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Energy and Spectrum Aware Clustering Routing Protocol for Cognitive Radio Sensor Networks

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Abstract: Cognitive radio technology is introduced to identify the spectrum holes dynamically. Such dynamic spectrum access operations cause the nodes in the cognitive radio sensor networks (CRSNs) into energy depletion problem. To handle this problem or to utilize the entire network's energy efficiently, clustering is found as one of the best solution. Even though uniform clustering mechanism reduce the energy consumption but it is not suitable when the network node density increases. Hence, this paper proposes a new clustering mechanism called as energy and spectrum aware clustering routing protocol (ESCRP) for CRSNs. Initially, the entire network is clustered non-uniformly into several clusters. Next, energy, channel availability rate, geographical and temporal correlation metrics are used to select the cluster head (CH) for each cluster. Finally, the collected information from each CM is transferred to the sink node through multi-hop communication between CHs. Extensive simulation experiments are carried out over the proposed ESCRP and the performance is measured with several performance metrics including Network lifetime and average energy consumed. From the experimental results, we observed that the weight combination $\alpha = \frac{1}{8}, \beta = \frac{1}{8}, \gamma = \frac{3}{4}$ consumed less energy than the remaining combination weight values. Finally, the average energy consumed for the combination $\alpha = \frac{1}{8}, \beta = \frac{1}{8}, \gamma = \frac{3}{4}$ for 2-layered network and 3-layered network is approximately 0.4J and 1.2J respectively.

Keywords: Cognitive radio sensor networks (CRSNs), Non-uniform clustering, Energy, Channel availability, Routing protocol.

1. Introduction

From the past few years, the demand for radio spectrum has expanded dramatically as a result of the tremendous advancements in technology and applications of wireless sensor networks (WSNs). However, the traditional static spectrum allocation policies have resulted in a scarcity of radio spectrum. [1-3]. An emerging paradigm that effectively reduces spectrum scarcity and makes better use of the spectrum is the cognitive radio sensor network (CRSN) [4] where the cognitive sensor nodes (CSNs) opportunistically access the spectrum bands which are already licensed to the primary users (PUs) without interfering with them with the help of equipped cognitive radio module. In most of the cases, the nodes in the CRSN share the common available channel and they are powered by a limited-capacity battery. Moreover, the nodes are randomly deployed in different locations and they might take multiple hops to reach the destination. Such kind of routing depletes the node's energy as well as reduces the network life time. In addition, due to the multiple operations such as spectrum sensing and dynamic spectrum access performed by the CR technology, the sensor consumes additional energy and results in quick energy depletion [5]. To address this issue, few researchers have suggested clustering technique is one of the solutions for CRSNs.

Clustering minimizes the energy consumption by reducing the number of data packets t b transmitted using data compression and accumulation methods [6, 7] such that the network lifetime increases. In uniform clustering, cluster heads (CHs) nearer to the sink node exhibits more inter-cluster data communication tasks than the far CHs. Uniform clustering cannot balance the residual energy among the nodes and they create energy hole problem in the multi-hop CRSN [8]. To address the energy-hole problem in Multihop CRSNs, past research studies suggested non-uniform clustering mechanisms where the CH balances the residual energy and minimizes energy consumption by varying cluster radius. Even though non-uniform clustering extends the network lifetime, they have few limitations [9] in terms of multihop communication, dynamic channel accessibility, specific network configurations include node density, network size, and maximum transmission range, and energy consumption of data transmission. In order to handle all these issues, this work proposes a new energy and spectrum aware clustering routing protocol for CRSNs. The entire methodology is accomplished in four phases; they are (1) Spectrum sensing (SS), (2) Cluster formation, (3) CH selection, and (4) Multi-hop routing for data transmission. Therefore, the major contributions of this work are outlined as follows;

1. To utilize the available energy efficiently and to minimize the overall network energy consumption, this work proposes a new non-uniform clustering mechanism and CH selection mechanism. Here, available energy, channel utilization rate, and geographical & temporal correlation metrics are used to select the CH.
2. To enhance the network lifetime, this work proposes energy and spectrum aware clustering routing protocol (ESCRP) which considers the energy and distance metrics.

The remaining paper is organized into four sections. Section 2 describes the related past works relevant to the CRSNs, section 3 elaborates system model and proposed methodology, section 4 demonstrates the simulation experiments to validate the performance of proposed methodology, and finally section 5 explores the conclusion of this work.

2. Related work

Non-uniform clustering-based routing protocol is one of the prominent solutions to handle energy depletion CRSNs. This section describes related past research works of non-uniform clustering routing protocols in CRSNs. Mortada *et al*. [10] proposed clustering mechanism for CRSNs. In this mechanism, CH performs spectrum sensing, collects the data, and forward it to the destination using in-network data aggregation (IDA) method. The authors used ad-hoc network model where the network node density is related to the energy consumption. Further, to select the best number of clusters, a study is derived aiming to extend the network lifespan, taking the SS requirements, the IDA effect, and the energy consumed by both SS and transmission into consideration. However, the dynamic nature of PUs is not considered, so that inaccurate paths may get selected and it increases energy consumption.

To maintain the stability of the network structure and to reduce the communication overhead of the distributed cognitive network, Xiaoyan Li *et al.* [11] suggested a combination weighted clustering algorithm. Initially, geographic location, available channel, and experienced data of Sus are used to formulate the clustering algorithm. Further, CH is selected based on the three metrics such as channel quality, stability, and average channel capacity. Next, gateway nodes and CMs are chosen based on the location information and weight formula. They majorly concentrated on data transmission but energy is drastically depleted when the nodes are distant from the sink node.

To ensure stability, scalability, efficient spectrum management, and reduce communication overhead, Santhosh kumar *et al.* [12] suggested a localized clustering scheme. The authors computed weights of each node and selected a node as CH which has maximum weight. Next, vice-CH is chosen to provide the fault tolerance. Even though, they reduced the communication overhead, they didn't concentrate on path selection through which the data reaches the sink node. J. Wang and C. Liu [13] proposed an imperfect spectrum sensing-based multi-hop clustering routing protocol (ISSMCRP) to alleviate the impact of imperfect spectrum sensing on network performance. They selected the CH using detection level of available channels with high spectrum sensing capability. To deliver the data successfully to the destination, the authors introduced inter-cluster and intra-cluster channel selection criterion. Further, they clustered the network into various clusters based on the cluster radii to reduce the energy consumption due to control overhead.

However, the authors didn't consider the dynamics of clusters which increases the energy consumption of the network.

To solve the problems of low spectrum utilization and channel congestion caused by the static division of spectrum resource, Ye, H. and Jiang, J [14] proposed an optimal linear weighted cooperative spectrum sensing for clustered-based CRNs. They assigned the weight values for each node by considering historical sensing accuracy and SNR of cognitive users. Next, after clustering the cognitive users into few clusters, CHs are selected based on the available channel characteristics. They achieved better detection probability but network lifetime was reduced due to static weight values assignment for CH selection.

Surajit Basak and Tamaghna acharya [15] used a convex optimization framework to determine the closed form expression for each transmitting node's optimal transmit power. Routing algorithm called as spectrum aware-minimum outage intelligent cooperative routing (SA-MOICR) method is proposed which chooses a minimum outage path and determines the number of nodes and a unique PU channel to transmit along the path for each hop. However, the channel state information is not included in the routing process.

Next, to minimize the energy consumption and to improve the network lifetime, G. A. Safdar *et al.* [16] proposed an energy efficient fuzzy logic-based clustering (EEFC) algorithm. The CH selection is done by considering a set of fuzzy input parameters. Mamdani method is used for fuzzification and they incremented the fuzzy input parameters from three to four to achieve better results. Further, the authors used Centroid method for defuzzification. However, the fuzzy logic increases the computational complexity and decreases network lifetime. A. Verma *et al.* [17] introduced CHEF is a distributed clustering algorithm that uses both a probabilistic approach and parameters to select CHs. This method did not involve the BS to monitor and collects the characteristics of each SN in the network. Fuzzy input parameters namely local distance and residual energy are used to compute output parameters and to chose the CH. However, the major disadvantage is that the local distance is not a suitable parameter for selecting efficient CHs and hence resulted in re-clustering overhead in every round.

Shakhov *et al.* [18] Proposed an Efficient Clustering Protocol for CRSNs. Initially, they considered quality of available common channels and remaining energy to select the CH. Next, secured clustering routing protocol is introduced to send the data to the destination more securely. The authors not considered the distance between the nodes to choose the CH. Further, the weighted clustering metric introduced by Wang. T *et al.* [19] includes correlation parametrs, confidence level, and residual energy. They assume the Euclidean distance between any two nodes in the network is known and does not change. Furthermore, the channel state was also ignored.

M. Zheng *et al.* [20] suggested a Stability-Aware Cluster-Based Routing (SACR) protocol for CRSNs. To address the issues like stability and large communication overhead, the authors considered energy consumption and spectrum dynamics to form the clusters. To select the CH, they formulated the composite metric which includes number of available channels, cluster size, and hop distance to the gateway. However, they didn't utilize a dedicated common control channel and they didn't consider the cluster dynamics. E. Pei *et al.* [21] proposed heterogeneous nodes based low energy adaptive clustering hierarchy (HLEACH) algorithm. Initially, sink node broadcasts optimal number of clusters and average cluster radius to all the nodes. Upon receiving this information, each cognitive user computes its competition radius and participate in the competition for CH selection. In clusters' formation stage, non-CH cognitive nodes and sensor nodes synthetically consider the distance and the connection degree of CHs such that the distribution of CNs among clusters and the energy consumption among CHs can be energy efficiently balanced. Even they achieved better energy balancing among the nodes, the dynamic nature of PUs is not considered and resulted in inaccurate path selection.

3. Proposed approach

3.1 System model

Here, we consider N number of Sensor Nodes with CR capability, randomly deployed in a circular shaped region and *M* number of primary users can access the spectrum opportunistically which are distributed stochastically in the monitoring region. Next, Semi-Markov ON/OFF state model is considered to observe the dynamic behavior of PUs [22]. Specifically, each licensed or primary user operating in two states such as ON and OFF whose time durations are distributed exponentially. Moreover, these two States are independent each other. Each SN is assigned to a fixed ID after their deployment in a fixed location. One sink node is deployed at the center of the monitoring region and it has the provision of unlimited power supply and the processing capability [23-24]. Here, each SN obtains its own remaining energy, geographical location, available channels, and other relevant information. The Euclidian distance between SN and sink node ensures the minimum data transmission delay and the entire monitoring region is partitioned into few angular layers as shown in the Fig.1. Each angular layer has equal radius which is equal to the maximum transmitting sensing range of SN i.e., R_{max}. The layer nearer to the sink node is assumed as layer 1 and if the distance from sink node increases then the number of layers also increases. Each SN can obtain its layer number ($R_l(i)$) among the number of layers such as $l\epsilon\, 1, 2, \ldots p \ldots P$, where P represents maximum number of layers. Based on the Euclidian distance between the sink node and the SN i, the $R_l(i)$ is calculated as

$$R_l(i) = \frac{d_i^{sink}}{R_{max}} \tag{1}$$

Where d_i^{sink} represents the Euclidean distance between the SN i and sink node. The sensor nodes which are present in the same layer p ($p \neq 1$) form clusters by exchanging the local information. Cluster Members (CMs) forwards the collected data to CH and then the CH transfers it to sink node through multiple hops.

3.2 Energy consumption model

Here, basic energy consumption model is used to estimate the energy consumption during the data transmission in CRSNs. Generally, two types of propagation models are used based on the distance *(d)* between the sender and receiver node; they are free space and multi path propagation models. Further, the selection of each model (d^2 or d^4) is done based on the threshold distance (d_{Th}) [25]. If $d \leq d_{Th}$, the free space energy model (d^2 power loss) is employed otherwise multipath energy model (d^4 power loss) is employed. Mostly, four states such as idle, sleep, transmitting, and receiving are considered to evaluate the energy consumption at each SN. Among these four states, sleep and idle states consume negligible amount of energy. Hence, we consider energy consumption during transmitting and receiving states only. The amount of energy consumed to transmit a packet of *b*-bit length [25] over the distance *d* is given by

$$E_{transmitting}(b,d) = \begin{cases} b \times E_{el} + b \times \varepsilon_{fs} \times d^2, \ if\ d \leq d_{Th} \\ b \times E_{el} + b \times \varepsilon_{mp} \times d^4, \ if\ d > d_{Th} \end{cases} \tag{2}$$

Where, E_{el} denotes total energy consumed during the transmission or reception of 1-bit of information at the transceiver, and ε_{mp} and ε_{fs} signifies the energy consumption coefficients of power amplifier in multipath propagation environments and free space respectively. Further, d_{Th} represents the threshold distance and $d_{Th} = \sqrt{E_{fs}/E_{mp}}$. The amount of energy consumed to receive a packet of *b*-bit length [25] is given by the following:

$$E_{receiving}(b) = b \times E_{el} \tag{3}$$

3.3 ESCRP

The proposed model is designed to reduce entire network's energy consumption by balancing the energy in each layer. It is accomplished in four phases; Spectrum Sensing, CH selection and cluster formation, route establishment and data transmission. In phase 1, each SN independently senses the channel availability at its own location through spectrum sensing and then determines its available channel information C_i which is used for CHs selection, cluster formation, and inter-cluster route selection. Here $C_i = [C_{i_1}, C_{i_2}, \ldots, C_{i_c}, \ldots C_{i_N}]$, where N denotes total number of licensed channels, C_{i_c} denotes channel identifier indicating that whether the channel at node *i* is available or not and $1 \leq C_{i_c} \leq N$. If sensed channel is idle then $C_{i_c} = 1$, otherwise $C_{i_c} = 0$.

In phase 2, sensor node in each layer except 1^{st} layer computes the weight and determines whether that node become CH by comparing its weight value with neighbor nodes' weight value. The weight value for each node is computed based on the energy, channel utilization ratio, geographical & temporal correlation between the nodes. Further, each non-CH node selects its CH and requests to join the cluster. In phase 3, each CH in the outer layers ($p \neq 1$) cannot directly reach the sink node and it is routed through multiple hops for inter-cluster communication. In phase 4, the aggregated data is forwarded to the sink node through selected CHs. In this manner, at each and every phase, the energy is optimized efficiently by determining channel availability information, selecting appropriate CHs and forming an energy efficient cluster, route and data being transmitted.

3.3.1. CH selection and cluster formation

The channel availability information is used to select the appropriate CH. Here, the layer 1 nodes are independently acts as CHs [26] to acquire the following benefits; i) No additional energy is

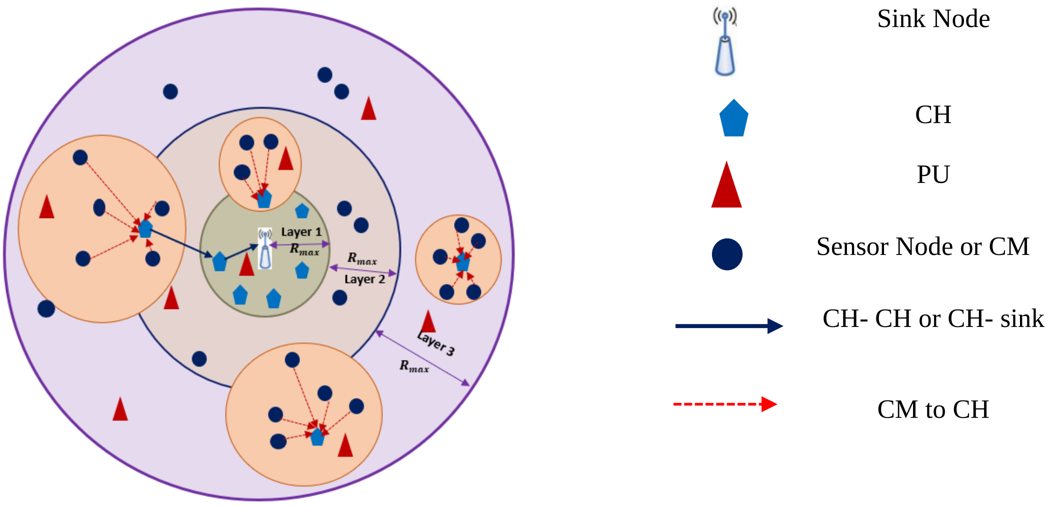

Figure. 1 Network model

consumed when they exchange control information to compete for CHs and formulate clusters. ii) When the number of CHs increases for inter-cluster data communication tasks sharing and it prolongs the network lifetime by minimizing the energy consumption. A node in each layer in the CRSNs exchange the information related to geographical location (x_i, y_i), residual energy $(E_R(i))$, and channel availability information (C_i) with other nodes within cluster radius R_{cl}. After obtaining the information, a node i computes its weight value $W_{CH}(i)$ using Eq. (4) and compare with neighbor nodes' weight values. If node i acquires highest weight value than the remaining node's weights, then node i is nominated as CH and broadcasts a notification message as CH within R_{cl}. After receiving notification message as CH then non-CH nodes broadcasts a quit message. The other non-CH nodes within the radius of j receive the quit message and delete j from their CHs competitor list.

$$W_{CH}(i,t) = \alpha \times E(i,t) + \beta \times C_{uti}(i,t) + \gamma \times (E(G_c(i,t).E(T_c(i,t)) \quad (4)$$

Where, α, β and γ represents the weight coefficients of energy, channel utilization rate, and geographical & temporal correlation respectively, $E(i,t)$ represents the energy related term in t^{th} round of clustering computed as $E(i,t) = E_R(i,t)/E_{Avg}(i,t)$, where $E_R(i,t)$ denotes the residual energy of a node i, $E_{Avg}(i,t)$ denotes the average energy consumption of a node i. $C_{uti}(i,t)$ represents the channel utilization ratio of node i, the term $E(G_c(i,t).E(T_c(i,t))$ represents geographical & temporal correlation between the node i and its one-hop nodes. $E_{Avg}(i,t)$ is the average energy consumption of a node i, given by

$$E_{Avg}(i,t) = E_D(i,t) + E_C(i,t) \quad (5)$$

Where, $E_D(i,t)$ and $E_C(i,t)$ denotes the energy consumption during the data and control packets transmissions respectively. They are mathematically expressed as

$$E_D(i,t) = \frac{[(|n_n(i,t)|+1)(E_{el}+E_{CD})+\varepsilon_{fs}(d_i^{sink})^2]\times S_d}{|n_n(i,t)|} \quad (6)$$

And

$$E_C(i,t) = \frac{[(|n_n(i,t)|+1)E_{el}+\varepsilon_{fs}(R_{cl})^2]\times 3S_c}{|n_n(i,t)|} \quad (7)$$

Where, $n_n(i,t)$ indicates list of neighbor nodes of i within the radius of R_{cl}, R_{cl} denotes cluster radius, E_{CD} indicates energy consumed during data accumulation, S_d and S_c indicates data and control packet size respectively.

Next, the available channel utilization rate denotes the communication capability of a node i which is derived from physical proximity and joint spectral perspectives. Therefore, the available channel utilization rate $(C_{uti}(i,t))$ is given by

$$C_{uti}(i,t) = \frac{\sum_{j \epsilon n_n(i,t)} C_i(t).C_j(t)}{|n_n(i,t)|\times C} \quad (8)$$

Where, $C_i(t).C_j(t)$ represents the available channel information for node i and j respectively, C represents the number of available channels. The availability of channels for all nodes depends on the geographical locations. If the nodes are closer, the probability of channel availability is high in a cluster [27]. Therefore, the relation between the geographical location and channel availability is derived using the parameter named as geographical correlation parameter, mathematically expressed as

$$G_c(i,j,t) = \begin{cases} 1 - \frac{d_i^j(t)}{\min(cr_i, cr_j)}, & d_i^j(t) < \min(cr_i, cr_j) \\ 0, & d_i^j(t) \geq \min(cr_i, cr_j) \end{cases} \quad (9)$$

Where, $G_c(i,j,t)$ denotes the geographical correlation between the node i and j in t^{th} round of clustering, $d_i^j(t)$ represents the Euclidean distance between the node i and node j, the term $d_i^j(t) < \min(cr_i, cr_j)$ represents the nodes are within the communication range, and cr_i, cr_j represents the communication range of node i and j respectively. Further, the average of geographical correlation between the node i and its one-hop neighbors is estimated using the expectation of geographical correlation, mathematically expressed as

$$E(G_c(i,t)) = \frac{1}{n_n(i,t)} \sum_{j=1}^{n_n(i,t)} G_c(i,j,t) \quad (10)$$

Further, behavior of a PU is observed through semi-Markov ON-OFF process and the nodes which are present in PU's communication range can detect the idle channels simultaneously. The availability of these channels are correlated with the timestamp and it is evaluated based on the parameter named as temporal correlation and it is given by

$$T_c(i,j,t) = \frac{|C_i(t) \cap C_j(t)|}{n_n(i,t)} \quad (11)$$

Where the term $|C_i(t) \cap C_j(t)|$ denotes the number of common available channels between the node i and j. Therefore, the mean temporal correlation between the node i and its one-hop neighbors is given in terms of expectation of temporal correlation and it is given by

$$E(T_c(i,t)) = \frac{1}{n_n(i,t)} \sum_{j=1}^{n_n(i,t)} T_c(i,j,t) \quad (12)$$

Hence, the higher expectation value of temporal correlation indicates the number of common available idle channels between the nodes i and its one-hop neighbors is more and it makes the more nodes in a cluster.

Upon selecting the CH using Eq.(4) then cluster formation is done using Eq. (13). According to Eq. (13), the non-CH node j choses a node i with highest weight as CH (CH_i) based on energy, channel utilization rate, geographical & temporal correlation. Then, node j sends the join request message to CH_i. Upon receiving the request message by CH_i it joins the node j as CM. If node j cannot receive any notification message which is broadcasted by CH, then node j becomes a CH automatically. Therefore, the weight function for CM ($W_{CM}(j)$) is given by

$$W_{CM}(j,t) = \frac{C_{CH_i}.C_j}{E_{Transmit}} = \frac{C_{CH_i}.C_j}{E_{el} + \varepsilon_{fs}(d_j^{CH_i})^2 \times S_d} \quad (13)$$

Where, $d_j^{CH_i}$ is the Euclidean distance between the node j and CH_i. After CH selection and cluster construction process, there should be a common channel for information exchange. The common channel selection is done by CH and it is common for CH and CMs. If there is no availability of common channel for information exchange, then the CH selects random channel and assign it as a common channel for CMs in the corresponding cluster.

3.3.2. Multihop routing and information transmission

With the limitation in the node transmission range, the CHs in outer layer ($p \neq 1$) forwards their accumulated data to the sink node through multiple adjacent inner layer CHs which in turn called as inter-cluster data transmission. Here, the route selection process is initiated after the layer 1 and the CHs of layer 1 can directly send their data to the sink node. But the CHs which are present above the layer 1 can broadcasts their messages including geographical location, residual energy, and available channel information within the node transmission range R_{max}. Then, CH_j in the layer above the layer 1 prepares a candidate relay set and choses appropriate CH based on the energy and distance. Further, Eq. (14) is used to find out the next-hop relay node to transfer the information to the sink node and its mathematical expression is given by

$$Route_i(j,t) = \begin{cases} \frac{E_R(CH_i) \times E_T(CH_i, CH_j)}{E_T(CH_i, sink)}, & if\ C_{CH_i}.C_{CH_j} > 0 \\ 0, & otherwise \end{cases} \quad (14)$$

Where, $E_R(CH_i)$ represents the residual energy of CH_i, $E_T(CH_i, CH_j)$ represents the total estimated energy consumption during the data transmission between the CH_i and CH_j, and $E_T(CH_i, sink)$ represents the total estimated energy consumption to transfer the information from CH_i to the sink node. According to the Eq. (14), the ratio of $E_R(CH_i)$ and $E_T(CH_i, sink)$ signifies the communication capacity

Table. 1 Simulation set up under different network layers

Number of Network Layers	Radius of the Network	Total number of sensor nodes in the CRSNs
Two-Layered CRSN	100m	40
Three-Layered CRSN	150m	80

Table. 2 Simulation set up

Parameter	Value
Initial Energy of each sensor node	0.5J
E_{el}	50nJ/bit
Control packet size (S_c)	100bit
ε_{fs}	10pJ/bit/m^2
ε_{mp}	0.0013pJ/bit/m^4
E_{CD}	5nJ/bit/packet
Data packet size (S_d)	1000bit
Number of Primary users *(M)*	10
Threshold Distance (d_{Th})	87.7m
R_{max}	50m

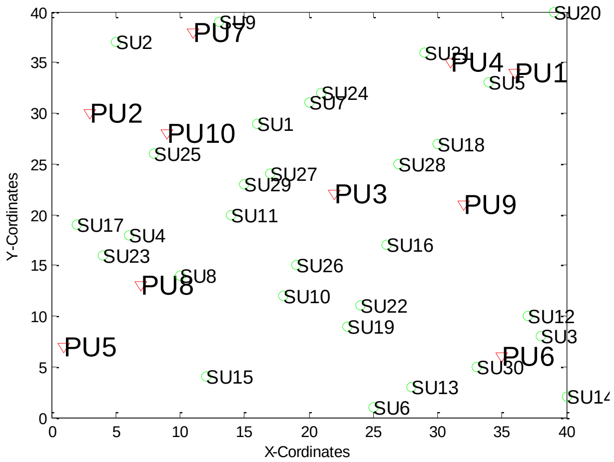

Figure. 2 Sample two layered CRSN with 10 PUs and 30 SUs

of CH_i in concern with the energy. Therefore, $E_T(CH_i, CH_j)$ and $E_T(CH_i, sink)$ is given by

$$E_T(CH_i, CH_j) = \left(2E_{el} + \varepsilon_{fs}(d_{CH_j}^{CH_i})^2\right) \times S_d \quad (15)$$

And

$$E_T(CH_i, sink) = \begin{cases} \left(E_{el} + \varepsilon_{fs}(d_{CH_i}^{sink})^2\right) \times S_d, & if\ d_{CH_i}^{sink} \le d_{Th} \\ \left(E_{el} + \varepsilon_{fs}(d_{CH_i}^{sink})^4\right) \times S_d, & otherwise \end{cases} \quad (16)$$

According to the Eq. (10), CH_j unicasts its routing related message to the selected relay and that selected node receives the message and transfers the data to the sink node. If CH_j cannot find its relay from the inner CHs, then it selects the CM node which is nearer to the sink node to transfer the data. In this manner, the route selection process continues till the accumulated data reaches the sink node.

After selecting the efficient route, each CH follows TDMA schedule to collect the data from the CMs in the specified time slot. Then the data collected by the CH is getting aggregated and transmitted to the next-hop relay. This process continuous until the collected data reaches sink node. As network operation goes on, CHs changes among nodes in layer p ($p \neq 1$). In addition, by selecting proper next-hop relays, the inner CHs in layer p ($p \neq P$) will act as relays and forward the data packets from outer layers to the sink. Such kind of process can balance the residual energy among nodes in the same layer and improves the network lifetime.

4. Simulation experiments

In this section, we explore the complete details of performance analysis of proposed approach. Initially, the details of simulation setup are explored and then the obtained results through different performance metrics. Simulations are conducted with varying network parameters like number of nodes and number of rounds and at every phase, we measure the performance through number of alive nodes, packet delivery ratio and average energy consumption. The complete details are explored in the following sub-sections.

4.1. Simulation setup

The current sub-section explains the details of simulation setup formulated to validate the performance of proposed method. The performance is evaluated for two layered and three-layered networks by with varying number of nodes deployed in the network. For Two-layered CRSN, the radius of network is fixed to 100 m while for the three-layered CRSN; the network area is fixed to 150 m. Next, the number of nodes considered for two-layered and three layered CRSNs is 40 and 80 receptively.

Fig. 2 shows an example network with 10 PUs and 30 SUs and Fig. 3 shows the CRSN with 20 PUs and 60 SUs. Next, the initial energy of Sensor node is fixed to 0.5J, the energy consumed for 1-bit transmission at transmitter is fixed to 50nJ. The size of control packets is set to 100 bits while the size of data packet is set to 1000 bits.

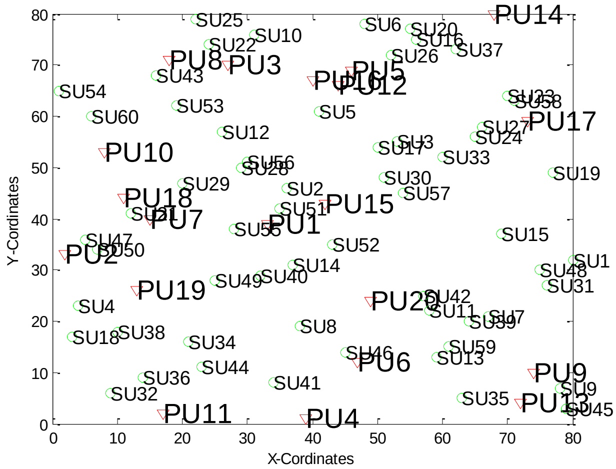

Figure. 3 Sample three layered CRSN with 20 PUs and 60 SUs

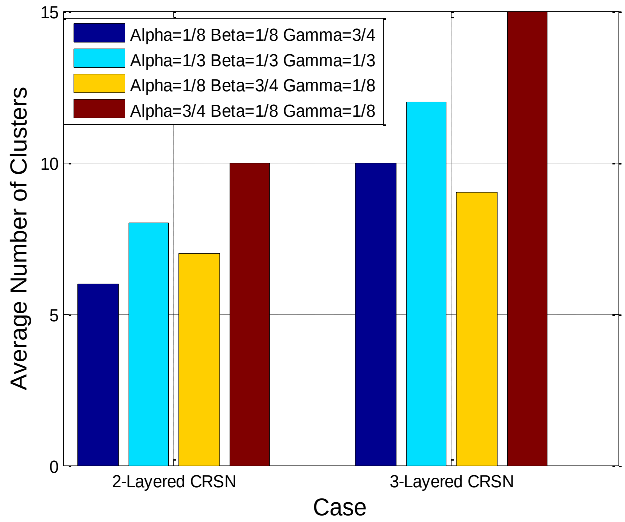

Figure. 4 Average number of clusters formulated at two cases with different weight combinations

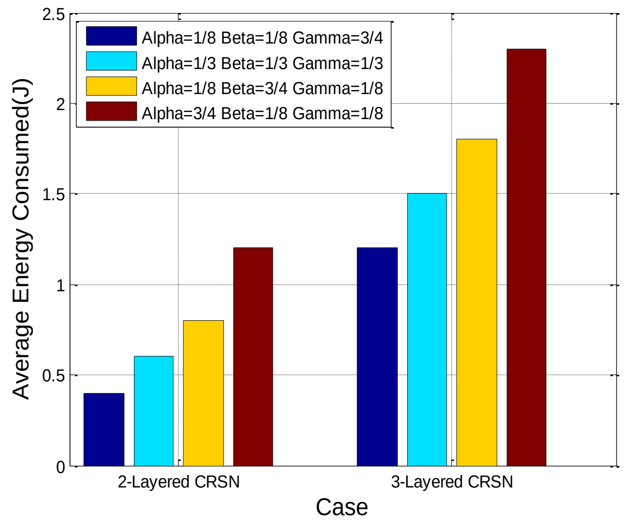

Figure. 5 Average energy consumed at two cases with different weight combinations

4.2 Results

Under this section, we explore the effectiveness of proposed approach through different simulation experiments. At each experiment, the performance is measured through several performance metrics including Average number of clusters, packet delivery ratio, average number of alive nodes and average energy consumption. Further, we analyze the impact of several network parameters like number of nodes, communication radius, number of rounds and varying weights.

4.2.1. Impact of weight coefficients

During the implementation of proposed approach, we observed that the weight factors play an important role in formation of cluster and CH selection. Three weight coefficients namely α, β and γ are defined to signify the weight of three parameters namely energy, channel utilization rate, and geographical & temporal correlation respectively. In the initial experiments, we assigned equal values for all the weights, i.e., $\alpha = \beta = \gamma = 0.3333$. However, in real time the significance of three parameters is different. For example, in the applications related to serious data transmission, the clustering mainly think about the channel utilization rate because more reliable nodes detecting the channels in a cooperative manner ensure a better quality of service at the destination node. On the other hand, for the applications related to video streaming, the requirement of more residual energy is very important. Hence, the clustering needs to analyze the impact of residual energy on the proposed CH selection metric.

Fig. 4 shows the Average number of clusters formulated at two cases with different weight combinations. From the observations, we found that the combination of $\alpha = \frac{1}{8}, \beta = \frac{1}{8}, \gamma = \frac{3}{4}$ achieved less number of clusters. It shows that the number of clusters formulated for two-layered CRSN is 6 while for three layered CRSN it is observed as 10. In this case, the proposed selection metric gives more importance for geographical & temporal correlation of location of sensor nodes.

Next, Fig. 5 shows the Average energy consumed at two cases with different weight combinations. In this case also, we observed less energy consumption at the same combination, i.e., $\alpha = \frac{1}{8}, \beta = \frac{1}{8}, \gamma = \frac{3}{4}$ and higher energy consumption is observed at $\alpha = 3/4, \beta = \frac{1}{8}, \gamma = \frac{1}{8}$. From these observations, we can state that the geographical & temporal correlation plays an important role in the proposed spectrum

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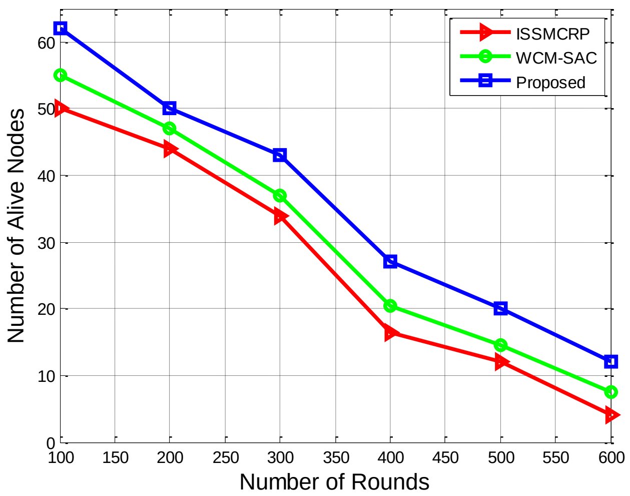

Figure. 6 Average number of alive nodes comparison with varying number of rounds

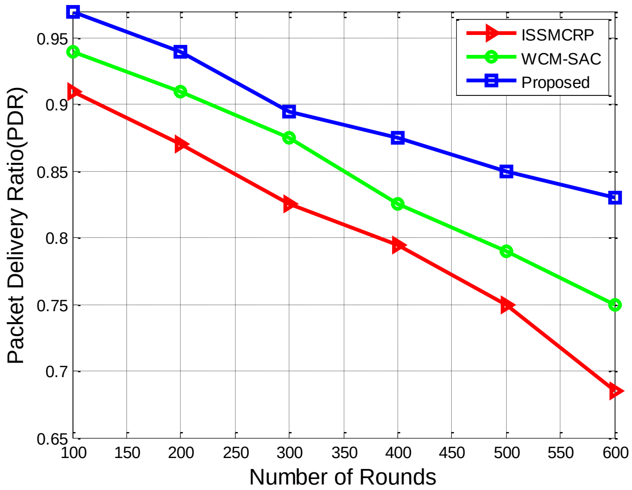

Figure. 7 Average packet delivery ratio comparison with varying number of rounds

aware clustering. Our proposed approach well utilized the property to achieve better quality of service.

4.2.2. Impact of number of rounds

In the proposed method, the sensor nodes that are present in the layer 1 are directly transmit their data to the sink node whereas the nodes in the layer 2 and above can take multiple hops to transmit the data to the sink node. Figure.6 represents average the number of alive nodes for varying number of rounds. From the results, it can be observed that as number of rounds increases, the number of alive nodes decreases. But the proposed method's number of alive nodes decrement is less than the existing methods' decrement due to efficient CH selection, cluster formation, and routing for data transmission. For example, the number of alive nodes for proposed method, WCM-SAC [19], and ISSMCRP [13] are approximately 20, 15, and 12 respectively for two-layered CRSN. In the proposed method, the layer 1 nodes can transmit the data directly through single-hop to the sink node which can reduce the number of control messages exchanging and minimizes the energy consumption for CH selection and cluster formation for the upper layers due to varying cluster radius. Whereas, the existing methods like ISSMCRP and WCM-SAC consumes more energy for cluster formation, CH selection, and continuous broadcasting of control information exchange. We can observe that on an average the number of alive nodes for proposed method is approximately 29, for WCM-SAC they are 23, and for ISSMCRP they are 20. Hence, the proposed method achieves good performance in terms of number of alive nodes for varying number of rounds than the existing methods.

Next, we analyze the impact of number of round son the quality of service through packet delivery ratio. Packet delivery ratio is defined as the total number of sensor nodes that are successfully transmitted to the sink node to the total number of alive sensor nodes in the CRSN. Fig. 7 shows the average packet delivery ratio for varying number of rounds. According to the results we can see that as number of rounds increases the packet delivery ratio decreases for all the methods. The packet delivery ratio for proposed method is higher than the existing methods at each round due to random accessing of channels to transmit the data. If the multiple channels are available to the nodes in the cluster in proposed method, then it will select the common channel for all the nodes randomly such that less energy is consumed to transfer the data and for frequent channel switching. So, the random channel selection can improve the data transmission capability. Whereas in existing methods there is no enough channel availability information, limited transmission range, and huge number of CM nodes then there are a smaller number of packets to be delivered to the destination. We observe that on an average packet delivery ratio for proposed method, WCM-SAC, and ISSMCRP are approximately 0.94, 0.89, and 0.87 respectively.

5. Conclusion

This paper majorly concentrated on the improvisation of network lifetime in CRSNs through an energy efficient path selection with the help of ESCRP. A composite metric is established here with the help of three individual metrics namely energy, channel utilization rate and Geographical & temporal correlation. ESCRP is a spectrum aware mechanism which majorly concentrated on the service provision for SUs and hence, it tried to optimize the channel parameters like Channel utilization rate and distance correlation between nodes. Simulations have been conducted in a widespread manner with varying network parameter like number of nodes, communication radius, number of rounds and weights of coefficients. A best combination is determined through the simulation of proposed at $\alpha = \frac{1}{8}, \beta = \frac{1}{8}, \gamma = \frac{3}{4}$. Further, the performance of proposed method is compared with the existing methods through packet delivery ratio and number of alive nodes with increasing number of rounds and proved that the ESCRP is superior to the all the existing methods in improving the network lifetime.

Conflicts of Interest

The authors declare no conflict of interest

Author Contributions

Conceptualization by Abbas Ahmad S M K M, Design by Devanna H, Development and implementation by Dustakar Surendra Rao and Validation and proofread by Mohammed Ali Sohail.

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