor nodes in each grid. Although the number of sensor nodes in each grid are not same but for the sake of mathematical representation $\mathbf{Q}$ is defined as a matrix. Consider $S_{(j,i)}$ is assigned with a value to classify the existence of a sensor node which is defined as:

$$S_{(j,i)} = \begin{cases} 1, & \text{if } i \leq p_j \\ -1, & \text{if } i > p_j \end{cases} \tag{12}$$

where 1 represents the existence of a sensor node and -1 represents the non-existence of a sensor node. Let $\mathbf{D}_1$ is a matrix of dimensions $(q \times p)$ which presents the distance of all the sensor nodes from the center of their grids and expressed as:

$$\mathbf{D}_1 = \begin{bmatrix} d_{1(1,1)} & d_{1(1,2)} & \ldots & d_{1(1,p)} \\ d_{1(2,1)} & d_{1(2,2)} & \ldots & d_{1(2,p)} \\ \vdots & \vdots & \ddots & \vdots \\ d_{1(q,1)} & d_{1(q,2)} & \ldots & d_{1(q,p)} \end{bmatrix} \tag{13}$$

where each row of matrix $\mathbf{D}_1$ represents the distance of sensor nodes from their grid center. Let $\mathbf{d}_{1(q)}$ presents the distance of the sensor nodes from the center of q^{th} grid which is expressed as $\mathbf{d}_{1(q)} = \{d_{1(q,1)}, d_{1(q,2)}, \ldots, d_{1(q,p)}\}$. All the sensor nodes are characterized as either normal nodes or cluster head nodes. Let ξ_q constitutes the information of the sensor node which is at a minimum transmission distance from the q^{th} grid center and can be defined as $\xi_q = min(abs(\mathbf{d}_{1(q)} \backslash \psi))$. Where "\" represents the difference between two sets. Consider, initially $\psi = \emptyset$ and it will keep the record of the sensor nodes that are elected as cluster heads throughout the lifetime of the network. Let p^{th} sensor node is at a minimum transmission distance from the q^{th} grid center which is denoted as $d_{1(q,p)}$ and defined as $d_{1(q,p)} \backslash \psi = \{d_{1(q,p)} \in \mathbf{d_{1(q)}} | d_{1(q,p)} \notin \psi\}$. In addition to minimum transmission distance requirement, the energy of the candidate sensor node is compulsory to be greater than the threshold δ_{ch}. Once a sensor node is designated as a cluster head, it is assigned with $\varsigma = 1$ which shows its status as cluster head. This process iterates until all q cluster heads are defined and update $\psi = \xi$ in each iteration. Let $\mathbf{Q}_s$ is a matrix of dimensions $(q \times p)$ and presents the status of the sensor nodes which is defined as:

$$\mathbf{Q}_s(i,j) = \begin{cases} \text{Cluster Head (CH)}, & \text{if } \varsigma = 1 \\ \text{Normal Node (N)}, & \text{otherwise} \end{cases} \tag{14}$$

Let Q_{ch} is a set of all the cluster heads in the network which is defined as:

$$Q_{ch} = \{S_j^{ch} \mid j = 1, 2, \ldots, q\} \tag{15}$$

where q is the total number of cluster heads and S_j^{ch} denotes the cluster head from j^{th} cluster. All the sensor nodes with status N are expected to join the cluster head which is at minimum transmission distance. Let $\mathbf{D}_2$ contains the distances of all the normal sensor nodes with the q number of cluster heads which is defined as:

$$\mathbf{D}_2 = \begin{bmatrix} d_{2(1,1)} & d_{2(1,2)} & \ldots & d_{2(1,q)} \\ d_{2(2,1)} & d_{2(2,2)} & \ldots & d_{2(2,q)} \\ \vdots & \vdots & \ddots & \vdots \\ d_{2(n,1)} & d_{2(n,2)} & \ldots & d_{2(n,q)} \end{bmatrix} \tag{16}$$

where $\mathbf{D}_2$ is a matrix of dimensions $(n \times q)$ and d_2 is calculated by using the function presented in (8) and expressed as:

$$d_2 = \mathcal{F}(ch_x, ch_y, s_x, s_y) \tag{17}$$

where

$$\mathcal{F}(ch_x, ch_y, s_x, s_y) = \mathcal{F}(\lambda_x^1 = ch_x, \lambda_y^1 = ch_y, \lambda_x^2 = s_x, \lambda_y^2 = s_y) \tag{18}$$

(ch_x^j, ch_y^j) are the coordinates of the cluster heads while $j = \{1, 2, \ldots, q\}$ and $(s_x^{\breve{i}}, s_y^{\breve{i}})$ are the coordinates of the sensor nodes where $\breve{i} = \{1, 2, \ldots, n\}$. Let $\mathbf{d}_2^{\breve{i}}$ is the $\breve{i}^{th}$ row of $\mathbf{D}_2$ which provides the transmission distance information of $\breve{i}^{th}$ sensor node from q number of cluster heads. The $\breve{i}^{th}$ sensor node is expected to join the cluster head which is at minimum transmission distance that is defined as $min\{\mathbf{d}_2^{\breve{i}}\}$. New boundaries of the clusters are defined as shown in Fig. 2. The proposed dynamic clustering scheme is summarized in Algorithm 1.

Let $\hat{Q}_j$ represents a set of sensor nodes in the j^{th} cluster which is defined as:

$$\hat{Q}_j = \{S_i^j \mid i = 1, 2, \ldots, \hat{p}_j\} \tag{19}$$

And $\hat{\mathbf{Q}}$ is the set of all the clusters which is expressed as:

$$\hat{\mathbf{Q}} = \{\hat{Q}_j \mid j = 1, 2, \ldots, q\} \tag{20}$$

Since cluster heads are required to carry out additional tasks for their respective sensor nodes, their energy depleted more

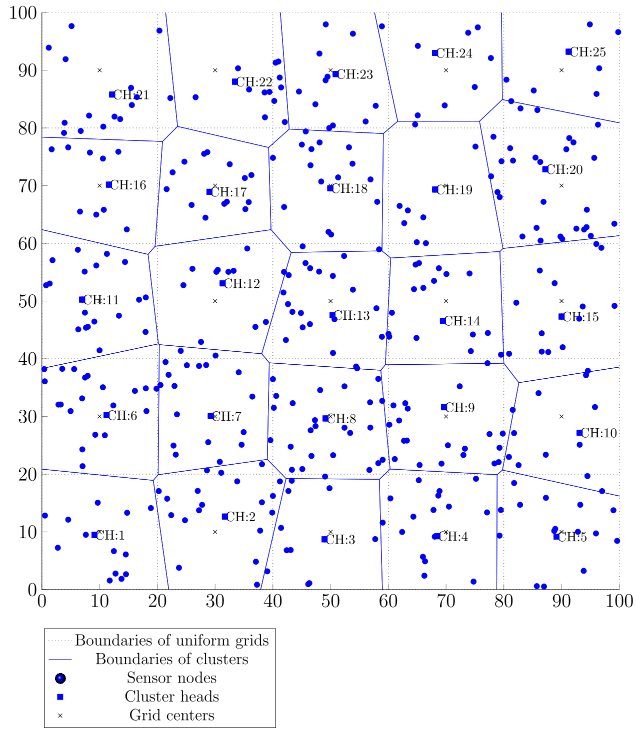

FIGURE 2. Implementation of dynamic cluster formation scheme within WSN.

quickly than non-cluster head sensor nodes. As the proposed dynamic clustering scheme is expected to rotate the cluster head role among all sensor nodes while minimizing the frequency of re-clustering, it is important to define δ_{ch} carefully.

1) HARD THRESHOLD

It is defined as a function of residual energy in the cluster heads. Let $\Psi = \{\psi_1, \psi_2, \ldots, \psi_{\ddot{n}}\}$, where Ψ represents the range of energy within a sensor node i.e. $\Psi \in [0, 1]$. Therefore the task for system design engineer is to find the optimum value from Ψ to define δ_{ch} which requires extensive simulation experiments. As the distribution of sensor nodes is expected to be random in most of the applications, dynamic clustering is required to be implemented to adapt with variable conditions within the network. Consequently, the criteria to find optimum threshold might change throughout the lifetime of the network that can lead to erroneous decisions on the selection of δ_{ch}, hence can cause unbalanced energy consumption within the network. To overcome these limitations with aforementioned threshold selection method, a soft decision based threshold selection method is defined as follows.

2) SOFT THRESHOLD

It is defined based on an iterative method that compute $\ddot{k}$ number of optimum threshold values from Ψ, which are denoted as $\delta^1_{ch}, \delta^2_{ch}, \ldots, \delta^{\ddot{k}}_{ch}$ and defined as:

$$\delta^{\hat{k}}_{ch} = \frac{|\psi_1 - \psi_{\ddot{n}}|}{\Gamma^{\hat{k}}} \quad \textit{where } \hat{k} = \{1, 2, \ldots, \ddot{k}\} \tag{21}$$

Algorithm 1 Proposed Dynamic Clustering Scheme

Require:
The number of sensor nodes n within the network, their coordinates $(x_{\breve{i}}, y_{\breve{i}}) \mid \breve{i} = 1, 2, \ldots, n$ of each sensor node, their energy which is denoted as $S^E_{\breve{i}}$, the coordinates of the center of each grid $(x_j, y_j) \mid j = 1, 2, \ldots, q$ and cluster head selection threshold energy δ_{ch}

Ensure:
$S^{ch}_{(.)} \leftarrow \min\{\mathbf{d}_1\}$ and $S^E_{\breve{i}} \geq \delta_{ch}$

$\mathbf{D}_1 \leftarrow \varnothing$, $\mathbf{d}_1 \leftarrow \varnothing$
$\mathbf{P}_1 \leftarrow \varnothing$, $\mathbf{p}_1 \leftarrow \varnothing$
$\mathbf{Q}_s \leftarrow \varnothing$
for $j \leftarrow 1$ **to** q **do**
  for $\breve{i} \leftarrow 1$ **to** n **do**
    $\mathbf{d}_1(\breve{i}) \leftarrow d_1$ where d_1 is calculated from (9)
  end for
  $\mathbf{d}_1 \leftarrow$ Sort $\{\mathbf{d}_1\}$, (Sort in ascending order and save their respective indices in $\mathbf{p}_1$)
  $\mathbf{D}_1(j) \leftarrow \mathbf{d}_1$
  $\mathbf{P}_1(j) \leftarrow \mathbf{p}_1$
end for
$\tau \leftarrow 0$
for $j \leftarrow 1$ **to** q **do**
  for $\breve{i} \leftarrow 1$ **to** n **do**
    $\mathbf{Q}_1(j, \breve{i}) \leftarrow$ Mapping of sensor nodes based on $\mathbf{D}_1$ and $\mathbf{P}_1$
    if $S^E_{(.)} \geq \delta_{ch}$ & $\tau = 0$ **then**
      $\mathbf{Q_s} \leftarrow$ Update the status of $S_{(j,\hat{i})}$ as Cluster Head (CH) or Normal Node (N)
      $\tau \leftarrow 1$
    end if
  end for
end for
$\mathbf{D}_2 \leftarrow \varnothing$, $\mathbf{d}_2 \leftarrow \varnothing$
for $j \leftarrow 1$ **to** q **do**
  for $\breve{i} \leftarrow 1$ **to** n **do**
    $\mathbf{d}_2(\breve{i}) \leftarrow d_2$ where d_2 is calculated from (17) & (18)
  end for
  $\mathbf{D}_2(j) \leftarrow \mathbf{d}_2$
end for
for $\breve{i} \leftarrow 1$ **to** n **do**
  $\mathbf{Q}_{ch}(\breve{i}) \leftarrow \min\{\mathbf{D}_2(1:q, \breve{i})\}$
  Assign the task of cluster head to the sensor nodes in $\mathbf{Q}_{ch}$
end for
return $\mathbf{Q}_{ch}$

where Γ is a tuneable parameter. The sensor nodes within each cluster are expected to serve as cluster heads until their energy depletion level reach the threshold value δ^1_{ch}. Once all the sensor nodes served as cluster heads, the cluster head role will repeat among the nodes with energy depletion level δ^2_{ch} and so on. It is expected that by defining soft threshold energy consumption is balanced through out the network at the cost of higher rate of re-clustering than would have with hard threshold.

B. EVENT-TRIGGERED SENSING

The selection of a group of sensor nodes, in response to an incident is one of the core elements of the proposed optimization process. Hence, this section describes the set out criteria of such incident triggered dynamic grouping schemes, such as neighborhood. One of the main tasks of sensor nodes is to monitor, detect and collect various significant occurrences of events within WSNs. The occurrence of the behavioral change that sensor nodes are expected to detect is called an event. Let there are k number of events occurred within a cluster at time instant t. It is assumed that the location of the events are implicitly deterministic. The trend of the sensing parameters and the knowledge of that trends at the cluster heads make the location of events implicitly deterministic. Consider, the coordinates of the location of events are denoted as $(e_x^{\hat{f}}, e_y^{\hat{f}})$, where e_x and e_y denotes the coordinates of the location of an event and $\hat{f} = \{1, 2, \ldots, k\}$. A neighborhood consists of a group of sensor nodes which are selected based on certain criterion i.e. distance from the location of an event, sensing capability etc. are expected to take part in the detection of the events. All the sensor nodes within a neighborhood are expected to cooperate with each other. For the sake of simplicity, it is assumed that each neighborhood at time instant t will consist of n_b number of sensor nodes where n_b varies from neighborhood to neighborhood. Let there are k number of neighborhoods formed by the occurrence of k number of events at time instant t. The total number of sensor nodes involved to form k^{th} number of neighborhood is denoted as $\mathcal{N}_e^k$ and is defined as:

$$\mathcal{N}_e^k \mid_t = \{s_{\hat{e}}^k \mid \hat{e} = 1, 2, \ldots, n_b^k\} \tag{22}$$

It is assumed that all the neighborhoods formed at time instant t will not overlap with each other which is defined as:

$$\mathcal{N}_e^1 \mid_t \;\cap\; \mathcal{N}_e^2 \mid_t \cap \cdots \cap \mathcal{N}_e^k \mid_t \in \emptyset \tag{23}$$

Depending on the depth of the event, the set of sensor nodes involved to form a neighborhood for an event detection at time instant t can be same or can be different from an event that will be detected at time instant $t+1$, even both events occur at same location. With the aim of achieving energy conservation, the sensor nodes are expected to form a neighborhood by fulfilling the following criteria:

1) CRITERION 1

It is defined based on the Euclidean distance of the sensor nodes from the location of an event. Let $\mathcal{N}_e^{\hat{f}}$ is the $\hat{f}^{th}$ neighborhood which is defined as:

$$\mathcal{N}_e^{\hat{f}} = \begin{cases} S_{\hat{e}}^{\hat{f}} \in S_{(.)}, & \text{if } \hat{d}_{\hat{e}}^{\hat{f}} \le \delta_d \\ S_{\hat{e}}^{\hat{f}} \notin S_{(.)}, & \text{otherwise} \end{cases} \tag{24}$$

where $\hat{d}_{\hat{e}}^{\hat{f}}$ denotes the distance of $\hat{e}^{th}$ sensor node from $\hat{f}^{th}$ event and δ_d is the threshold distance defined by the fusion center receiver.

2) CRITERION 2

This criterion is based on the sensitivity threshold δ_s defined by the fusion center receiver. Each sensor node is expected to be a part of the neighborhood if it can sense the event with the predefined sensitivity threshold δ_s. Let $\mathcal{N}_e^{\hat{f}}$ is the $\hat{f}^{th}$ neighborhood which is defined as:

$$\mathcal{N}_e^{\hat{f}} = \begin{cases} S_{\hat{e}}^{\hat{f}} \in S_{(.)}, & \text{if } \nu_{\hat{e}}^{\hat{f}} \ge \delta_s \\ S_{\hat{e}}^{\hat{f}} \notin S_{(.)}, & \text{otherwise} \end{cases} \tag{25}$$

where $\nu_{\hat{e}}^{\hat{f}}$ denotes the sensitivity range of $\hat{e}^{th}$ sensor node from $\hat{f}^{th}$ event.

3) CRITERION 3

This criterion is unification of both aforementioned criteria. On the occurrence of an event, the sensor nodes are selected to form the k^{th} neighborhood based on the criterion which is defined as:

$$\mathcal{N}_e^{\hat{f}} = \begin{cases} S_{\hat{e}}^{\hat{f}} \in S_{(.)}, & \text{if } \hat{d}_{\hat{e}}^{\hat{f}} \le \delta_d \cap \nu_{\hat{e}}^{\hat{f}} \ge \delta_s \\ S_{\hat{e}}^{\hat{f}} \notin S_{(.)}, & \text{otherwise} \end{cases} \tag{26}$$

The detailed procedure of neighborhood formation is explained in Algorithm 2.

C. CQI BASED ADAPTIVE COOPERATIVE COMMUNICATION

A cooperation based transmission scheme is proposed that is expected to optimize network communication and transmission reliability by dynamically selecting the degree of cooperation among sensor nodes. In order to enable ample determination on the selection of suitable degree of cooperation among sensor nodes, an estimate of transmission quality for given channel conditions is required which is usually measured from frame error probability. A CQI model presented in [30] is used in this paper, which is defined based on a measure that maps frame error probability. It is expected that CQI based adaptation will provide robustness against signal distortions and interference caused by propagation and channel conditions respectively. Also, it will provide adequate decision on the degree of cooperation in order to optimize resource utilization while maintaining demanded quality of service. The measure of CQI can be calculated as:

$$\mathrm{CQI} = f(\tilde{\mathrm{E}}[(\boldsymbol{\Lambda} - \boldsymbol{\mu})^2]) \tag{27}$$

where $\tilde{\mathrm{E}}$ denotes the expectation value and CQI can be simplified as:

$$\mathrm{CQI} = \frac{1}{n_t} \sum_{\hat{i}=1}^{n_t} \mid \boldsymbol{\Lambda}_{\hat{i}} - \mu \mid^2 \tag{28}$$

Algorithm 2 Proposed Neighborhood Formation Scheme

Require:
The number of sensor nodes n, the coordinates $(s_x^i, s_y^i) \mid i = 1, 2, \ldots, n$ of each sensor node, Total number of events k, the coordinates $(e_x^{\hat{f}}, e_y^{\hat{f}}) \mid \hat{f} = 1, 2, \ldots, k$ of each event, desired neighborhood selection criteria parameter α and β, Optimum distance threshold δ_d and Optimum sensitivity level threshold δ_s.

Ensure: $\hat{d}_{\hat{e}}^{\hat{f}} \le \delta_d$ and $v_{\hat{e}}^{\hat{f}}$, where $\hat{d}$ is the distance and $\hat{s}$ is the sensitivity level of $\hat{e}^{th}$ sensor node from $\hat{f}^{th}$ event.

$\mathbf{D_n} \leftarrow \varnothing$, $\mathbf{d_n} \leftarrow \varnothing$
$\mathbf{P_n} \leftarrow \varnothing$, $\mathbf{p_n} \leftarrow \varnothing$
$\mathbf{s_n} \leftarrow \varnothing$
if $(\alpha = 1) \cup (\alpha \cap \beta = 1)$ **then**
  for $\hat{f} \leftarrow 1$ **to** k **do**
    for $\hat{e} \leftarrow 1$ **to** n **do**
      $\mathbf{d_n}(\hat{e}) \leftarrow \hat{d}_{\hat{e}}^{\hat{f}}$
    end for
    Sort $\{\mathbf{d_n}\}$ in ascending order and save the indices in $\mathbf{p_n}$
    $\mathbf{D_n}(\hat{f}) \leftarrow \mathbf{d_n}$
    $\mathbf{P_n}(\hat{f}) \leftarrow \mathbf{p_n}$
  end for
  for $\hat{f} \leftarrow 1$ **to** k **do**
    for $\hat{e} \leftarrow 1$ **to** n **do**
      if $\mathbf{D_n}(\hat{e}, \hat{f}) \le \delta_d$ **then**
        Assign the corresponding sensor nodes to $\mathcal{N}_e^{\hat{f}}$
      end if
    end for
  end for
end if
if $(\beta = 1) \cup (\alpha \cap \beta = 1)$ **then**
  for $\hat{f} \leftarrow 1$ **to** k **do**
    for $\hat{e} \leftarrow 1$ **to** n **do**
      $S_{\hat{e}}^{\hat{f}} \ge \delta_s(\hat{f})$
    end for
    Assign corresponding sensor nodes to $\mathcal{N}_e^{\hat{f}}$
  end for
end if
return $\mathcal{N}_{\mathbf{e}}^{\mathbf{k}}$

where

$$\mu = \frac{1}{n_r} \sum_{\hat{j}=1}^{n_r} \boldsymbol{\lambda}_{\hat{j}} \tag{29}$$

where $\boldsymbol{\Lambda}$ is a set of eigen vectors channel coefficient matrix $\mathbf{H}$ of dimension $(n_r \times 1)$ which is defined as:

$$\boldsymbol{\Lambda} = \{\boldsymbol{\lambda}_{\hat{j}} \mid \hat{j} = 1, 2, \ldots, n_r\} \tag{30}$$

where $\lambda_{(\cdot)}$ represents the eigen values of channel coefficients. The degree of cooperation is to be selected based on classification of signal propagation conditions that can be acquired from CQI which is indexed from 1 to the required degree of considered cooperation. The higher index refers to the requirement of higher degree of cooperation in order to maintain the required quality of service.

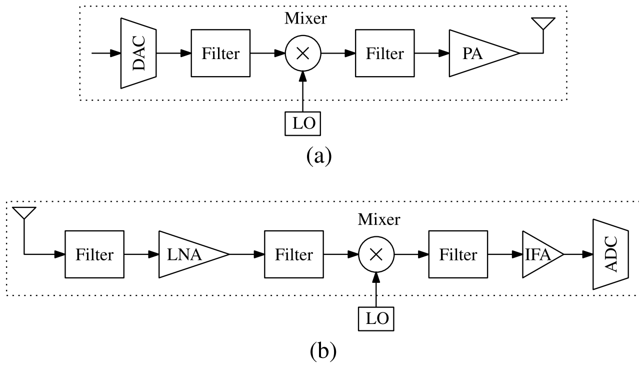

FIGURE 3. **(a) Transmitter circuit blocks, (b) Receiver circuit blocks.**

V. NETWORK LIFETIME MODEL

Network lifetime can be defined as the time span over which the network operates effectively. Several WSNs lifetime definitions have been introduced in the literature e.g. network connectivity is used to define WSN lifetime. But most commonly used WSN lifetime definition is based on the percentage of alive nodes or dead nodes in the network, which reflects the quality of network coverage and connectivity as discussed in [31]. In this section, a network lifetime model is presented based on energy model described in [23]. It is assumed that each cluster consists of $\hat{p}$ number of sensor nodes. Each sensor node is expected to sense L bits and transmits it to the respective cluster head node. As sensor nodes in a cluster are closely spaced, the sensed data is expected to be correlated. So, cluster heads are expected to aggregate the received data. All the sensor nodes are expected to be equipped with one transceiver. The transmitter and receiver blocks used in this model are shown in Fig. 3(a) and Fig. 3(b) respectively. For a fixed rate system, the total energy per bit is denoted as E_{bit} and defined as:

$$E_{bit} = \frac{P_{PA} + P_c}{R_b} \tag{31}$$

where P_{PA} is the power consumption of power amplifier, P_c is the power consumption at transceiver circuitry and R_b is the bit rate. P_{PA} is expressed as:

$$P_{PA} = (1 + \alpha) P_{out} \tag{32}$$

where $\alpha = (\xi/\eta) - 1$ with ξ is the peak to average ratio and η is the drain efficiency of the radio frequency power amplifier. P_{out} represents the transmit power which can be calculated based on link budget relationship, particularly when the channel experiences only a square law path loss as described in [32] and expressed as:

$$P_{out} = \bar{E}_b R_b \frac{(4\pi d)^2}{G_t G_r \lambda^2} M_l N_f \tag{33}$$

where $\bar{E}_b$ represents the required energy per bit at the receiver for a given bit error rate requirement, R_b represents the bit rate, d represents the transmission distance, G_t and G_r represent the transmitter and receiver antenna gains respectively, λ represents the carrier wavelength, N_f represents the receiver noise figure which is defined as $N_f = N_r/N_o$, where N_r is the power spectral density (PSD) of the total effective noise at receiver input and N_o is the single sided thermal noise PSD at room temperature, and M_l represents the link margin for compensating the hardware processing variations and additive background noise. Let

$$\mathcal{P} = (1+\alpha)\bar{E}_b R_b \frac{(4\pi)^2}{G_t G_r \lambda^2} M_l N_f \tag{34}$$

Therefore, (32) can be represented as:

$$P_{PA} = \mathcal{P} d^2 \tag{35}$$

The power consumption of transceiver circuitry is further divided into power consumption at transmitter and receiver circuitry which is $P_c = P_{c_{tx}} + P_{c_{rx}}$. Where $P_{c_{tx}}$ is defined as:

$$P_{c_{tx}} = P_{DAC} + P_{filt} + P_{mix} \tag{36}$$

where P_{DAC}, P_{filt} and P_{mix} represents the power consumption at digital to analogue converter, filter and mixer respectively. $P_{c_{rx}}$ is defined as:

$$P_{c_{rx}} = P_{LNA} + P_{mix} + P_{filt} + P_{IFA} + P_{ADC} \tag{37}$$

where P_{LNA}, P_{IFA} and P_{ADC} represents the power consumption at low noise amplifier, intermediate frequency amplifier and analogue to digital converter respectively.

A. LOCAL COMMUNICATION

The communication between the sensor nodes and their respective cluster heads is referred to as local communication.

1) ENERGY CONSUMPTION OF INTRA-CLUSTER COMMUNICATION

The energy required by the sensor nodes to communicate with their cluster heads is denoted as E_{IntraC} and defined as.

$$E_{IntraC} = \sum_{j=1}^{q} \left(\sum_{\check{i}=1}^{\hat{p}} LE^j_{s(\check{i})} + LE^j_{ch}\hat{p} \right) \tag{38}$$

where E^q_{ch} represents the energy required by the q^{th} cluster head to receive one bit data from its $\hat{p}^{th}$ sensor node which can be defined as:

$$E^q_{ch} = \frac{E_{da} P_{c_{rx}}}{R_b} \tag{39}$$

where E_{da} represents the energy required to aggregate one bit. Let $E^j_{s(\check{i})}$ for $\hat{p}^{th}$ sensor node of q^{th} cluster is denoted as $E^q_{s(\hat{p})}$ and defined as:

$$E^q_{s(\hat{p})} = \frac{1}{R_b} \left(\mathcal{P}(d^q_{2(\hat{p})})^2 + P_{c_{tx}} \right) \tag{40}$$

where $d^q_{2(\hat{p})}$ represents the distance of $\hat{p}^{th}$ sensor node from q^{th} cluster head. All the sensor nodes within the network are expected to forward their sensing data to their respective cluster heads. Once a cluster head receives data from all of its member sensor nodes within the cluster, it performs data aggregation. As the sensor nodes within a cluster are closely spaced, their sensing data is correlated. Therefore, data aggregation at the ratio of 10:1 is assumed and the sensing data after aggregation is denoted as L_{da}.

B. GLOBAL COMMUNICATION

Two types of global communication approaches considered in this paper which are defined as:

1) DIRECT COMMUNICATION BETWEEN CLUSTER HEADS AND FUSION CENTER RECEIVER

The energy required for direct communication between cluster heads and fusion center receiver is denoted as E_D and defined as:

$$E_D = \sum_{j=1}^{q} L_{da} E^j_{sh} \tag{41}$$

where E_D is the energy required by q cluster heads to forward the sensing data to the fusion center in one round and E^j_{sh} is the energy consumed by j^{th} cluster head to forward one bit of sensing data to the fusion center e.g. the energy required by q^{th} cluster head is defined as:

$$E^q_{sh} = \frac{1}{R_b} \left(\mathcal{P}(d^q_3)^2 P_{c_{tx}} \right) \tag{42}$$

where d^q_3 is the transmission distance of q^{th} cluster head from fusion center. The total energy required by the network for one round can be defined as:

$$E_{or.sh} = E_{IntraC} + E_{SH} \tag{43}$$

By substituting (38) and (41), (43) can be defined as:

$$E_{or.sh} = \sum_{j=1}^{q} \left(\sum_{\check{i}=1}^{\hat{p}} LE^j_{s(\check{i})} + LE^j_{ch}\hat{p} \right) + \left(\sum_{j=1}^{q} L_{da} E^j_{sh} \right) \tag{44}$$

For simplified solution it is assumed that the transmission distance of the sensor nodes from its cluster heads is d_2 and the transmission distance from cluster heads to fusion center receiver is d_3. Therefore, (43) can be further simplified by substituting (39), (40) and (42) which can be represented as:

$$\begin{aligned} E_{or.sh} &= \frac{Lq\hat{p}}{R_b} \left(\mathcal{P}(d_2)^2 + P_{c_{tx}} + E_{da} P_{c_{rx}} \right) \\ &\quad + \frac{qL_{da}}{R_b} \left(\mathcal{P}(d_3)^2 + P_{c_{tx}} \right) \end{aligned} \tag{45}$$

$$\begin{aligned} E_{or.sh} &= \frac{q}{R_b} \Bigg[(1+\alpha)\bar{E}_b R_b \frac{(4\pi)^2 M_l N_f}{G_t G_r \lambda^2} \left(\hat{p} L d_2^2 + L_{da} d_3^2 \right) \\ &\quad + (L\hat{p} + L_{da}) P_{c_{tx}} + E_{da} L \hat{p} P_{c_{rx}} \Bigg] \end{aligned} \tag{46}$$

2) MULTI-HOP COMMUNICATION BETWEEN CLUSTER HEADS AND FUSION CENTER RECEIVER

a: SELECTION OF COOPERATIVE CLUSTER HEADS

As mentioned in previous section $\mathbf{d}_3$ represents the transmission distance of all the cluster heads from fusion center receiver which is defined as $\mathbf{d}_3 = \{d_3^1, d_3^2, \ldots, d_3^{\hat{p}}\}$ and $\xi^{\hat{n}_t}$ represents the distance of $\hat{n}_t^{th}$ cooperative cluster heads which is defined as:

$$\xi^{\hat{n}_t} = min(abs(\mathbf{d}_3 \backslash \omega)) \tag{47}$$

where Initially $\omega = \emptyset$ and $d_3^{\hat{n}_t} \backslash \omega$ is defined as:

$$d_3^{\hat{n}_t} \backslash \omega = \{d_3^{\hat{n}_t} \in \mathbf{d_3} | d_3^{\hat{n}_t} \notin \omega\} \tag{48}$$

The sensor nodes presented by ξ^k are classified as cooperative cluster head if their energy is greater than the threshold δ_{coop}, where $k = \{1, 2, \ldots, \hat{n}_t\}$. Once $\hat{n}_t$ number of cooperative cluster heads are selected, sensor nodes status matrix $\mathbf{Q}_s$ is updated. This process is summarized in Algorithm 3:

Algorithm 3 Cooperative Sensor Nodes Selection Scheme

Require:

The q number of cluster heads Q_{ch}, their transmission distances from the sink node which is denoted with $\mathbf{d}_3$, cooperative sensor node selection threshold energy value δ_{coop} and the sensor nodes status matrix $\mathbf{Q}_s$

Ensure:

$S_{(.)}^{coop} \leftarrow \min\{\mathbf{d}_3\}$ and $E_j^{ch} \geq \delta_{coop}$

$\hat{\mathbf{d}}_3 \leftarrow \emptyset$, $\hat{\mathbf{Q}}_{ch} \leftarrow \emptyset$
$\mathbf{Q}_{c.coop} \leftarrow \emptyset$, $\hat{\mathbf{Q}}_{c.coop} \leftarrow \emptyset$
$\hat{\mathbf{d}}_3 \leftarrow sort\{\mathbf{d}_3\}$
$\hat{\mathbf{Q}}_{ch} \leftarrow sort\{Q_{ch}\}$ corresponding to $\hat{\mathbf{d}}_3$
for $j \leftarrow 1$ **to** q **do**
  $S_{c.coop} \leftarrow S_j^{ch}$
  if $S_{coop}^E \geq \delta_{coop}$ **then**
    $\mathbf{Q}_{c.coop}(j) \leftarrow S_{c.coop}$
  end if
end for
$\hat{\mathbf{Q}}_{c.coop} = \mathbf{Q}_{c.coop}(\mathbf{Q}_{c.coop} \neq 0)$
for $k \leftarrow 1$ **to** $\hat{n}_t$ **do**
  $\mathbf{Q}_{coop}(k) \leftarrow \mathbf{Q}_{c.coop}(k)$
end for
return

b: ENERGY CONSUMPTION OF INTER-CLUSTER COMMUNICATION

The energy required by the cluster heads to communicate with each other is denoted as E_{InterC}. Let $\hat{n}_t$ number of cluster head nodes are selected to cooperate and communicate with the fusion center receiver, then the remaining $q - \hat{n}_t$ number of sensor nodes are denoted as $\hat{q} = q - \hat{n}_t$.

$$E_{InterC} = \sum_{j=1}^{\hat{q}} L_{da} E_{n.coop}^j + q_1 L_{da} E_{coop} \tag{49}$$

where E_{coop} represents the energy required by the cooperative cluster head node to receive one bit data from the non-cooperative cluster head nodes which is defined as $E_{coop} = P_{c_{rx}}/R_b$. Consider $E_{n.coop}^{\hat{q}}$ represents the energy required by the $\hat{q}^{th}$ non-cooperative cluster head node to transmit one bit of data to the cooperative cluster heads, which is defined as:

$$E_{n.coop}^{\hat{q}} = \frac{1}{R_b}\left(\mathcal{P}(d_4^{q_1})^2 + P_{c_{tx}}\right) \tag{50}$$

3) ENERGY CONSUMPTION OF LONG-HAUL COMMUNICATION

The $\hat{n}_t$ number of selected cooperative cluster head nodes are expected to collaborate and act as virtual MIMO antenna to transmit the sensing data to the fusion center receiver. The energy consumed in this process can be categorized into E_{Lh-SM} if cooperation among the transmitting nodes is exploited to achieve spatial multiplexing and E_{Lh-DIV} if transmission diversity is required which are described as:

a: CASE I

$$E_{Lh-SM} = \sum_{k=1}^{\hat{n}_t - 1} \frac{qL_{da}}{\hat{n}_t} E_{col.}^k + \sum_{k=1}^{\hat{n}_t} \frac{qL_{da}}{\hat{n}_t} E_{lh}^k \tag{51}$$

b: CASE II

$$E_{Lh-DIV} = \sum_{k=1}^{\hat{n}_t - 1} qL_{da} E_{col.}^k + \sum_{k=1}^{\hat{n}_t} qL_{da} E_{lh}^k \tag{52}$$

where

$$E_{col.}^{\hat{n}_t} = \frac{1}{R_b}\left(\mathcal{P}(d_5^{\hat{n}_t})^2 + P_{c_{tx}} + P_{c_{rx}}\right) \tag{53}$$

where $d_5^{\hat{n}_t}$ is the distance of the $\hat{n}_t^{th}$ cooperative cluster head from other cooperative cluster heads.

$$E_{lh}^{\hat{n}_t} = \frac{1}{R_b}\left(\mathcal{P}(d_6^{\hat{n}_t})^2 + P_{c_{tx}} + P_{syn}\right). \tag{54}$$

where d_6 is the distance of the cooperative cluster head from fusion center and P_{syn} represents the power required to synchronise the transmitting data from multiple nodes. Let $E_{o.r}$ represents the total energy requires to transmit L_{da} bits. It is assumed that one round is the transmission of data from all the sensor nodes to the fusion center. $E_{o.r}$ is defined as:

$$E_{o.r} = E_{IntraC} + E_{InterC} + E_{Lh} \tag{55}$$

Therefore, (55) can be simplified as (56), as shown at the top of the next page. As $\hat{q} \gg n_t$, so lets assume $q \approx \hat{q}$, so it can further be simplified into (57) and (58), as shown at the top of the next page, where (58) provides a generalized equation for energy consumption of time-driven and event-driven scenario. Based on the type of sensing, the parameters in (58) are obtained as follows:

$$\begin{cases} \mathcal{Q} = q, \mathcal{N} = \hat{p}, \mathcal{D} = d_2 & \text{Time-driven} \\ \mathcal{Q} = k, \mathcal{N} = n_b^k, \mathcal{D} = d_7 & \text{Event-driven} \end{cases}$$

$$E_{o.r}=\sum_{j=1}^{q}\left(\sum_{i=1}^{\hat{p}}LE^{j}_{s(\check{i})}+LE^{j}_{ch}\hat{p}_j\right)+\left(\sum_{j=1}^{\hat{q}}L_{da}E^{j}_{n.coop}+\hat{q}L_{da}E_{coop}\right)+\left(\sum_{k=1}^{\hat{n}_t-1}\frac{qL_{da}}{\hat{n}_t}E^{k}_{col.}+\sum_{k=1}^{\hat{n}_t}\frac{qL_{da}}{\hat{n}_t}E^{k}_{lh}\right) \tag{56}$$

$$=\frac{Lq\hat{p}}{R_b}\left(\mathcal{P}(d_2)^2+P_{c_{tx}}+E_{da}P_{c_{rx}}\right)+\frac{\hat{q}L_{da}}{R_b}\left(\mathcal{P}(d_4)^2+P_{c_{tx}}+P_{c_{rx}}\right)$$
$$+\frac{qL_{da}}{R_b}\left(\mathcal{P}(d_5)^2+P_{c_{tx}}+P_{c_{rx}}\right)+\frac{qL_{da}}{R_b}\left(\mathcal{P}(d_6)^2+P_{c_{tx}}+P_{syn}\right) \tag{57}$$

$$=\frac{\mathcal{Q}}{R_b}\Bigg[\left((1+\alpha)\bar{E}_bR_b\frac{(4\pi)^2}{G_tG_r\lambda^2}M_lN_f\left(\mathcal{N}L\mathcal{D}^2+L_{da}(d_4^2+d_5^2+d_6^2)\right)\right)$$
$$+(\mathcal{N}L+3L_{da})P_{c_{tx}}+(\mathcal{N}LE_{da}+2L_{da})P_{c_{rx}}+L_{da}P_{syn}\Bigg] \tag{58}$$

C. EVENT-DRIVEN SENSING

The energy required by the sensor nodes to transmit event data to cluster head is denoted as $E_{IntraNH}$ and defined as:

$$E_{IntraNH}=\sum_{\hat{m}=1}^{k}\left(\sum_{\hat{l}=1}^{\hat{n}_b^{\hat{m}}}LEs^{\hat{m}}_{\hat{l}}+LE^{\hat{m}}_{ch}\hat{n}_b\right) \tag{59}$$

where $Es^{\hat{m}}_{\hat{l}}$ for $\hat{n}^{th}_b$ sensor node of k^{th} neighborhood is denoted as $Es^{k}_{\hat{n}_b}$ and defined as:

$$Es^{k}_{\hat{n}_b}=\frac{1}{R_b}\left(\mathcal{P}(d^{k}_{7(\hat{n}_b)})^2+P_{c_{tx}}\right) \tag{60}$$

where $d^{k}_{7(\hat{n}_b)}$ represents the distance of $\hat{n}^{th}_b$ sensor node from k^{th} neighborhood head. E^{k}_{ch} represents the energy required by the k^{th} cluster head to receive event data from n_b sensor nodes which is defined as:

$$E^{k}_{ch}=\frac{E_{da}P_{c_{rx}}}{R_b} \tag{61}$$

The cluster head receives the sensing data from all the sensor nodes within the neighborhood, it performs data processing locally, detects the event and transmits the decision to fusion center receiver through cooperative nodes. This approach will accelerate the decision making process by making cluster heads self reliant and also minimize the number of transmissions to fusion center receiver that results in energy conservation.

VI. PERFORMANCE ANALYSIS

This section demonstrates the performance analysis of the proposed dynamic and cooperative clustering and neighborhood formation scheme for WSNs. The proposed framework is expected to facilitate the applications that consider either time-driven sensing, event-driven sensing or both denoted as hybrid sensing. To demonstrate the effectiveness of the proposed schemes, a WSN model is simulated. Moreover, all the proposed schemes are analyzed in terms of network lifetime i.e. number of alive nodes and residual energy. To enhance the transmission reliability, the dynamic behavior among sensor nodes is adopted to adapt dynamic channel conditions which is expected to provide a tradeoff between energy efficiency and transmission reliability.

A WSN model is simulated with a sensing area of $(100\times100)m^2$ with $n=100$ sensor nodes with initial energy E_o=1J which are randomly distributed within the network. Furthermore, the simulation environment is composed of a fusion center receiver that is located at a distance of 50 m from the nearest boundary of the sensing region. After deployment, the network is expected to perform dynamic clustering to divide the sensor nodes into clusters. Once settled, all the sensor nodes within the network are expected to sense the environment and transmit sensed data to their respective cluster heads which are responsible to perform data correlation and relay it to fusion center receiver through cooperative nodes. The process from re-clustering to data transmission to fusion center receiver is defined as one round. At each round, the cluster heads are expected to evaluate themselves and withdraw from cluster head role if they do not fulfil cluster head role criteria, and trigger re-clustering process. Table 2 presents the parameter values considered in the simulations as described in [33].

A. PERFORMANCE ANALYSIS OF PROPOSED DYNAMIC CLUSTERING SCHEME WITH SOFT THRESHOLD AND HARD THRESHOLD

The performance of the proposed dynamic clustering scheme with cluster head selection criterion based on either soft or hard threshold are presented in Fig. 4. It is observed that the soft threshold based cluster head election criterion enhances the lifetime of the network by increasing the degree of load balance among sensor nodes and reducing the uneven energy consumption within the network. The results demonstrates that the soft threshold based dynamic cluster head election enhances the network life represented as number of alive nodes by 21%, 16% and 12% for rounds 33%, 50% and 67% respectively, where number of alive nodes and rounds are denoted as denoted as $\mathcal{N}_A$ and R respectively.

TABLE 2. Simulation parameters and their values.

Parameter	Value
Central Frequency (f_c)	2.5 GHz
Transmitter Gain (G_t)	5 dBi
Receiver Gain (G_r)	5 dBi
Bandwidth (B)	10 kHz
Power Consumption Value (PCV) at Mixer (P_{mix})	30.3 mW
PCV at Tx Filter (P_{filt})	2.5 mW
PCV at Rx Filter (P_{filr})	2.5 mW
Targeted Probability of Error ($\bar{P}_b$)	10^{-3}
Receiver Noise Figure (N_f)	10 dB
PCV at Intermediate Frequency Amplifier (P_{IFA})	3 mW
PCV at Frequency Synthesiser (P_{syn})	50 mW
PCV Low Noise Amplifier (P_{LNA})	20 mW
PCV at A/D Convertor (P_{ADC})	6.566 mW
PCV at D/A Convertor (P_{DAC})	15.435 mW
Link Margin (M_L)	40dB
Drain Efficiency (η)	0.35
σ^2	-174 dBm/Hz
β	1

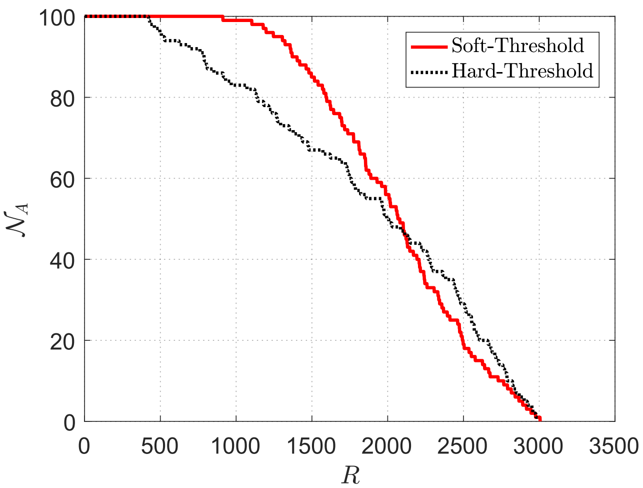

FIGURE 4. Performance analysis of the proposed dynamic clustering scheme with soft threshold and hard threshold for number of alive nodes $\mathcal{N}_A$ and rounds R.

B. PERFORMANCE COMPARISON OF PROPOSED DYNAMIC CLUSTERING SCHEME WITH EXISTING CLUSTERING SCHEMES

This section demonstrates the performance evaluation of the proposed dynamic clustering scheme with existing clustering schemes in the literature. In order to perform fair comparison, three simulation platforms have been simulated in this section denoted as model 1, model 2 and model 3 for performance comparison with homogeneous, heterogeneous and cooperative WSNs respectively which are described as:

1) MODEL 1

It provides a platform to compare the performance of the proposed dynamic clustering scheme with LEACH proposed by Heinzelman *et al.* in [6]. It is assumed that all the sensor nodes are homogeneous and cluster heads are responsible for relaying data to fusion center receiver. It is observed from Fig. 5 that the first node died (FND) for proposed dynamic clustering scheme at 1370 rounds while the FND for LEACH at 903 rounds. Also, the half nodes died (HND) for the proposed scheme and for LEACH at 2334 and 1198 rounds respectively. Moreover, the last node died (LND) at 3415 and 1862 rounds for the proposed scheme and existing scheme LEACH respectively. Hence, the proposed scheme enhances the lifetime of sensor nodes by 51%, 94% and 83% rounds for number of alive nodes 100%, 50% and 1% respectively.

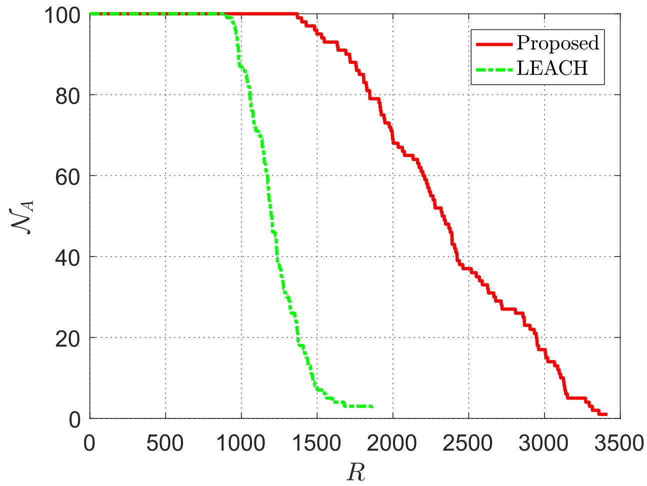

FIGURE 5. Performance analysis comparison of the proposed scheme with LEACH [6] considering homogeneous network for number of alive nodes $\mathcal{N}_A$ and rounds $\mathcal{R}$.

2) MODEL 2

To evaluate the performance of the proposed dynamic clustering scheme for heterogeneous WSNs, model 2(a) and 2(b) are simulated for two level and three level heterogeneous sensor nodes respectively. The performance of the proposed dynamic clustering scheme is compared with the existing clustering scheme for heterogeneous WSNs i.e. DEEC [9], DDEEC [34] with two level heterogeneity and EDEEC [35] and EDDEC [36] with three level heterogeneity as presented in Fig. 6 and Fig. 7 respectively. In model 2(a) the WSN is comprised of sensor nodes which are categorized as normal sensor nodes and advanced sensor nodes based on their initial energy where the number of normal sensor nodes and advanced sensor nodes $n \times (1 - m)$ and $n \times m$. While in model 2(b), sensor nodes are categorized as normal sensor nodes, advanced sensor nodes and super sensor nodes, where the number of normal sensor nodes, advanced sensor nodes and super sensor nodes are calculated as $n \times (1 - m)$, $n \times m \times (1 - m_o)$ and $n \times m \times m_o$ respectively; where m and m_o are assumed as 0.3. The advanced sensor nodes and super sensor nodes energy can be calculated as $(1 + a)E_o$ and $(1 + b)E_o$ respectively, where a and b are assumed as 2 and 3.5. It is observed from Fig. 6 that the FND, HND and LND for the proposed scheme at 2151, 2777 and

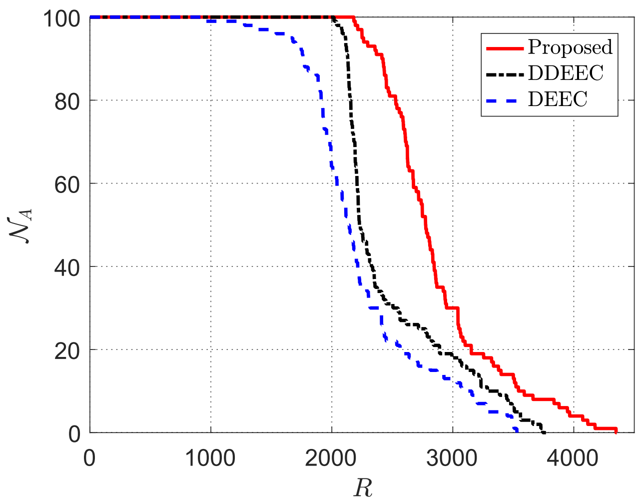

FIGURE 6. Performance analysis comparison of the proposed scheme with DEEC [9] and DDEEC [34] considering two level of heterogeneous network for number of alive nodes $\mathcal{N}_A$ and rounds $\mathcal{R}$.

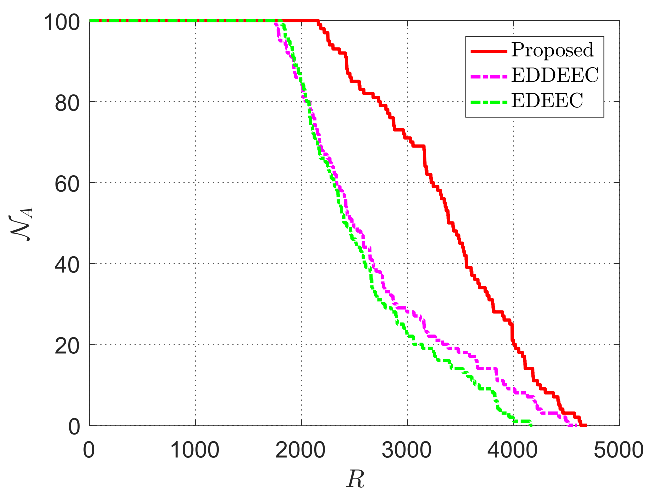

FIGURE 7. Performance analysis comparison of the proposed scheme with EDEEC [35] and EDDEEC [36] considering three level of heterogeneous network for number of alive nodes $\mathcal{N}_A$ and rounds R.

4351 rounds respectively. While the FND for DEEC and DDEEC at 936 and 2013 respectively, the HND at 2145 and 2232 rounds respectively, and the LND at 3531 and 3770 rounds respectively. Hence, the proposed scheme quantifies the network lifetime by 23.2% and 15.4% rounds as compared to DEEC and DDEEC respectively. Also, Fig. 7 validates that the FND,HND and LND for the proposed scheme at 2158, 3391 and 4635 respectively. While the FND for EDEEC and EDDEEC at 1813 and 1761 respectively, the HND at 2401 and 2492 rounds respectively, and the LND at 4157 and 4520 rounds respectively. Therefore, the proposed scheme enhance the network lifetime by 11.5% and 2.6% as compared to EDEEC and EDDEEC respectively.

3) MODEL 3

It provides the network lifetime analysis with cooperation among sensor nodes while transmitting data to fusion center receiver. The simulation parameters are considered as provided by authors in [37]. The simulation results presented in Fig. 8 demonstrates that the FND, HND and LND for the proposed scheme at 601, 2101 and 2801 rounds respectively for $(n_t, n_r) = 2$. While for the COOP-LEACH presented in [37] the FND, HND and LND at 890, 3165 and 4643 rounds respectively for $(n_t, n_r) = 2$. Similarly, the LND for the proposed scheme and the COOP-LEACH at 4185 and 2251 rounds respectively when $(n_t, n_r) = 3$, at 3756 and 1801 rounds respectively when $(n_t, n_r) = 4$, and at 3145 and 1551 rounds respectively when $(n_t, n_r) = 5$. Hence, the proposed scheme increases the network lifetime by 50.6%, 35%, 40.5% and 49% with $(n_t, n_r) = 2, 3, 4$ and 5 respectively for 50% alive nodes as compared to COOP-LEACH; while cooperation among sensor nodes is exploiting diversity to achieve transmission reliability.

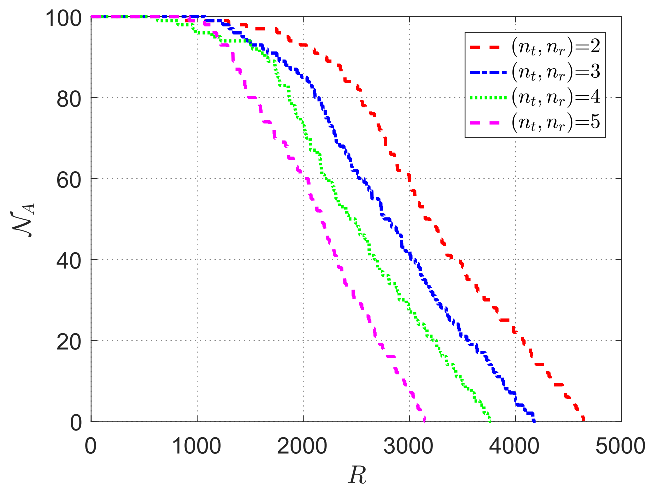

FIGURE 8. Performance analysis of the proposed scheme for cooperative communication realizing virtual MIMO transmission and exploiting diversity for number of alive nodes $\mathcal{N}_A$ and rounds R.

A detailed comparison analysis of the proposed dynamic clustering scheme with the aforementioned existing schemes is presented in Table 3. It is validated from the Table 3 that the proposed scheme outperforms the existing schemes.

C. PERFORMANCE ANALYSIS OF PROPOSED UNIVERSAL FRAMEWORK

The performance analysis of the proposed framework is presented in this section. It is assumed that the location of the events is randomly distributed and their occurrence is at least 10 m away from each other. Network lifetime analysis is presented in Fig. 9, Fig. 11 and Fig. 13 for time-driven, event-driven and hybrid scenarios respectively. To achieve transmission reliability, cooperation among sensor nodes is considered while data transmission to fusion center receiver. Fig. 15 demonstrates that the higher degree of cooperation increases the detection reliability. Moreover, performance analysis of the proposed schemes in terms of average residual energy per node is presented in Fig. 10, Fig. 12 and Fig. 14 for time-driven, event-driven and hybrid scenarios respectively.

TABLE 3. Comparison of the proposed dynamic clustering scheme with existing schemes for homogeneous and heterogeneous WSNs.

Scenerio	Reference	Sensors Type	Protocols	Cooperation	Activity Factor		
					100%	50%	0
Model 1	Fig. 5	Homogeneous	LEACH [6]	-	902	1197	1861
			Proposed		**1369**	**2333**	**3414**
Model 2(a)	Fig. 6	Heterogeneous (Level 2)	DEEC [9]	-	935	2144	3530
			DDEEC [34]		2012	2231	3769
			Proposed		**2150**	**2776**	**4350**
Model 2(b)	Fig. 7	Heterogeneous (Level 3)	EDEEC [35]	-	1812	2400	4156
			EDDEEC [36]		1760	2491	4519
			Proposed		**2157**	**3390**	**4634**
Model 3	Fig. 8	Homogeneous	COOP-LEACH [37]	Diversity 2	600	2100	2800
			Proposed		**889**	**3164**	**4642**
			COOP-LEACH [37]	Diversity 3	1030	2075	2250
			Proposed		**1087**	**2794**	**4184**
			COOP-LEACH [37]	Diversity 4	1250	1750	1800
			Proposed		**625**	**2461**	**3755**
			COOP-LEACH [37]	Diversity 5	1150	1450	1550
			Proposed		**925**	**2179**	**3144**

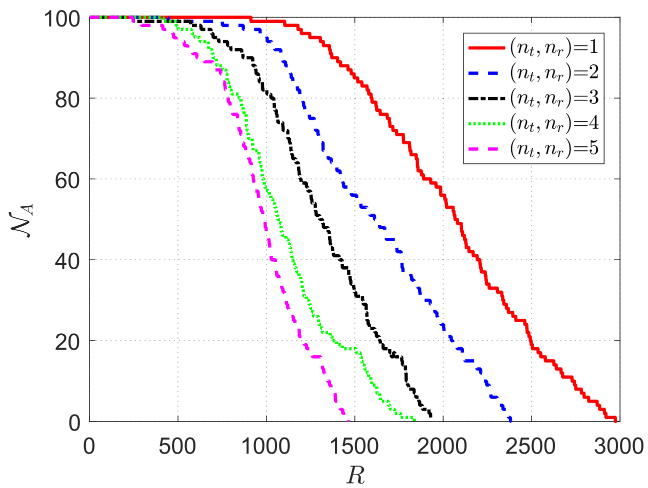

FIGURE 9. Performance analysis of the proposed scheme for time-driven applications for number of alive nodes $\mathcal{N}_A$ and rounds R.

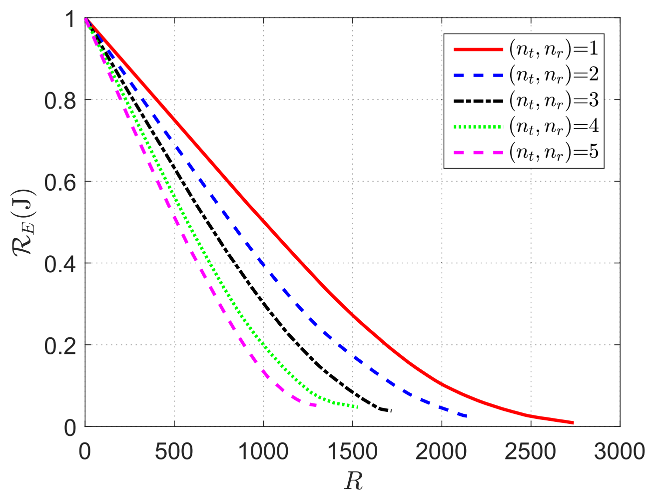

FIGURE 10. Performance analysis of the proposed scheme for time-driven applications for average residual energy $\mathcal{R}_E$ and rounds R.

It is found that by increasing the number of cooperative sensor nodes, the proposed universal framework provides a tradeoff between the network lifetime and data transmission reliability. Also, exploiting diversity increases the signal to noise ratio (SNR) gain of 13 dB, 17.5 dB, 20 dB and 21.5 dB with the decrease in network lifetime by 20%, 35.2%, 38.4% and 50.8% for degree of cooperation 2, 3, 4 and 5 respectively to achieve 10^{-3} probability of error $\mathcal{P}_e$ as compared to conventional transmission. A detailed performance comparison of the proposed scheme is described in Table 4.

D. PERFORMANCE ANALYSIS OF THE PROPOSED UNIVERSAL FRAMEWORK WITH CQI

In this section, the performance of the proposed framework with the adaptation of variable conditions of channel propagation is analyzed. It is assumed that the fusion center receiver is equipped with multiple antennas to act as a virtual MIMO system, while receiving data from cooperative sensor nodes. Fig. 15 demonstrates the probability of error for a given range of signal quality i.e. 0 to 40 dB which is simulated from (62)

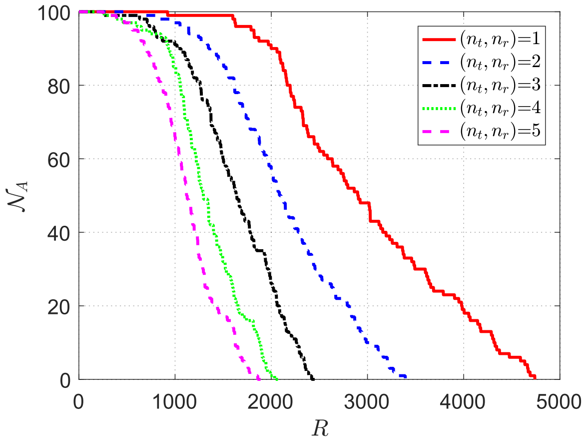

FIGURE 11. Performance analysis of the proposed scheme for event-driven applications for number of alive nodes $\mathcal{N}_A$ and rounds R.

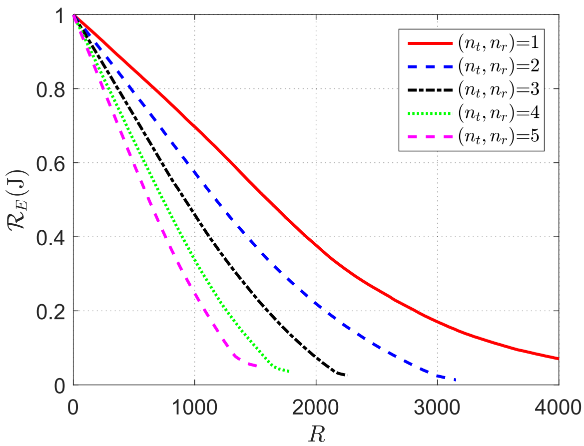

FIGURE 12. Performance analysis of the proposed scheme for event-driven applications for average residual energy $\mathcal{R}_E$ and rounds R.

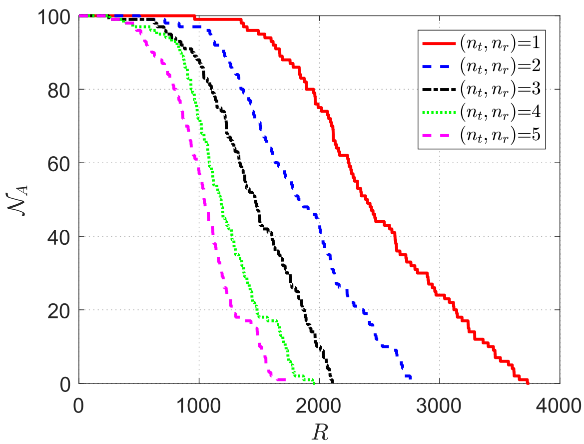

FIGURE 13. Performance analysis of the proposed scheme for hybrid applications for number of alive nodes $\mathcal{N}_A$ and rounds R.

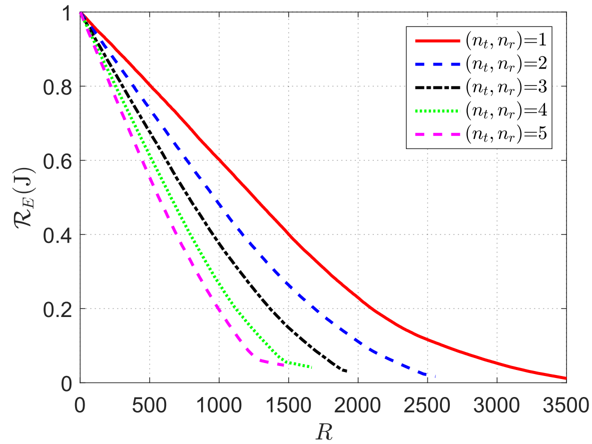

FIGURE 14. Performance analysis of the proposed scheme for hybrid applications for average residual energy $\mathcal{R}_E$ and rounds R.

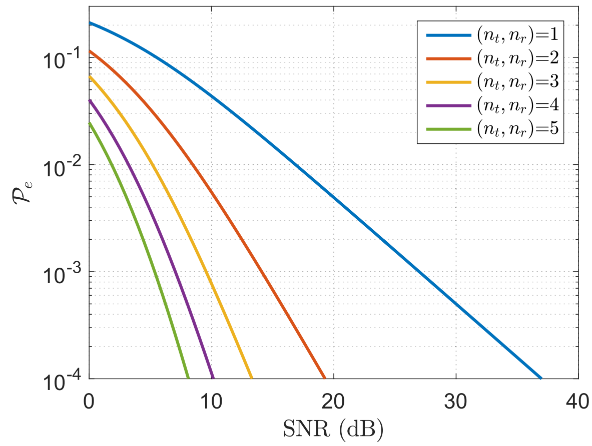

FIGURE 15. Probability of error for conventional transmission with one transmit-receive antenna pair and cooperative transmission for degree of diversity 2, 3, 4 and 5.

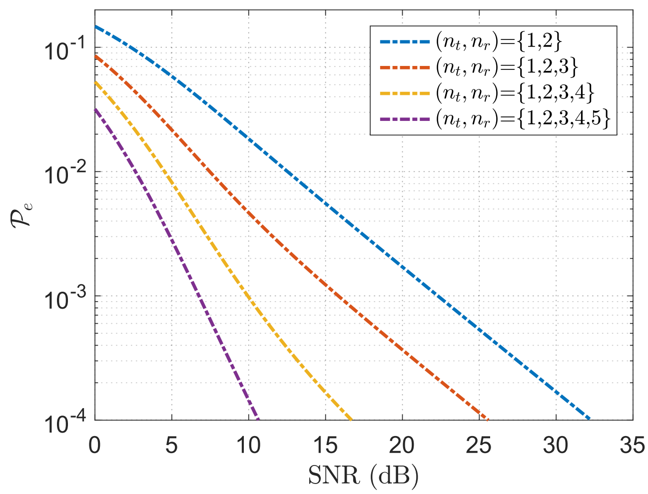

FIGURE 16. Probability of error for cooperative transmission with channel quality index (CQI) based adaptation for degree of diversity 2, 3, 4 and 5.

as stated in [38].

$$\mathcal{P}_e = \left[\tfrac{1}{2}(1-\mu)\right]^L \sum_{\hat{l}=0}^{L-1} \binom{L-1+\hat{l}}{\hat{l}} \left[\tfrac{1}{2}(1+\mu)\right]^{\hat{l}} \tag{62}$$

where $\mu = \sqrt{\frac{\gamma}{1+\gamma}}$ with average received SNR γ and L represents the total number of bits in one transmission. The effect of dynamic adaptation in the selection of number of

TABLE 4. Performance analysis of the proposed universal framework for time-driven, event-driven and hybrid scenario within WSNs.

Cooperation (No. of Nodes & Type)	Sensing Type	Activity Factor 100%	Activity Factor 50%	Activity Factor 0	Residual Energy 50%	Residual Energy 20%	SNR (dB) for $\mathcal{P}_e$ (10^{-3})	Trade-off: Reduction in Active Time	Trade-off: SNR Gain
1	TD	912	2073	2979	1002	1687	27 dB	-	-
	ED	922	2905	4740	1600	2817		-	
	Hybrid	950	2389	3738	1254	2095		-	
2 Diversity	TD	439	1616	2381	816	1425	14 dB	20%	13 dB
	ED	507	2085	3394	1178	2080		28.4%	
	Hybrid	505	1839	2760	965	1689		26.16%	
3 Diversity	TD	245	1314	1929	682	1193	9.5 dB	35.25%	17.5dB
	ED	260	1642	2420	920	1601		48.9%	
	Hybrid	250	1468	2108	782	1366		43.6%	
4 Diversity	TD	412	1074	1837	573	998	7 dB	38.34%	20dB
	ED	255	1294	2064	739	1263		56.46%	
	Hybrid	246	1183	1966	648	1117		47.41%	
5 Diversity	TD	245	989	1464	516	889	5.5 dB	50.86%	21.5dB
	ED	249	1125	1863	623	1082		60.7%	
	Hybrid	245	1041	1743	564	994		53.3%	

TABLE 5. Channel classification and degree of cooperation selection criterion.

Normalized Channel Quality Measure	<0.4	0.4-0.55	0.55-0.7	0.7-0.85	>0.85
CQI	0	1	2	3	4
Seletion of Degree of Cooperation	$(n_t, n_r) = 1$	$(n_t, n_r) = 2$	$(n_t, n_r) = 3$	$(n_t, n_r) = 4$	$(n_t, n_r) = 5$

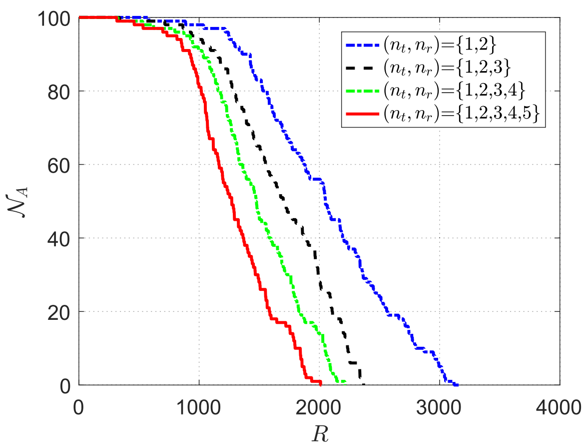

FIGURE 17. Performance analysis of the proposed universal framework with channel quality index (CQI) based adaptation for number of alive nodes $\mathcal{N}_A$ and rounds R.

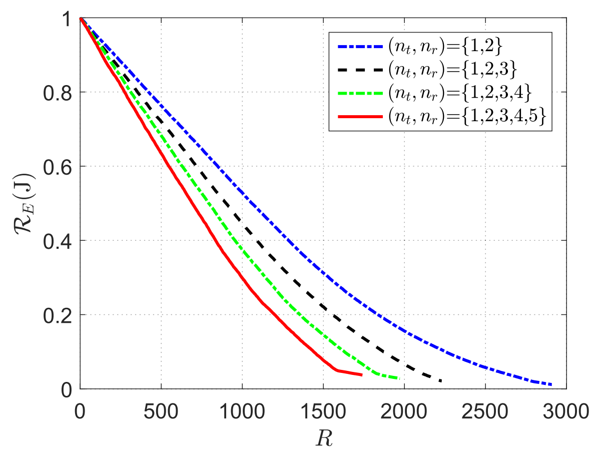

FIGURE 18. Performance analysis of the proposed universal framework with channel quality index (CQI) based adaptation for average residual energy $\mathcal{R}_E$ and rounds R.

cooperative nodes based on the signal propagation conditions to maintain required quality of service are presented in Fig. 16, Fig. 17 and Fig. 18. These simulation results demonstrates the performance analysis of the proposed framework for probability of error, number of alive nodes and average residual energy of the network respectively.

TABLE 6. Performance analysis of the proposed universal framework with CQI based adaptation for network lifetime and detection reliability.

CQI based Adaptation $(\tau_{(\cdot)})$	Activity Factor			Res. Energy		SNR (dB) for $\mathcal{P}_e$ (10^{-3})	Trade off					
							Activity Factor		Res. Energy		SNR Gain	
	100%	50%	0	50%	20%		τ^-	τ^+	τ^-	τ^+	τ^-	τ^+
τ_2 = [1,2]	582	2050	3147	1054	1837	22dB	-15.8%	14%	-12.3%	8.7%	5dB	-3dB
τ_3 = [1,2,3]	356	1705	2367	898	1525	15.5dB	-36.6%	12.2%	-27.2%	11.6%	11.5dB	-6dB
τ_4 = [1,2,3,4]	340	1474	2213	792	1353	9.5dB	-40.8%	12.5%	-35.4%	21.1%	17.5dB	-2.5dB
τ_5 = [1,2,3,4,5]	315	1272	2011	689	1195	7dB	-46.2%	15.4%	-42.9%	20.2%	20dB	-1.5dB

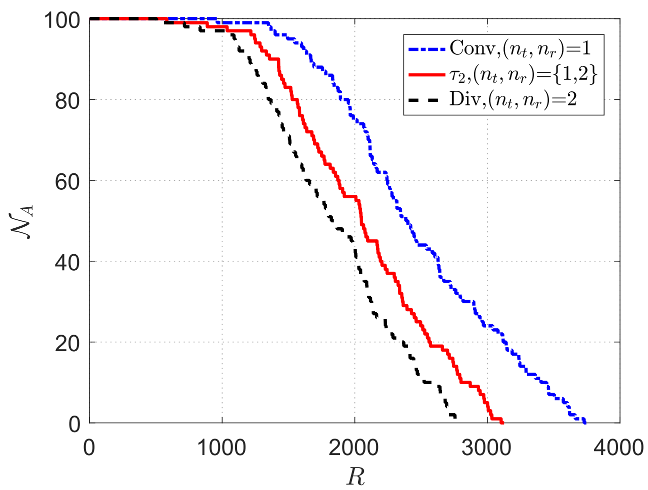

FIGURE 19. Performance comparison of the proposed universal framework with channel quality index (CQI) based adaptation $(n_t, n_r) =$ {1,2} represented by (τ_2), conventional cooperative transmission $(n_t, n_r) = 1$ represented by (Conv) and virtual MIMO diversity for $(n_t, n_r) = 2$ represented by (Div) for number of alive nodes $\mathcal{N}_A$ and rounds R.

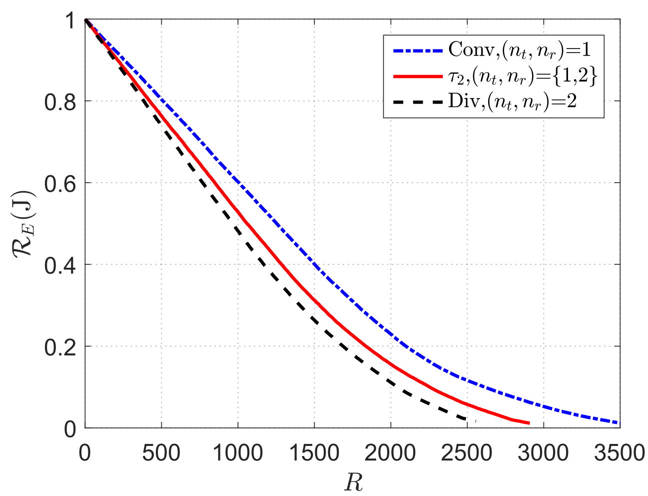

FIGURE 20. Performance comparison of the proposed universal framework with channel quality index (CQI) based adaptation $(n_t, n_r) =$ {1,2} represented by (τ_2), conventional cooperative transmission $(n_t, n_r) = 1$ represented by (Conv) and virtual MIMO diversity for $(n_t, n_r) = 2$ represented by (Div) for average residual energy $\mathcal{R}_E$ and rounds R.

Let τ_5 represents the set of transmit-receive antennas $\{1, 2, 3, 4, 5\}$, τ_5^- is $\min\{\tau_5\}$ and τ_5^+ is $\max\{\tau_5\}$. It is observed that the adaptive selection of number of cooperative nodes enhance detection reliability and network lifetime by 15.4% and achieve 20 dB SNR gain as compared to τ_5^- and τ_5^+ number of cooperative nodes. For $\tau_4 = \{1, 2, 3, 4\}$, the CQI based cooperative transmission for hybrid scheme can enhance network lifetime by 12.5% and achieve 17.5 dB SNR gain as compared to τ_4^+ and τ_4^- respectively. Performance comparison of hybrid scheme with adaptive transmission, conventional cooperative transmission $(n_t, n_r) = 1$ and virtual MIMO diversity for $(n_t, n_r) = 2$ are presented in Fig. 19 and Fig. 20. It is found that the dynamic property of the proposed framework provides a tradeoff between network lifetime and detection reliability. It is observed that proposed scheme enhance the network lifetime by 14% as compared to τ_2^+ with the cost of 3 dB SNR. Moreover, it achieve 5 dB SNR gain as compared to τ_2^- with the cost of 15.8% network lifetime. The decision on the selection of degree of cooperation is presented in Table 5 and a detailed comparison of the proposed hybrid scheme with adaptive cooperative transmission is summarized in Table 6.

VII. CONCLUSION

Considering energy conservation in the design of WSNs, the challenges of attaining energy efficient solutions with dynamic clustering are addressed. A novel unified framework for collaborative sensing and cooperative communication is proposed for resource constrained WSNs. The proposed framework incorporates a dynamic clustering scheme that ensures even distribution of energy demand among sensor nodes and a neighbourhood formation scheme to optimize the number of sensor nodes involved in the detection and reporting of events. A soft or hard decision based tuneable thresholding parameter for the selection of cluster heads is also presented to facilitate the system design engineer to optimize the frequency of re-clustering within the network. The proposed dynamic clustering and neighbourhood formation scheme is fully decentralized which reduces the amount of information required to be broadcasted. Such distributive capability accelerates the decision-making process and enhances the energy conservation. To estimate the energy consumption within WSNs, a mathematical model is also formulated. The proposed framework is universal in nature that supports diverse range of applications independent of the nature of sensing type e.g. time driven, event driven or hybrid. The performance of the proposed framework for both homogeneous and heterogeneous networks is evaluated, and it is observed from the simulation results that the UDCS outperforms the existing schemes in energy conservation. To attain data transmission reliability while utilizing optimum resources, an adaptive cooperation among sensor nodes while transmission is considered. The basis of adaptation is based on CQI estimated at the receiver and fed back to the transmitter through feedback link. The results have shown that the proposed framework provides a trade-off model for network lifetime and data transmission reliability that makes it suitable for WSNs to operate in wide range of sensing environment.

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MUHAMMAD KAMRAN NAEEM (S'16) received the B.Eng. degree (Hons.) in electrical (telecom) engineering from Air University, Pakistan, in 2008, and the M.Sc. degree in telecommunication engineering from Staffordshire University, Stoke-on-Trent, U.K., in 2011, where he is currently pursuing the Ph.D. degree in electronic engineering. He is a member of Sensing, Processing, and Communication Research Group with Staffordshire University. His current research interests include wireless communications, channel estimation and equalization techniques, multi-antenna systems, wireless sensor networks, and Internet of Things.

MOHAMMAD PATWARY (SM'11) received the B.Eng. degree (Hons). in electrical and electronic engineering from the Chittagong University of Engineering and Technology, Bangladesh, in 1998, and the Ph.D. degree in telecommunication engineering from The University of New South Wales, Sydney, Australia, in 2005.

He was with General Electric Company of Bangladesh from 1998 to 2000 and with Southern-Poro Communications, Sydney, from 2001 to 2002, as an Research and Development Engineer. He was a Lecturer with The University of New South Wales from 2005 to 2006, and then a Senior Lecturer with Staffordshire University, U.K., from 2006 to 2010. He was then a Full Professor of Wireless Systems and Digital Productivity and the Chair of the Centre of Excellence on Digital Productivity with Connected Services, Staffordshire University, until 2016. He is currently a Full Professor of Telecommunication Networks and Digital Productivity and the Head of Research with the Centre for Cloud Computing (CCC), School of Computing and Digital Technologies, Birmingham City University. His current research interests of CCC include digital productivity with wireless connectivity, sensing, and processing for intelligent systems, such as manufacturing, healthcare, future network infrastructure, intelligence, and QoE measures, wireless communication systems design and optimization, signal processing and energy-efficient systems, future generation of cellular network architecture, integration of expertise with energy joint source-channel characterization for wireless sensor networks (heterogeneous networks and IoT), and spatial diversity schemes for wireless communications.

MOHAMED ABDEL-MAGUID (SM'11) received the B.Eng. degree (Hons) in electronics and communications engineering (marine electronics) from AAST, Egypt, in 1992, the M.Sc. degree in telecommunications engineering, and the Ph.D. degree in electronic engineering from Staffordshire University, U.K. He held a number of senior positions, both in the U.K. and internationally, and served as a Senior Technology Advisor for government organizations, where he advised on the development of telemedicine initiatives, the use of smart technologies to improve road safety and technology enhanced learning. He is an Adjunct Professor with the Maastricht School of Management, a fellow of the Chartered Management Institute, and a Co-opted Member of the BiNDT. He is currently a Professional Engineer, an Entrepreneur, and a Research- and Enterprise-Focused Academic, with over 25 years of experience in both business and academia. He is currently the founding Chair of the Department of Science and Technology, University of Suffolk, where he is with the forefront of a number of regional STEM skills, and research and innovation agendas in Suffolk. His research interests include telecommunications and intelligent multimodal signal processing and their application to the development of smart systems and intelligent environment. He is particularly interested in next-generation networks, cognitive radio, Internet of Things, and data analytics for security, integrated care, and transport applications. He led a portfolio of successful and award winning Applied Research and Business-University collaboration initiatives. His work received the UHNS Clinical Innovation Award in 2010 and the Lord Stafford Award Impact through Innovation in 2009.