Enhanced Cooperative MIMO based Routing Protocol for QoS Enriched and Energy Efficient Transmission over WSNS

Kummathi Chenna Reddy, Geetha D Devanagavi, Thippeswamy M N

Abstract*: In this paper, a robust mobility assisted WSN routing protocol named QoS oriented and Energy Efficient Routing Protocol for Cooperative Multiple Input Multiple Output (MIMO) based mobile WSNs (Q-E2RPC) has been developed that exploits the efficiency of network partitioning, Fuzzy Clustering Mean (FCM) and Expectation Maximization (EM) based clustering, Fuzzy Logic Controller (FLC) based Cluster Head (CH) selection and mobile sink based data gathering to meet QoS demands and energy efficiency. The use of single mobile sink avoided multi-hop transmission and signaling overheads that eventually reduced energy consumption. Q-E2RPC protocol exhibited timely data delivery, low energy consumption, and reduced signaling overheads. The results exhibited that Q-E2RPC outperforms other state-of-art techniques in terms of higher throughput, low delay and energy consumption, and higher network efficacy.

Index Terms*: CMIMO; Fuzzy Logic Controller; Expectation Maximization; Wireless Sensor Networks.

I. INTRODUCTION

WSN has gained significant attention to enable low cost communication solution for Internet of Things (IoT) ecosystem, primarily in Low Power Lossy Network (LLNs) [1]. The decentralized and infrastructure-less nature of WSN make it a dominating solution to meet major communication demands. To fulfill quality of service (QoS) demands and energy efficient communication, numerous efforts have been made on achieving higher bandwidth utilization, minimal end-to-end delay, minimum data loss and energy consumption, reliable communication etc. However, limited energy and continuous sensory communication forces WSN to undergo exhaustion and node-dead condition. Additionally, factors like channel fading, interference, and spectrum irregularity introduce significant problems in enabling QoS and energy efficient routing. Among major solutions, Multiple-Input Multiple-Output (MIMO) technique has been found potential [2] to support efficient routing, it plays vital role in alleviating the key issues of low transmission rates and low reliability. Constructing WSN nodes having multiple antennas could be difficult because of the size and complexity related constraints. To deal with this situation, WSNs can apply MIMO in cooperative way that can assure reliable communication but also energy efficient transmission over defined network region. In CMIMO multiple nodes construct transmission and receiving clusters by performing synchronization and synchronize data exchange to ensure that the clusters could apply standard MIMO for communication. It intends to reduce energy consumption and delay while enabling higher throughput at the receiver to meet QoS provision. In this technique, multiple sensor nodes are physically connected or clustered to perform communication, where within a cluster, sensor nodes communicate with relatively low power than to inter-group communication. Typically, data redundancy is caused because of relaying the signal to nearby users working as the intermediate nodes. CMIMO techniques alleviate the issue of data redundancy that makes data aggregation efficient, before forwarding it to the next hop or the sink. Clustering based WSN routing protocol encompasses node grouping and CH selection, which is performed in such manner that the non-CH nodes could communicate with connected CH directly. In CMIMO based WSN, CH forwards gathered data to the sink directly or in multi-hop paradigm. However, factors like the optimal number of clusters, optimal CH selection, and transmission play decisive role in WSN performance. Unlike generic multi-hop transmission based WSNs, the use of a single mobile sink can avoid unwanted retransmission and hence can assure higher throughput, low energy consumption and delay. With this motivation, in this paper an emphasis is made on applying an enhanced grid partitioning, hybrid (or dual phase) clustering, multi-parameters (distance, RSSI, responsiveness) based CH selection, cooperative MIMO based transmission, and mobile sink based data collection to meet QoS demands and energy efficient communication over WSNs.

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II. RELATED WORK

He et al. [3] developed CMIMO model by applying clusters of different sizes. Authors found that with clusters of the same size, CH with relatively lower residual energy might undergo fast energy exhaustion than the one with more residual energy. To avoid energy consumption authors applied the trade-off between residual energy of CH and the size of cluster. Vidhya et al. [4] proposed energy-efficient LEACH (EE-LEACH) and CMIMO where they performed network partitioning into fixed regions having equal angle that avoided the possibility of non-uniform CH distribution . Authors [5-7] exploited

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CMIMO and cluster based WSN to perform energy efficient communication over WSN and revealed independent relationship between the number of nodes in CMIMO and the number of nodes having data for transmission. Siam et al. [8] applied multi-hop transmission to achieve efficient transmission however could not be address energy exhaustion due to multi-hop traversal. Islam et al. [9] developed a channel condition aware CH selection and energy efficient CMIMO for WSNs. Chaibrassou et al. [10] developed a distributed Multi Channel CMIMO model for cluster based WSNs (MCMIMO) that finishing clustering exhibits weighted link exploitation for the best cooperative nodes identification. Authors [11][12] applied Virtual MIMO (VMIMO) concept to derive a distributed Cooperative Clustering Protocol (CCP), where they used VMIMO diversity gain by performing CN selection within each cluster. Authors [13][14] developed a cluster-based VMIMO for energy-constrained WSN communication. Authors applied Space-Time Block Coding (STBC) based VMIMO [15] in conjunction with LEACH to achieve energy efficient routing. Medhia et al. [16] applied mobility and CMIMO for WSN. To enable CMIMO communication each mobile node applied Alamouti diversity algorithm. The mobile sensor could move to a defined network location to collect sensed data and transmit it to the sink using CMIMO [17]. Zhang et al. [18] where authors applied residual energy and the link quality between the CHs to perform data transmission. Energy Based Clustering Self organizing map (EBCS) based clustering was developed by Enami et al. [19]. Amri et al. [20] developed a Multi-hop Hierarchical Routing Protocol using Fuzzy Logic (EMHR-FL), where Fuzzy Logic Inference System (FIS) was used to perform next-hop selection by considering residual energy of CHs, distance between CHs and node density.

III. Our Contribution

Considering large scale network, unlike classical clustering, in our routing protocol at first a large scale network is split into groups, which is then followed by clustering in each group. In Q-E2RPC routing protocol a hybrid clustering approach having dual phase implementation is developed, where in first phase FCM algorithm is applied that exploits inter-node distance to cluster nodes. In the second phase, an enhanced EM model is applied that exploits degree of dependence of a node on cluster to perform final clustering, before executing CH selection. This combined model ensures optimal number of clusters in the network that eventually reduces energy exhaustion and signaling overheads. Furthermore, considering significance of CH selection in WSN, the use of multiple network parameters can be vital. In CH selection model, node information, residual energy, Signal to Noise Ratio (SNR) or RSSI and node responsiveness is taken into consideration. The use of a single parameter such as the residual energy or the distance can be easy to decide CH of a cluster; however selecting CH with multiple parameters even under dynamic topology can be a trivial task. To deal with it, Q-E2RPC incorporates FLC that learns multiple network states to perform optimal CH selection. In practice, multi-hop transmission intends to assure reliable transmission without data loss, however at the cost of retransmission and higher energy consumption. To alleviate such issues, introducing mobile sink can be vital, where a mobile sink can collect data from the CHs directly to avoid unwanted traversal and resulting energy exhaustion. Q-E2RPC protocol exploits CMIMO transmission features to perform inter-node communication from CH to mobile sink. This as a result makes overall communication energy, delay and resource efficient.

A. WSN Model

Considering real-time communication large number of sensors distributed across the field, Q-E2RPC has been developed with dense network with multiple sensor nodes. To alleviate contention and data losses during traversal across large network, Q-E2RPL protocol splits overall network into sub-network or regions called “Group”. An illustration of the applied network region is given in Fig. 1.

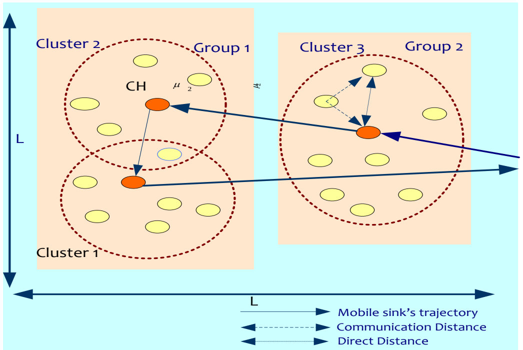

Fig. 1. WSN Network

In Fig. 1, circles presents N sensors distributed across the network with dimension $L \times L$. Here, the solid circle C presents the CH formed, which is supposed to be visited by the mobile sink for data collection by means of CMIMO transmission scheme. The solid-fill circles refer nodes in a group, while dotted region presents the cluster. Here, the term “Group” signifies a set of nodes which are able to communicate with each other. The nodes in other groups are unable to communicate due to high inter-node distance. Let G be the total number of groups in the network and N_g and C_g be the total number of sensor nodes and the number of clusters in gth group, respectively. Unlike traditional approaches, the total number of groups is estimated by exploiting the location of the nodes and its radio range R. Here, each CN shares its information to perform CH selection. Once receiving the data from CNs, CH forwards it to the mobile sink using CMIMO transmission. In Q-E2RPC, it is assumed that each node is aware of its own position and cluster’s location. Practically, it can be achieved through certain node positioning algorithm. Here, each node has a definite communication range R and therefore transmission can be successful only within R. CHs collect sensed data from CNs through CMIMO transmission approach and meanwhile mobile sink collect data from CHs in the similar manner. To avoid unwanted multi-hop traversal, in Q-E2RPC a single mobile sink has been applied that assures timely data gathering to enable swift decision. It

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not only reduces traversal time but also reduces energy exhaustion due to retransmission.

The efficiency of a clustering based WSN routing protocols depends on two key factors, clustering and CH selection. The use of real-time network parameters such as network link, radio strength, energy level and channel gain [21] etc. can make CH selection more efficient. However, applying multiple parameters to decide CH is intricate and can become more trivial under dynamic topology. To alleviate such issues, in our model FLC algorithm has been applied that learns the network parameters to perform CH selection. Here, it should be noted that in Q-E2RPC, before executing clustering and CH selection, we have executed network partitioning that splits overall network into two groups that makes overall computation efficient. Each node forwards sensed data to the connected CH via CMIMO transmission where CH further combines those data to transmit towards the destination node.

B. System Design

Q-E2RPC incorporates the following steps:

Step-1 Fuzzy cluster mean (FCM) and Expectation Maximization based clustering,
Step-2 Fuzzy Logic Control (FLC) based CH selection,
Step-3 Cooperative communication based data transmission using Single Mobile Sink node.
A brief of the implementation model is given as follows:

C. Dual Phase Clustering

Unlike classical clustering approaches, we have applied dual phase clustering, where at first FCM is executed to perform initial clustering over two groups. Once performing initial clustering, we have executed EM based centralized clustering that uses the cluster information and associated CNs information to re-structure the clusters. A brief of this clustering paradigm is given as follows:

1) FCM Based Initial Clustering

FCM is used to perform pattern recognition by providing membership to each data point related to each cluster center, where the summation of membership for all data points should be equal to one. In FCM based clustering intends to minimize an objective function given in (1).

$$\min_{\mu_{ij}, m_j} (v_q), \qquad (1)$$

Where

$$v_q = \sum_{i=1}^{N} \sum_{j=1}^{M} \mu_{ij}^{q} \left\| \theta_i - m_j \right\|^2, \qquad (2)$$

Noticeably, the deployed WSN network considers node distribution in such manner that it depicts like a network graph G, with each vertex signifying the node's position in 2D space. Mathematically, a sensor node is positioned as $q_i = [X_i, Y_i]^T$ for the ith node. Thus, in above equation, q_i signifies the location parameter of a node. If the two nodes i and j are located within their communication or radio ranger r, their link could be defined in terms of an edge. In (2) M states the total number of clusters, q presents the fuzziness exponent (>1), μ_{ij} presents the degree of membership of ith node in jth cluster and m_j states the center of cluster j and m_k refers center of cluster$k$. The value of μ_{ij} exists in the range of 0 to 1 for each CN to the CH. Here, we have performed fuzzy partitioning by means of an iterative optimization where it intends to minimize the objective function μ_{ij} (3).

$$\mu_{ij} = \frac{1}{\sum_{h=1}^{M} \left(\frac{\left\| \theta_i - m_j \right\|}{\left\| \theta_i - m_k \right\|} \right)^{\frac{2}{q-1}}}, \qquad (3)$$

Finally the cluster center m_j obtained is (4).

$$m_j = \frac{\sum_{i=1}^{N} \mu_{ij}^{q} \cdot \theta_i}{\sum_{i=1}^{N} \mu_{ij}^{q}}. \qquad (4)$$

Once reaching stopping criteria the iterative optimization is stopped. Noticeably, in FCM based clustering the stopping criteria is defined as $\{\mu_{ij}^{k+1} - \mu_{ij}^{k}\} < \sigma$, where, k signifies the iteration step. The snippet of the applied FCM based clustering is given as follows (Fig. 2):

Algorithm-1 FCM based Clustering

Initialization: membership values
$\mu_{i,j}\ \forall h = 1,2,..M\ \ \forall i = 1,2,...N$
Cluster Centers Initialized
while $\{\mu_{ij}^{k+1} - \mu_{ij}^{k}\} < \sigma$ ***do***
for $j = 1,2,...M$ ***do***
$m_j = \frac{\sum_{i=1}^{N} \mu_{ij}^{q} \cdot \theta_i}{\sum_{i=1}^{N} \mu_{ij}^{q}}$
end for
for $i = 1,2,..N$ ***do***
for $j = 1,2,..M$ ***do***
which is μ_{ij}^{k}
if $\left\| \theta_i - m_j \right\| > 0$ ***then***
Calculate μ_{ij} as

$$\mu_{ij} = \frac{1}{\sum_{h=1}^{M} \left(\frac{\left\| \theta_i - m_j \right\|}{\left\| \theta_i - m_k \right\|} \right)^{\frac{2}{q-1}}}$$

which is μ_{ij}^{k+1}
end if
end for
end for
end while

Fig. 2. FCM based clustering

To further strengthen clustering, a centralized clustering approach named EM has been applied.

2) Expectation Maximization Based Clustering

EM is a generic clustering model that assumes that all sensor nodes are distributed as per Gaussian Mixture Model (GMM) (5).

$$E(\mathrm{x}) = \sum_{c=1}^{C} \pi_c A(x|\sigma_c, \Sigma_c) \tag{5}$$

In (5), variables C and σ_c present total clusters and a combination factor for the cth cluster, respectively. Here, $A(\mathrm{x}|\sigma, \Sigma)$ is obtained using (6).

$$A(x|\sigma, \Sigma) = \frac{1}{(2\pi)|\Sigma|^{1/2}} exp\left\{-\frac{1}{2}(x-\sigma)^T \Sigma^{-1}(x-\sigma)\right\}, \tag{6}$$

In (6), x and σ signify the location vector of CNs and the location vector of CH of the cth cluster, respectively. The variable Σ_c states a 2×2 Covariance Matrix (CM) of the cth cluster. Unlike FCM, EM calculates Degree of Dependence (DoD) of each CN that is nothing else but the Responsiveness of a node on the connected cluster. We have estimated "Responsiveness" of a node n on kth cluster using (7).

$$\varphi_{nc} = \frac{\pi_c A(x_n|\sigma_C, \Sigma_C)}{\sum_{j=1}^{c} \sigma_j A\left(x_n|\sigma_j, \Sigma_j\right)}. \tag{7}$$

Typically, the value of responsiveness (7) remains in the range of 0 and 1.

Once performing FCM based initial clustering and retrieving the location vector of the CHs, the communication distances $\mathrm{D_{nc}}$ between each CN and associated CH is estimated. In this way, two components location vector (σ) and covariance matrix (Σ) are obtained. Now, to deal with the complexity due to the large size (i.e., dense) network, the overall network is partitioned into groups. Once initiating the EEM based clustering phase, the proposed Q-E2PRC model selects a particular group with the highest value of the proportion of the number of residing nodes to the total cluster counts in group g. In other words Q-E2PRC routing protocol selects a group with the highest value of the parameter v_g, which is mathematically obtained by (8).

$$v_g = \frac{C_g}{N_g} \tag{8}$$

In (8), C_g states the number of clusters in the group and N_g states the total number of nodes in the group. Thus, in the selected group having the highest value of v_g, Q-E2PRC model selects all those nodes which belong to the group g and updates the node responsibility factor, φ_{nc} for these all nodes. In our proposed routing model the value of φ_{nc} signifies the extent to which a node n belongs to the cluster k. Thus, employing the updated responsibility factor, φ_{nc} the cluster centroids, and covariance matrix are re-estimated and the total number of nodes belonging to the kth cluster is obtained using (9).

$$N_c = \sum_{x_n \in X} \varphi_{nc} \tag{9}$$

Thus, this process continues till the difference between newly estimated log-likelihood and the previously estimated log likelihood becomes lower than the value of ϵ. In EM based CCP model, C signifying weighted Center of Gravity (CoG) of a 2D-location vector is estimated for each node. To achieve it, the responsiveness of each node is considered. Later, location of the CH can also be changed by the weighted CoG. EM estimates the log likelihood to estimate optimal number of clusters using (10).

$$\mathbb{L} = ln\, E(X|\sigma, \Sigma, \sigma) = \sum_{n=1}^{N} ln\left\{\sum_{c=1}^{C} \sigma_c A(x_n|\sigma_c, \Sigma_c)\right\} \tag{10}$$

Similar to the FCM based approach; EM continues iterating until convergence. The value of (10) reduces uneventfully thus making EM terminate. EM updates the key information such as, σ_c and φ_{nc} of each node to the cth cluster that eventually leads reduction in the Sum of Square (SoS) of the distance between each node and cluster. It finally gives the optimal clustering results. Once performing clustering, CH selection is performed for each cluster for which FLC is applied that learns over the network parameters to select the best node so as to become the CH for further data transmission.

D. Cluster Head (CH) Selection

The selection of CH often plays decisive role in assuring optimal performance. With this motivation, we have applied multiple network parameters to perform CH selection. The parameters being used in our model are as follows:

- *Location information of each sensor node within the cluster,*
- *Distance of each sensor node with respect to the base station of sink location,*
- *Residual energy of each node, and*
- *SNR of the reporting channel of the CH and base station.*

Here, location information enables the selection of CH near CNs that consequently minimizes multi-hop transmission and hence energy consumption. We perform CH selection in such manner that the distance between CNs and CH is lower enough to communicate in single-hop. Since, CH is selected near CNs and hence, the distance between CH and mobile sink might increase. Under such scenarios, the probability of link failure can't be ignored. Considering such issues, we have used SNR of the link from CH to the sink as an additional parameter for CH selection. Realizing the fact that the successful data transmission also depends on the residual energy of the forwarding node, we have used residual energy of each node to assess its suitability to become the CH of that cluster. Exploiting multiple parameters for CH selection can be an intricate task that becomes more tedious during topological variations (due to sink mobility). To deal with this, we have applied FLC that learns over the network parameters to decide CH for each cluster. In our model, we have applied four key network parameters including distance (i.e., node position), residual energy, SNR and responsiveness to decide optimal CH for a cluster. The decision variables and respective conditions are presented in Table 1.

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TABLE 1 CH SELECTION CONDITIONS

Parameters	Suitability
Distance	Low
Residual Energy	High
SNR	High
Responsiveness	High

FLC model learns over the network parameters and intends to achieve a defined objective function. To select CH of mth cluster, an exclusive objective function is derived (11).

$$\Psi_i^{(m)} = \max_{CH}\left(\frac{\mho_i^{(m)}\gamma_i^{(m)}\varphi_i^{(m)}}{\alpha PL_i^{(m)} + (1-\alpha)PL_{MS}^{(m)}}\right) \tag{11}$$

Where $\mho_i^{(m)}$ presents the residual energy of ith sensor (i.e., CN), $\gamma_i^{(m)}$ signifies the SNR of the link between the ith node and the sink, and $\varphi_i^{(m)}$ refers the responsiveness of ith node. The other parameter $PL_i^{(m)}$ presents the average path loss of the channels between the ith node and the other CNs. The variable $PL_{MS}^{(m)}$ refers path loss of ith CN and sink, and α presents a weight parameter assigned to the path loss components $PL_i^{(m)}$ and $PL_{MS}^{(m)}$, i.e., CN to CH and CH to the mobile sink, respectively. In (11) the value of α exists in between 0 and 1. The distances between nodes are also maintained low between possible CH and CNs. We have estimated the path loss $PL_i^{(m)}$ using (12).

$$PL_i^{(m)} = \frac{\sum_{i=1}^{N_m} PL_{i,j}^{(m)}}{N_m} \tag{12}$$

Where N_m presents the total number of sensor nodes in the mth cluster. The path loss between the ith sensor and CNs (i.e., ith sensor) is given by $PL_{i,j}^{(m)}$. Mathematically,

$$PL_{i,j}^{(m)} = 10\ n\ log_{10}\left(R_{i,j}^{(m)}\right) \tag{13}$$

In (13), $\left(R_{i,j}^{(m)}\right) = \left\|\theta_j^{(m)} - \theta_i^{(m)}\right\|$ gives the distance between jth CN and ith CH, where the position of the ith CH is $\theta_i^{(m)} = \left\{x_i^{(m)}, y_i^{(m)}\right\}$ and the position of the j th node is $\theta_j^{(m)} = \left\{x_j^{(m)}, y_j^{(m)}\right\}$. The variable n presents the path loss exponent. The path loss between CH of mth cluster and sink is obtained as (14)

$$PL_{MS}^{(m)} = 10\ n\ log_{10}\left(R_{MS}^{(m)}\right), \tag{14}$$

Where $R_{MS}^{(m)} = \left\|\theta_i^{(m)} - \theta_{MS}\right\|$, with $\theta_{MS} = \{x_{ms}, y_{ms}\}$ as the mobile sink location. Estimating network parameter, FLC is executed that performs CH selection. The CH selection algorithm is given as follows:

Algorithm-2 FLC based CH Selection

Initialize FLC based CH selection
while $m = 1,2,\dots,M$ ***do***
Selecting CH for mth Cluster
for $j = 1,2,\dots N_{m,i}$ ***do***
Calculate $\mho_i^{(m)}, \gamma_i^{(m)}, \varphi_i^{(m)}, PL_i^{(m)}$ and $PL_{MS}^{(m)}$
Execute FIS learning and classification
if $\Psi_i^{(m)} = \max_{CH}\left(\frac{\mho_i^{(m)}\gamma_i^{(m)}\varphi_i^{(m)}}{\alpha PL_i^{(m)}+(1-\alpha)PL_{MS}^{(m)}}\right)$ ***then***
mth $CH \leftarrow$ ith sensor
else
Cluster member $\leftarrow$ ith sensor
end if
end for
end while

Fig. 3. FLC based CH Selection

E. CMIMO Based Data Transmission

Once performing clustering and CH selection, the mobile sink starts patrolling to collect data from CHs. The use of a single mobile sink might lead a situation where it could not be able to reach CHs for data collection. In such cases the probabilities of data loss and delay can't be ignored. Additionally, as the speed of mobile node is comparatively slower than the electrical communication, enhancing movement pattern of the mobile sink remains an open challenge. To deal with this problem, heuristic approaches such as Traveling Salesman Problem (TSP) can be applied to assist sink to reach CHs for early data gathering. To collect data from CHs, we have applied MIMO technique. In Q-E2RPC protocol CHs transmit data to the mobile sink using MIMO, where to collect data; mobile sink transmits a Data Transmission Request (DTR) to the CHs that further broadcasts to the CNs. Receiving DTR response from CH, mobile sink re-sends the data transmission request which is followed by relaying data from CH to the mobile sink. One more novelty introduced in Q-E2RPC is the provision of direct communication between CNs and mobile sink. Typically, CNs transmit data to the connected CH, that then forwards it to the mobile sink; however the in-depth analysis shows the scope for further enhancement, particularly for delay efficient transmission. In Q-E2RPC, transmission is scheduled in such manner that finding mobile sink nearer than the CH, a CN can transmit sensed data to the mobile sink directly that avoids transmission delay caused during transmission through CH. To minimize energy consumption during transmission, here CNs transmits data based on the responsiveness factor. As discussed, responsiveness is estimated using parameters μ, σ, and Σ, and hence these parameters can be appended to the DTR message to be transmitted back to the mobile sink. Once deploying CNs in the network, each node exchanges its location information with all CNs in the same cluster. Since, this exchange is performed only once after sensor nodes deployment that reduces the unwanted signaling overhead. In case a node belongs to multiple clusters, it can use responsiveness factor to decide best CH to forward data. For example, in case a node has the responsiveness of $\varphi_{n1} = 0.8$ and $\varphi_{n2} = 0.2$. Once receiving DTR from CH of the cluster 1, nth node transmits 80% of data. In case it receives DTR from cluster 2, it transmits remaining 20% of data to the mobile sink through CH of the second cluster. It ensures that the

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data reaches to the sink reliably and timely to meet QoS demands.

IV. Results and Discussion

In this research the overall emphasis was made on developing a novel QoS oriented and energy efficient WSN routing protocol, Q-E2RPC by employing enhanced clustering approach, CH selection, cooperative communication and single mobile sink based data collection. Considering the large scale network size, at first we performed network partitioning that structured overall network into two groups. Now, realizing the significance of the optimal number of clusters in the network, a two phase clustering model with FCM and EM based clustering. In Q-E2RPC, EM based clustering exploited initial cluster information to perform clustering, which was then followed by the use of multiple network parameters like inter-node distance, residual energy of node, signal to noise ratio and responsiveness of the node in a cluster to perform CH selection. Considering multiple decision variables, we applied FLC that estimated best node as CH of each clusters. Unlike classical methods of data transmission, Q-E2RPC incorporated cooperative communication amongst CNs and associated CHs, and then CHs to the mobile sink. To alleviate the issue of excessive energy consumption we deployed a mobile sink to collect data from each CH for QoS delivery and energy efficient communication. Noticeably, in Q-E2RPC the mobile sink movement was controlled based on data request from CHs. The routing model was developed in way that it not only focuses on energy efficiency but also assures QoS delivery by maintaining minimum end-to-end delay, bandwidth utilization and higher reliability. The total simulation time is 800 seconds, where the transmission was tested with 2kb/sec. To assess performance of Q-E2RPC protocol, we have developed simulation model using NS2. Further, to plot the graphs MATLAB 2015a tool was used. The simulation environment considered in this study is given in Table 2.

TABLE 1. SIMULATION ENVIRONMENT

Parameter	Value
MAC	IEEE 802.15.4
Efficiency of RF power amplifier	0.47
Link margin	40 dB
Gain factor	30 dB
Power density of AWGN channel	-134 dBm /Hz
Noise Figure (Receiver)	10 dB
Path loss	3-5
Carrier frequency	2.5 GHz
Bandwidth	20 KHz
BER performance	10-3
Transmitter circuit power consumption	98.2 mw
Receiver circuit power consumption	112.6 mw
Antenna gain of Transceiver	5 dB
Routing table update (exchange) period for each round	5
Routing table size	100
Transmission rate	2p/sec
Packet size	2 kbits
Transmission probability of each node	0.8

To assess the relative performance of Q-E2RPC, we simulated FCM based clustering at first, which has been followed by FCM and EM as cumulative clustering approach. Thus, the respective performance for FCM and FCM+EM (this is the clustering model applied in our proposed Q-E2RPC routing protocol) was obtained. For CH selection we have applied FLC. The results obtained in terms of packet delivery ratio (PDR), delay, energy consumption and efficiency are given in Fig. 4, Fig. 5, Fig. 6 and Fig. 7, respectively. As depicted in the results (Fig. 4 to Fig. 7), FCM refers simulation outcome with only FCM based clustering. In addition to it, we have developed a multi-hop transmission by exploiting K-Conid [22] based clustering, which comes under the category of centralized clustering method. Here, it should be noted that in all these simulations, we have applied FLC based CH selection and MIMO based transmission.

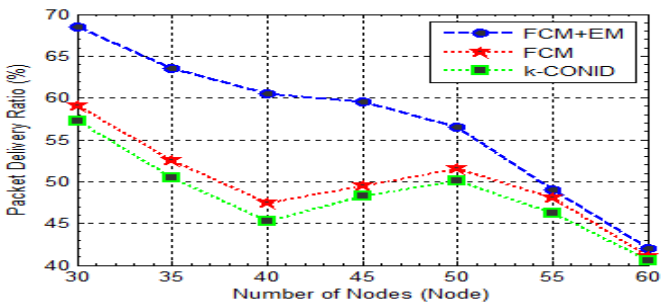

Fig. 4. Packet delivery ratio

Observing results, it can be found that Q-E2RPC outperforms both FCM and K-Conid clustering based routing. Fig. 4 presents the comparison of PDR between Q-E2RPC and FCM. The efficiency of FCM and EM for clustering optimization can be visualized in Fig. 4. Fig. 5 shows delay of all three simulation scenarios, where Q-E2RPC has shown minimum delay. In achieving such augmented results role of mobile sink can't ignored. Its impact can be seen in Fig. 6 and Fig. 7.

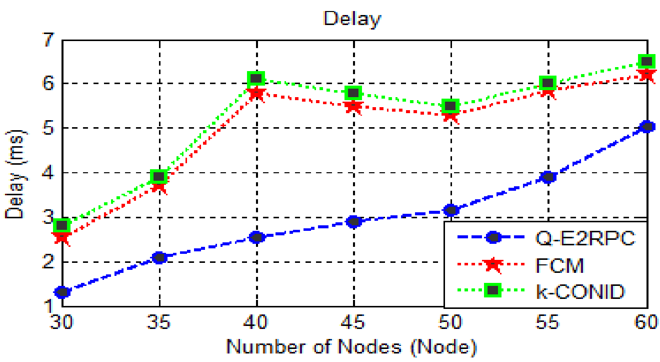

Fig. 5. Transmission or data gathering delay

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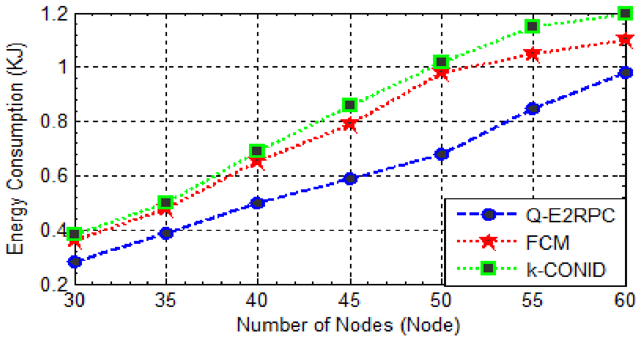

Fig. 6. Energy consumption by different techniques

Considering residual energy as one of the key decisive factor for success MIMO transmission, we estimated the energy consumed, E_{Trans} during transmission from sensor nodes to the mobile sink. Here, E_{Trans} states the energy required to transmit data from the sensor nodes to the mobile sink. If a sensor node is far away from its associated CH, $E_{Dat}$is assigned a value 0. In practice, $E_{Trans} = 0$ signifies inefficiency of the clustering method and hence can't assure energy conservation or even successful transmission. Considering it as a key motivation, we derived a performance parameter named "Efficiency", given in (15).

$$Efficiency = \frac{(Number\ of\ connected\ node)}{E_{Trans}} \tag{15}$$

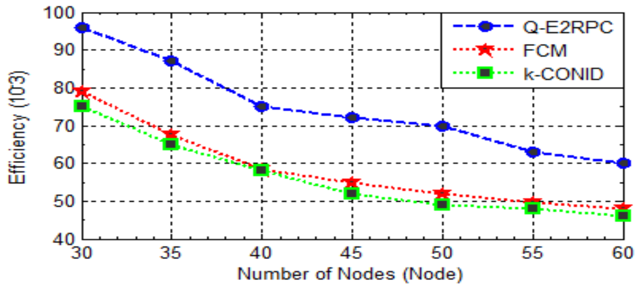

Fig. 7. Network communication efficiency

Q-E2RPC routing protocol enables better clustering thus augmenting overall performance. Q-E2RPC performs better than FCM based clustering. Here, the effectiveness of responsiveness clustering model can be visualized. This is because responsiveness assesses connectivity and degree of dependence of a node with its cluster that assures that a node having higher connectivity with a cluster would yield more efficient communication. Mobile sink node has strengthened Q-E2RPC to exhibit delay efficient communication. Non-deniably, CMIMO based communication among CNs and CH and further between CHs to mobile sink has further strengthened energy efficiency and higher throughput.

V. Conclusion

In this paper emphasis was made on enhancing the key components such as network partitioning, enhanced clustering, soft-computing based cluster head selection, and CMIMO based transmission. Unlike generic multi-hop transmission, Q-E2RPC used single mobile sink based communication that not only reduced energy consumption but also assured reliable and delay resilient transmission. Un-deniably, the use of FCM followed by (EM) based clustering assured the optimal number of clusters in the network to achieve energy efficient communication. As a novel value addition, a new network parameter named Responsiveness was derived that signified the connectivity and dependency of a node on a cluster. Here, FCM was used to learn network states including locations of the connected sensor nodes, residual energy of the nodes, and responsiveness that eventually enabled CH selection. In Q-E2RPC CH collected data from the connected sensor nodes and forwarded it to the mobile sink by exploiting CMIMO transmission technique. The overall results obtained in terms of packet delivery ratio, energy consumption, delay and efficiency exhibit that Q-E2RPC outperforms traditional approaches applying CMIMO and single parameter based CH selection. In future, some other decision algorithms such as Neural Network or Evolutionary computing based approaches can be explored to assist clustering and CH selection.

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