E^{2}CL, HC: Energy Efficient Cooperative Localized & Hierarchical Cluster Routing in CRN

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Abstract: With the advancement of Cognitive Radio Network (CRN), localization of primary users progress the improvement of network performance with respect to power adoption and reliability. Moreover, CRN localization is essential because storage energy of CR devices is limited and causes increased network lifetime. By considering these issues, we propose an Energy Efficient Cooperative Localization approach (EE-CL) in CRN, which is used for placing Primary User (PU) position with the help of mobile a aided CR. Moreover, communication among CRs cooperation which leads to demand of more energy, a mobile CR is allowed to manage the overall positional accuracy and wake up minimum number of CR to collaborate CR manager. In order to investigate influence of accurate location knowledge, a location-aware CR (LaCR) routing protocol employed and to improve the network life time a Hierarchical clustering approach is applied. We evaluated the simulation results for the proposed Energy Efficient Cooperative Localization (EE-CL) Routing approach which achieves better performance compared to existing Cooperative Localization (CL) with respect to energy efficiency. Furthermore, remarkable performance is accomplished by LaCR protocol in terms of PUs collision risk with the help of localization knowledge obtained from EE-CL approach. Also Hierarchical Cluster Routing protocol acheives significant performance in enhancing the network life time.

Keywords : Cooperative Sensing, CRN, Energy-efficiency, Hierarchical Routing, Localization.

I. INTRODUCTION

Nowadays ineffective spectrum utilization brings a new kind of networking approach which purely depend on additional adaptable opportunistic use of the spectrum currently accessible. Cognitive Radio (CR) offers a key enabled promising solution which can enhance the spectrum utilization efficiency. Particularly in Cognitive Radio Networks (CRNs), allow to use spectrum opportunistically some vacant parts that are currently unused by the users of the licensed one (Primary Users) by the CR users [1]. Similarly, many applications practically needs to have information about position of PU which totally mitigate the harmful interference opposite to PUs [2], for the effective design of CR power adoption [3], to employ Cognitive Radios mobility [4], powerful location aware routing protocols design [5]. This LaCR routing approach proves the CRNs location information. Also, protection of PU and routing performance of CR improves with the help of accurate location information. At the end the implementation effective hierarchical clustering method of routing mechanism [6] for the benefit of scalability and efficient communication. Generally, life time of network and CR routing accomplishment rely on by employing hierarchial clustering data updates. Cooperative localization of PU results [7], [8] have been introduced to diminish the interference against PUs with harsh channel circumstances. In fact, the communication between cooperative CRs which increases sensitivity detection more that eliminates uncertainty among the available channel to provide accurate PU location estimation. Specifically, the cooperative communication demands more energy-consumption, In order to achieve the performance problems of CRN, need a trade-off among localization accuracy and energy efficiency. It must effectively utilize the currently available energy efficiently with the energy-constrained CR, and moreover, due to fading and multichannel environment for handling the issue of mitigating the energy during optimization of accessing spectrum sensing and decision making. The proposed EE-CL scheme, which employs mobile manager having energy efficient with cooperative techniques, that offers a sensitive detector even though the conditions of the channel are bad, no need of requiring more hardware complexity. In view of the implementation, it progresses the reduced hardware complexity and cost. According to the proposed localization approach local region diminishes the communication overhead and enhances the energy efficiency where data acquisition condition manages accuracy of localization with the wake up of energy modeling.The Hierarchical-based approaches, by adding special benefits pertaining to scalability as well as effective communication. With this idea of hierarchical design, which achieves energy efficient routing mechanism in Cognitive Radio Network. Specifically, the architecture of hierarchical structure uses nodes with higher energy to process and forward data. In the event of nodes with low energy can be invloved for sensing which are very close to the area of targetted node. Especially few routing techniques belongs to

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this group are TEEN [9], PEGASIS [10], LEACH [11], and APTEEN [12]. The main objective is to increase the network lifetime and reliability effectively with adding some non-homogeneneous nodes in CR sensor network. We propose an energy efficient hierarchical clustered approach (EE-HC), which employs distributed mode in non-homogeneneous cognitive radio sensor networks for selecting the cluster heads. The cluster-head are stored with initial energy of node, probability of choosing cluster head is very close to the nodes of others in the network.

A. *Motivation*

In the spectrum sensing aided approach, it is necessary to investigate the channel availability as much as possible while managing the spectrum sensors sustainability. Particularly spectrum sensors assumes the capabilities of diverse nature of energy harvesting. However, spectrum sensing allows to minimize the energy consumption [13] not on network lifetime but uses localized cooperative energy efficient approach. In consideration with network lifetime, a study of new approach by applying hierarchical clustered routing motivates to enhance the lifetime of CRN network.

B. *Contribution*

Here, we present an energy efficient cooperative localization approach (EE-CL) that employs Received Signal Strenghth Detector (RSSD) acquires from PUs by sensing the spectrum cooperatively. The purpose is to compute the accuracy position of PU, where a mobile CR manager [14] is designed that collaborates on fixed number of CRs, It manages the essential requisites of power consumption and positional accuracy limitations. Specifically, for better routing use LaCR approach and hierarchical clustering technique to maximize the lifetime of network. Summarily, the contributions of this work is as follows:

- Formulate system architecture of CRN
- Introducing a mobile aided energy efficient cooperative localization scheme
- Study of Location Aware Routing applications
- Design the hierarchical clustering scheme which increases network lifetime

C. *Organization*

The paper is arranged in accordance, section II discusses related work, System Architecture is modelled in section III, energy-efficient localization scheme and the proposed cooperative localization solution are discussed in sections IV and V. Application LaCR routing and hierarchial-clustering routing approaches discussed in Sections VI and VII, the result and discussion is evaluated in Section VIII, finally concluded with conclusions in Section IX.

II. RELATED WORK

In [15], [16] proposed spectrum sensing energy efficient protocols, which uses sensor scheduling approaches in CRNs to optimally organize the characterstics of the cognitive devices. It offer the essential sensing improvement and maximize the throughput of cognitive radio system. Furthermore, the primary issues in CRNs are behaviour of non-cooperative PU and protection while implementing the localization technique.Generally, many works on energy with respect to localization ideas already proposed in related work for Cognitive Radio Sensor Networks (CRSNs) [17]. Nonethless, the communication hypothesis is totally different when compared to CRNs, therefore solutions of WSNs are not appropriate for CRNs techniques. Consequently, solutions for energy management in CRNs consider the data acquisition dissipate less energy compared to sensors transmission [17]. Indeed, practical scenario of CRNs does not support for various levels of applications. In CR, the process of spectrum sensing partialy equal to data acquisition in CRSNs but demands more energy compared to CR transmission [18]. Hence, the result obtained for CRNs using energy efficient localization should include the sensing process for covering the energy management.A network considered as flat type, the activity of every node plays same and associate altogether to achieve the sensing job. It is difficult to put a global identification for every node due to number of nodes is large. This causes with an assumption of data centric nodes by considering Base Station forwards some queries to particular area and looks for information from the sensor nodes which are located in some specified regions. Since, it is essential to indicate the characterstics of data in attribute base naming because data is needed in the form of query are presented in few routing approaches like SPIN, EBRP, Directed Diffusion, Rumor Routing. The main objective is to maintain the energy utilization efficiently by sensor nodes which is important for cluster based routing approach. Which involves them in multihop communication between a cluster, performance of aggregating the data and decrease the fusion for total messages transmitted to destination also sensor nodes transmission distance. The Low-Energy Adaptive Clustering Hierarchy (LEACH) [11],[19] focuses on distributed cluster routing based techniques in WSNs. In a network, LEACH selects few nodes not uniformly as cluster heads and balances the energy utilization of sensor nodes by rotating it. The selected cluster heads fused and aggregated for data arrival from nodes which is being the resepective cluster. Moreover, these cluster heads forwards aggregated data to sink in order to lower the total data and transmission of duplicated data. Since, collection of data is totally centralized towards destination and performs periodically. Its functions are classified into set up phase and steady state phase. Cluster heads are chosen and organized in setup phase. Especially in steady state phase transmission of actual data takes place to sink. shylesh et al.,[20] studied the review on spectrum management techniques which supports sensing, deciding and allocation. This analyzes the energy efficient routing protocols with several metrics to forwards the available information from source to sink by optimally reducing the energy consumption. In [19] proposed an enhancement over LEACH approach, named as LEACH-C which deploy centralized clustering technique and same as steady-state phase in LEACH. This scheme produces better while spreading the cluster heads with entire network. According to set-up phase in LEACH-C, every node forwards the data regarding details of current position. In order to identify the best clusters and the sink

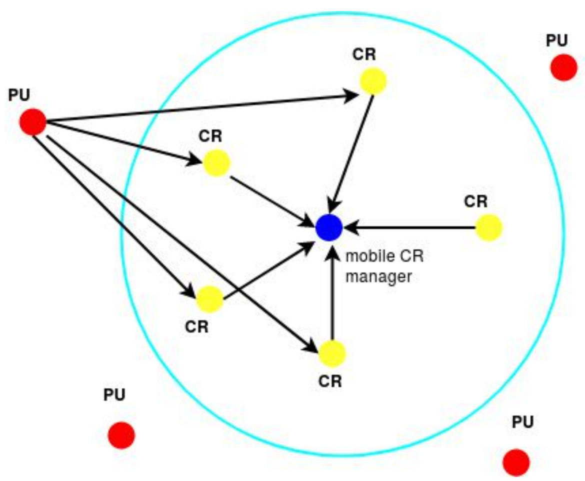


Fig. 1: System Architecture

requires to guarantee distributed energy load is equally between every nodes. In order to achieve this, sink calculates the average energy of a node and identifies the nodes energy which are below the average.In [21] analyzed the existing clustering algorithms which identifies the strengths and weakness issues of every category type, and study the characteristic of WSNs is important. Furthermore, it is necessary for enhancement of energy efficiency for WSNs. The algorithm proposed can be improved by balancing the lifetime of cluster by considering directional data traffic which simply increase the overhead by adopting clusters separately. In [22], authors assumed an event detection in non-homogeneous network by considering nodes of two types like type-1 and type-0, where node type-1 have more battery energy compared to node type-0. A key aspect of formulation which is associated with supply of energy build the nodes, and analyzed performance of network lifetime. Currently, in [23] proposed an election of cluster head approach that uses fuzzy logic to eliminate deficiency of LEACH. Also, network lifetime is extended by employing fuzzy variables with respect to non-heterogeneous network system.

III. SYSTEM ARCHITECTURE

The Cognitive Radio (CR) network with n CRs and m PUs are taken for consideration into the network, we introduce a mobile CR manager shown in Fig.1 which helps in energy detection through spectrum sensing. Similarly each nodes (CRs) are equipped with different energy.

A. Channel Propagation

Here, we apply log-normal model to consider multi-channel and shadow fading effect.

$$RSSD_{i,j} = RSSD_{d0} - 10\,\alpha_{i,j}\log_{10}\frac{d_{i,j}}{d0} + L_s \tag{1}$$

RSSDi,j represents the signal received at i from j device, also j can either be a CR or a PU, it is measured in two cases one is from CR during localization of mobile CR manager and PU during PU localization. RSSD d0 is the signal received at some relative distance d0, identical to the difference of power and the path loss at d0 [24][25]. Similarly, αi,j denotes the path loss exponent between i and j and d i,j represents the distance between i and j devices respectively, Ls denotes the shadow fading in a large scale window.

B. CR Manager Mobility

In this work, it consists of single mobile node which is moving in order to achieve Random Waypoint Mobility (RWM)[26] model, called mobile CR manager. This model is grouped into four types namely controlled mobility, random mobility, predictable mobility and geographic mobility. Here, RWM model [27] is used as mobility model for mobile communication. So as to get more accurate localization results we use mobile node with controlled trajectory which ensure monitored mobile CR manager arrangment. Since it requires prior knowledge of mobile CR manager preferably RWM model [28]. The motion of mobile CR manager is divided into pause period, motion period with unknown direction. During pause period the mobile CR hold its position with specified time but in motion period mobile CR keeps moving varied direction with irreuglar speed [29]. Even after taking the new location, the mobile CR enters into pause period and stops until some period of time as compared to previous position.

C. Cooperative Sensing Spectrum

Generally, in cooperative spectrum sensing, cooperative communication of CR with help of RSSD obtained by (1).

In order to decide the presence of PU by comparing with a threshold value, then the respective CR forwards its one bit decision Di towards the mobile CR manager. Since, mobile CR makes use of logical decision fusion rule to combine all one bit decisions. The mobile CR manager, which combines all the decisions of one-bit value are fused as per the fusion order of logic decision [30], [31] also this decision is expressed as follows:

$$Y = \sum_{i=1}^{N} D_i \left\{ \begin{matrix} D_i \geq l & H1 \\ D_i < l & H0 \end{matrix} \right\} \tag{2}$$

where H1 and H0 represents the decision which are identified by mobile CR manager that marks the PUs presence or absence accordingly. The threshold value l is a whole integer number, expresses the l-out-of-N rule. Similarly, by observing OR rule confirms the case of l = 1, then AND rule corresponds to case of l = N . According to l-out-of-N rule, assumed that the mobile CR manager confirms H1 if l out of N CR users reported as value 1. In general, for cooperative sensing the probability detection of the mobile CR manager is Qd and false alarm probability Qf with respect to the rule expressed by [32]. The mobile CR manager finds out the probability of detection p̂d and probability of false alarm p̂f with the help of cooperative sensing expressed as follows.

$$Q_d = Prob\left[Y > l\left(\left[H\,1\right]\right)\right] = \sum_{i=l}^{N} \hat{P}_d^i \left(1 - \hat{P}_d\right)^{N-i}$$

$$Q_f = Prob\left[Y > l\left(\left[H\,0\right]\right)\right] = \sum_{i=l}^{N} \hat{P}_f^i \left(1 - \hat{P}_f\right)^{N-i} \quad (3)$$

Indeed for the purpose of practical scenario, we consider status of on − off for PU activity model by exponentially distributing the on times. It is noticed that the functions of PU like death rate λ as well as birth rate γ. According to the PU activity design, we are able to calculate a posteriori probabilities denoted by:

$$P_{on} = \frac{\gamma}{\lambda+\gamma}$$

$$P_{off} = \frac{\lambda}{\lambda+\gamma} \quad (4)$$

Where P_{on} represents the probability used near PUs and P_{off} represents the probability of PU idle duration. PU probability of detection P_d and probability false alarm P_f is represented as:

$$P_d = Q_d . P_{on}$$

$$P_f = Q_f . P_{off} \quad (5)$$

IV. ENERGY EFFICIENT LOCALIZATION MODEL

After selecting the minimum count of *CR*s in order to localize the *PU* which totally avoids wastage of energy. The mobile CR manager manages in a local region to wakeup required count of *CR*s at any point of time. Hence, it manages the requirement restrictions of power consumption and accuracy of position. We make use of energy for the data aggregation to get the measurements range with cooperative spectrum sensing for localization. Implementation of opportunistic wakeup energy modelling involves two steps: first states the local region and other involves wakeup probability of computation opportunistically.

A. Definition of Local Region

According to the observation made by adding more anchor nodes which improves the localization accuracy but due to the large number of message exchanges between them makes the process energy demanding one. For PU localization, it triggers only local CRs on behalf of making all CRs for aggregation of data and also, by lowering the CRs number automatically decreases the localization accuracy. To overcome this problem, mobile CR manager maintains fixed count of local local CRs that provides localization to unknown PU. Hence, the transmission power is directly propositional to forth power of distance.

There are two approaches for local region formation, called static and adaptive. Adaptive approach is expressed as per the mobile CR manager position and also, mobile CR manager moves along with the local region. Specifically, static approach is totally independent of mobile CR manager location, also local region is fixed with the specified PU location.

1) Adaptive approach: In this approach, the position of local region is varied in accordance with the position ofmobile CR controller. Initially mobile CR controller position is taken with respect to those three CRs having highest RSSD values [33]. Thereby, the mobile CR manager position is obtained, the local region is shaped in the form of circle in which mobile CR manager limit the radius. The energy optimization method gives the radius of local region, positional displacement of begining point can be acquired by mobile CR manager movement. Even if the manager of mobile CR is within the local region, eventually the current mobile CR manager is exploited and new one will be formed. Due to shifting of local region consumes more energy because it needs to change state of CRs from idle mode to active mode not preferable always. Eventhough, position of mobile CR manager is not so accurate which is only used to shape local region. This approach runs in a mobile CR manager trajectory and randomly the local region is acquired.

2) Static Approach: It is a different kind of adaptive method which gives raise to static approach where PU position is fixed. We assume two kinds of static scheme from the begining, region is almost centered with CRs having highest RSSD and those which lies closer to PU. The second approach depends on the initial estimate of PU. The local region of adaptive method in the local region is fixed and that gives fastest result as compared to that of adaptive method. Likewise local region is estimated according to the initial PU position. Even it is considered as static one, the movement of mobile CR manager can make its adaptive. Hence the static approach of local region may become adaptive.

B. Opportunistic wakeup probability computation

After obtaining the required local region, required to calculate the distance among PU and CRs by making use of energy detection. Only the CRs within the local region are taken for consideration, we accomplish to lower the number of local CRs which reduces energy consumption. However the local CRs in sleep mode can exchange the opportunistic data. In [34] describes the importance of selecting local CRs and probablistic wakeup protocol. In order to mitigate the active local CRs number, we manage to perform communication overhead for a network between local CRs which saves energy.

Specifically, the local CRs mutually exchanges opportunistic data in sleep mode. Hence, for completing the localization they regulate their off and on states.

Here, we take three reference local CRs for obtaining location information in order to get the location of PU in two dimensional area [8]. The local CRs are totally independent because count of local CRs employed in the process of localization where $k \geq 3$. Therefore, the purpose is to manage minimum probability that is used to locate PU position. It agrees the binomial probability P_{rq} (n, p wu), where n denotes the count of local CRs for a local region and p wu denotes the probability of wakeup by the local CRs.

The hypothesis stated which does not have any ambiguity in deputing the CRs, where probability of localization improves using the trilateration technique that is = 0.9 [35]. Since, the5 $P_{\bar{P}U}$ probability of identifying the location of PU can be estimated using P_{rq} [36], here P_{rq} is computed as:

$$P_{rq} = 1 - \binom{n}{0}(1-P_{wu})^{n} - \binom{n}{1}P_{wu}(1-P_{wu})^{n-1} + \binom{n}{2}P_{wu}^{2}(1-P_{wu})^{n-2} \quad (6)$$

specifically k denotes the count of local CRs required for localization [34]. It is possible to perform localization of PU function only where cooperative sensing detection achieves positive feedback. For locating the PU probability denoted by:

$$P_{\bar{P}U} = P_d \, . \, P_{rq} \quad (7)$$

In which P_d and P_{rq} represented in equation (5) and (6) accordingly. At any point of time, the $P_{\bar{P}U}$ probability location identifying PU must meet the lower value α, that is $P_{\bar{P}U} \geq \alpha$. Hence, different values of the probability localization threshold α is checked p wu values with local CR's count. The result obtained modifies the probability wakeup value for the local CRs count. In general, it consumes more energy for communication with higher count of local CRs, also decreases probability wakeup of local CRs time. By reducing the local CRs number, utilization of energy is balanced. For the purpose of maximizing the local CRs count in a local region, gradually we may increase the total count of CRs(nT) but distribution of local region radius r is considered uniformly. The earlier case maximizes the local CRs count by specific r in a local region irrespective of the region is stated locally. Meanwhile local region enlarges further and higher local Crs can communicate mutually. According to equation (6) and (7) maps the quantitative relation among count of local CRs and P P ˆ U . In order to obtain the relation among wakeup probability and local CRs count has been employed with the smooth curve fitting approach for the presented localization probability by assigning various values of a,b,c, and d as stated below:

$$P_{wu} = ae^{bn} + ce^{dn} \quad (8)$$

C. Channel and Distance Evaluation

In Cognitive Radio Networks, PUs and CRs do not

cooperate each other, thereby channel parameters are not possible to use in a CR network. In other words , we calculate the channel parameters with range measurements for a noisy channel circulation by exploring smoothing and fitting curve approaches. In fact, fixed CRs gather various records of RSSD values from PUs through spectrum sensing in harsh channel environment as given in eq (1). For every CR we get RSSD measurement values at different distances from PUs. Therefore a smoothing method is employed to smooth noisy RSSD measurements where we adopt loess-local regression smooth approach because it is resistant to outliers. After getting smoothed RSSD measurement values, a logarithmic fit curve is needed for smoothing RSSD values with 0.95 guaranteed intervals. Further $RSSD_{d0}$ (computed as d0 =1 m) and

α_{ij} for every communication link *i-j* are acquired with an interpolation. At last, based on channel parameters estimated, log-normal model in equation (1), distance between CR_i and PU_j are further calculated according to

$$d_{i,j} = 10\left(\frac{RSSD_{d0} - RSSD_{i,j}}{10\, x\hat{\alpha}_{i,j}}\right) \quad (9)$$

V. ENERGY EFFICIENT COOPERATIVE LOCALIZATION

In order to get the PU position accurately, mobile CR manager requires services of localization. Since, we assume CRs position is unknown, associate with other local CRs for position after obtaining the count of local CRs as well as opportunistic wakeup probability.

A. Mobile aided localization

A communication overhead and consumption of energy can be lowered by exploring the mobile CR manager. It manages to wake up specifically for suitable count of CRs in the local region, requirement of higher PU localization probability, and limitation of power consumption. Similarly, to get the PU position accurately, we use mobile CR manager as an anchor node. So, they cooperates with fixed CRs to calculate accuracy of PU location. Mobile CR manager estimates its own distance by the received RSSD reports from fixed GPS-equipped local CRs. Here, channel parameter values are obtained with the step explained in Section IV.C.

There after mobile CR manager obtains its distance estimation along with the velocity algorithm. The velocity algorithm based approach rely upon previous position of the

mobile CR manager and the linear prediction approach of the manager of mobile CR speed v_m. By using the fast history of the previous mobile CR manager estimation P_m^{cr} we can estimates the speed of v_m. After finding the velocity a boundary is defined as circle $P_m^{cr}(x_m, y_m)$ with radius $r_m = v_m(t_{m+1}, t_m)$ where t_m expresses m-th time stamp which allows to filter out the outlier estimations. Then mobile CR manager position is redefined and computed by comparing with previous values and the 2 bound is $(x - x_m)^2 + (y - y_m)^2 = r_m^2$. If the guess is outside the boundary [28] then we can say measured value is affected by noise. Hence, we assume that the actual position of P_m^{cr} along the line of calculated point and lies within the boundary.

B. Selection of best local CRs with Cooperative approach

Cooperative localization technique which regulates CRs *on-off* state based on the opportunistic wake up model by changing the wake up probability of every CRs. The count of active CRs is sufficient for PU probability localization, in which available CRs, mobile CR manages to find the best one inside the particular local region for estimating the PU position. The estimation of PU position with cooperative sensing is defined as follows:local CRs with minimum localization errors are considered to be the best set of local CRs. With an assumption of positioning PU location estimation for closest CR to the PU to compute the best available set of local CRs. By using any triplet of local CRs, the nearby CR position is estimated and best local CR set is selected among them. Thus we adapt min-max localization method which gives minimum localization error. Here, The Local CR set may be composed with fixed or variable positions. Since, the accuracy of localization increases with the higher number of CRs in the collaboration process. In general, local CR set probably contains with standard/different position of the mobile CR manager with local CR along the path.

The best way to group the local CRs set which cooperates to calculate the PU position and provides minimum error for PU localization. Also, local CRs does not associate with PU during message exchange between local CRs. By considering the estimation of closest CR to PU that computes the best local CRs set for positioning PU. With geometric approach, we find local CRs best set for CR positioning becomes the best set for positioning PU.

Consequently, the localization accuracy approach increases CRs number, involves cooperation process, and equipped with a large number of GPS-CRs are deployed [9]. In other words, we consider various positions of a mobile CR manager with various positions and well-known position of local CRs that reduces limitations of energy and cost. Subsequently, searching the best local CRs, which greatly outperforms accuracy of localization and further used in Energy Efficient Hierarchical Clustering protocol in Section. VI. This protocol investigates the hierarchicaal clustering information for channel selection, adaptation of CR power, and routing scheme. Moreover, PU positioning goes in the followed subsection.

C. Primary user localization

For the purpose of localizing the PU position we make use of best local CR group and min-max estimator. Iterative RWP mobility approach has various ways of mobile CR controller. Every step gives PU position which results in min-max estimator with the help of best local CR group. It is expected to eliminate few PU position by out-lier technique. The final PU position is found by calculating the mean of remaining positions of PU.

Finally, we achieve by assuming many position calculations before taking into account of final decision. Here, outside position is calculated, totally too far when compared to other positional estimates. In this case closeness level method, positions distance is calculated specifically between the focused dense area falls in the estimated position. By applying basic distance metric procedure, gives the distance estimation among any pair positions. Particularly, an estimated position p̂, d_r -neighborhood of p̂ which includes group of objects, completely within distance d_r from p̂. In general, the high probability estimates are closest to each other and real PU position is very close to it. Therefore, the estimation of PU position is selected within dense neighborhoods and the value d_r is so chosen by some evaluation and rely on value ρ noise of the shadow fading. Accordingly, in large scale area set d_r =2m, i.e., 100 × 100m and 200 × 200m for a realistic application scenario, ρ noise = 6 dB in indoor space. The current PU position is specified with d_r, then results are compared with other estimates of PU, resulting different paths of mobile CR manager. The weights are assigned either 0 or 1 with the following steps: it becomes 1 only when the available PU is lower than d_r then the weight w is estimated with the current PU position otherwise set to 0. The value of w set to 1 where proximity level positions number is defined and a matrix that contains k PU estimates position and its weights w considered for current estimation. Thus, the matrix having higher proximity level is chosen. Final PU position $P_{\hat{P}U}$ is computed based on the average of PU positions estimate $P_{\hat{P}U}$ having highest proximity level as per equation (10).

$$\hat{P}^{PU} = \frac{\sum_{i=1}^{k} w_i \hat{P}_i^{PU}}{\sum_{i=1}^{k} w_i} \tag{10}$$

where k represents the number for PU position estimate $\hat{P}_{PU}$ of the matrix selected. Similarly, outliers are eliminated automatically and the performance of localization improves.

D. Energy Consumption

The proposed energy based detection approach collects RSSD measurement values used for estimating the energy consumption in localization. This increases the energy consumption based on the local CRs communication within a local region in data acquisition phase. Let local CR be denoted by CR p in local region L, the product of energy consumption is almost equal to E q and P wl . Here, E q denotes the energy consumption of local CR q and P wl denotes a constant value for every local CRs belong to particular local region. Thus, sum energy is expressed as follows:

$$E = \sum_{i=1}^{L} \sum_{q=1}^{Q} E_q x p_{wl} \tag{11}$$

The consumption of energy rely on radius of local region r and localization probability P_{PU}. Find the values of r and P_{PU} that minimizes energy consumption, the optimization issue can be addressed by minimum of E, r, P_{PU}.

Hence it is given as $P_{PU} \geq \gamma$

$r \geq \hat{r}$

The $\hat{r}$ value ensures lower possible number of CRs for localizing PU and γ denotes the threshold for PU localization probability. The probability of localization varies in accordance with the chosen approach.

VI. LOCATION AWARE ROUTING PROTOCOLS

In order to improve the performance of CR power adaptation, channel selection and routing scheme we explore the PUs locations knowledge. We here studied in detail for improvement of performance with respect to PUs collision risk for the proposed Location aware CR (LaCR) routing [5] in section VIII. Here, we assume that a CR ad ahoc network uses a common control channel for the formation of routing process. This common control channel is also employed by CRs for sharing the knowledge with respect to the environment, detected by heterogeneous PUs, features, and their location. This information is useful for computing the achievable performance in a specified location area. According to spectral characterstics, the area is classified into clusters. After that the existing PUs, CRs try to explore the features of PU that is bandwidth and level of allowable interference influences directly to achieve certain rate in particular cluster [37].By considering these characterstics for the proposed work, a third approach is identified i.e. PUs location. In order to limit the harmful interference for the primary network, we use the information that needs to adapt CR transmission power efficiently. In this scenario, we explore the localization process in order to adapt CR power transmission and helps in routing protocol process. According to [37], developed a LaCR routing protocol, which computes the considered performance rate for every cluster. The proposed LaCR approach accounts for the localization error. It contains two steps procedure such as i)intra-cluster and ii)inter-cluster. Specifically, our system considers similar kind of spectral characteristics but different locations for a particular cluster. Hence, the procedure of intra-cluster chooses the path particularly depend upon the knowledge of location and spectrum bands available in the cluster. Similarly for the procedure of inter-cluster chooses the path only based on different spectral features among clusters.

Algorithm 1 EE-CL

1: *Get the Data acquisition(RSSD) and values of PU detection* (P_D)
2: *compute* $P_D = Q_d \; P_{busy}$ $RSSD_{i,j}, i, j, CR_{index}$
3: **if** *PU is detected* **then**
4: calculate the $\hat{p}^{MCR}$ *position*
5: *Compute the local region* $L(\hat{r}, \hat{p}^{MCR})$ $\hat{p}^{MCR}$
6: $\hat{r}$ *radius of local region*
7: **else**
8: *repeat detection process*
9: **end if**
10: **for** l=1:R, *R represents the number of local region* **do**
11: pwl $P\hat{P}U = PD \; Prq$
12: goto algorithm 2
13. estimate MCR, CR, CR *from PU* position
14. find the best set for localization CR, CR, CR (Ri, CRj, MCR, CRi, CRj)

$$\hat{P}^{PU} = \frac{\sum_{i=1}^{k} w_i \hat{P}_i^{PU}}{\sum_{i=1}^{k} w_i}$$

17. *end for*
18: *end*

Algorithm 2 Energy Consumption calculation

1: $p_{wl}, \forall\, \iota, q$ *represents the LCR index and local region*
2. $E = \sum \sum E_q x p_{wl}$
3. *Update*

VII. APPLICATION TO THE HETEROGENEOUS HIERARCHICAL MODEL FOR COGNITIVE RADIO SENSOR

In this paper, we introduced an example of heterogeneous cognitive radio sensor network and investigated the impact of heterogeneous resources.

A. *Heterogeneous resources types*

Mainly resource heterogeneity of sensor node are classified into three categories such as link heterogeneity, computational heterogeneity, and energy heterogeneity [14].

The energy heterogeneity is the important one among all these types of resource heterogeneity. However, these consume more energy

resources i.e., computational heterogeneity and link heterogeneity. In order to mitigate the network lifetime automatically brings negative heterogeneity effect to the complete sensor network.

B. Cognitive Radio Sensor Networks (CRSNs) Heterogeneous Effect

The CRN plays an important character while placing heteogeneous node and ensures three benefits as follows:

- extends network lifetime.
- Enhances the reliability in data transmission.
- Lowers the delay time in data transportation.

C. Performance measures

In this subsection, we measure and analyze the efficiency of clustering or hierarchical protocols.

- *Network lifetime:* In a sensor network, determines the duration between the begining of operation and end of the first node alive.
- *Counting cluster heads per round:* In this case, the spontaneous evaluation resulting in nodes count which automatically forwards to the sink for the available information collected from its cluster associated members. The number of alive nodes are determined per round as total nodes, super nodes,and normal nodes.
- *Throughput:* We analyze how much data rate sent across the network as well as forwarded from cluster heads to sink (base station), also forwards to cluster heads from the nodes.

D. Energy Efficient Hierarchical Clustering Approach

Consider a CRN with nodes of different initial energy and part of nodes are assigned with higher energy in consideration of normal nodes. Let n denotes the number of nodes n0, where m0 represents the percentage of m nodes called super nodes having α times more energy compared to normal nodes. Similarly, left out n*(1-m) represent normal nodes, those nodes are distributed in the sensor field uniformly. The network is assumed hierarchically clustered, we apply LEACH protocol to maintain cluster hierarchy. The Clusters establish connection once again for each round of LEACH protocol and cluster head is selected every time which results in a well8 balanced nodes distributed across the network. Almost all node transmits to the nearby cluster and divides the communication cost for a sink and also cluster head addresses to the sink periodically. Suppose LEACH offers an optimal percentage p opt of nodes which is going to be cluster heads in every round. Here, we show the election process of chosing cluster heads that is adopted in order to deal with heterogeneous nodes.

1) *Optimal Selection of Cluster Head :* The calculation goes as per the following simplification and assumption. Assume the intra-cluster communication where nodes sends its traffic to cluster heads and nodes of inter-cluster sends its data traffic to sink or base station. Before transmitting it to sink or base station data aggregation and compression is done by cluster head. In the filed of sensor network, the nodes are distributed uniformly and nodes probability being selected as cluster head is a procedure of spatial density. Hence, total energy is well distributed in the clustering and thus minimizes the total energy consumption. The selection of energy model has its importance on the best clustering. In accordance with

the radio energy dissipation model, *L*-bit message of signal-to-noise ratio transmitting in a given distance d, the energy spending by radio is expressed as follow:

$$E_{Tb}(L, d) = \begin{cases} L \times E_{bb} + L \times E_{fss} \times d^2 & if\ d \le d_0 \\ = L \times E_{bb} + L \times E_{emps} \times d^4 & if\ d > d_0 \end{cases} \qquad (12)$$

Here E_{bb} denotes how much energy dissipated for every bit in order to achieve transmitter or receiver circuit, E_{fss} and E_{emps} rely on the model of transmitter amplifier, and d denotes the distance between receiver and sender. After simplifying these statements at d = d0 , then we can have $d0 = \sqrt{\frac{E_{fss}}{E_{emps}}}$ .. Similarly for receiving an L bit message, d0 = E_{emps} then the radio dissipates ERx = L × E_{bb} .

It is assumed that n nodes are placed non-uniformly across M square meter Area A=M. Let the sink is placed at the end of the environment, and also distance of any node to sink or cluster head is almost ≤ d0 . Hence, the cluster head (hierarchical) node energy consumption for each round is expressed as follows:

$$E_{ed} = \left(\frac{n}{c}\right) 1\, xLxE_{bb} + \frac{n}{c} xLxE_{bss} + LxE_{fss} xd^2_{bss} \qquad (13)$$

Where c denotes the count of clusters, Ebss denotes the cost of processing bit that addresses sink or base station. dbss denotes the distance among head of cluster as sink. Energy dissipated in a non-cluster node head stated as follow:

$$E_{nc} = LxE_{bb} + LxE_{fss} xd^2_{CM} \qquad (14)$$

d_{CM} indicates the mean between head of the cluster anduser of the cluster. Assume those nodes are distributed equally and can be defined as follows:

$$d^2_{CM} = \int_0^{xmax} \int_0^{ymax} \lim (x^2 + y^2) x \varsigma (x, y) dxdy$$

$$D^2_{CM} = \frac{M^2}{2\varphi k} \qquad (15)$$

ς(x, y) represents the distribution of node. Hence, in the network total energy consumed is almost equal expressed as:

$$E = L \times \left(2 \times n \times E_{bb} + n \times E_{dA} + \left(K \times d_{bss}^2 + n \times d_{CM}^2\right)\right) \quad \textbf{(16)}$$

Differentiate E with c and apply it to zero, then finding the optimal number of formed head clusters to sink denoted by

$$d_{bs}^2 = \int_a \left(x^2 + y^2\right) \times \frac{1}{A} = 0.75 \times \frac{M}{2} \quad (17)$$

If the distance of d0 is less than nodes to sink percentage, further we get

$$C_{opt} = \sqrt{\frac{n}{2\pi}} \sqrt{\frac{E_{fss}}{E_{emp}}} \frac{M}{d_{bs}^2} \quad (18)$$

Accordingly, determining the optimal probability of node to cluster head p opt denoted by

$$P_{opt} = \frac{C_{opt}}{n} \quad (19)$$

Since the best chosen node probability becomes cluster (hierarchical) head which is highly critical. And total energy consumed in the cognitive radio network per each round is raised exponentially if the clusters are formed in non-deterministic approach.The heterogeneity is taken for consideration in case of LEACH protocol, the result obtained is not optimized in CRN for the consumption of energy resources. Because LEACH considers only geographical density of the sensors network. In the existence of LEACH protocol having heterogeneity, we assume the normal nodes dies faster than the other nodes and in the last round the nodes with higher energy that is only super nodes will be left out. Assume 100 × 100m sensor field, the optimal number of cluster per round denoted • as normal node and ◦ as super nodes is depicted in Figure 4. The goal of heterogeneous aware hierarchical routing protocol is to ensure stability and network lifetime in the absence of homogeneous nodes. Assumed that percentage of nodes highly equipped with more energy compared to normal nodes. So that m represents the some part of total count of nodes n and m0 is the portion of the total count of nodes called super nodes furnished with γ times of higher energy in comparison with normal nodes.Generally, normal nodes energy is n × (1 − m) × E0 , super nodes n ×m ×m0 ×E0 ×(1+γ) energy, E0 denotes the initial energy. Hence, sum energy can be computed as follows:

$$E = n \times (1 - m) \times E_0 + n \times m \times m0 \times E_0 \times (1 + \gamma)$$

$$E = n \times E_0 \left[1 - m\left[1 - m0 - m0 \times \gamma\right]\right] \quad \textbf{(20)}$$

Since the sum energy is improved by a factor 1 − m[1 − m0 −m0 × γ] which greatly improves the system with stable region where a new epoch is essentially matched to $\left(\frac{1}{P_{opt}} x\ 1 - m\left[1 - m0 - m0 \times \gamma\right]\right)$.

Let us consider Pn has the weighted probability of election in choosing normal nodes and Ps weighted probability of election by choosing super nodes. Therefore, probabilities can be determined by the following formula:

$$P_n = \frac{P_{opt}}{\left[1 - m\left[1 - m0 - m0 \times \gamma\right]\right]} \quad (21)$$

$$P_s = \frac{P_{opt}}{\left[1 - m\left[1 - m0 - m0 \times \gamma\right]\right]} x \left(1 + \gamma\right) \quad (22)$$

Let T(sn) be the normal nodes threshold value which can be found using P opt is stated as

$$T(sn) = \begin{cases} \dfrac{P_n}{1 - P_n \cdot \left(r \cdot \bmod \dfrac{1}{P_n}\right)} & if s \cdot G \\ 0 & \end{cases} \quad (23)$$

where r denotes the current round, G denotes the normal nodes group that never becomes cluster head particularly within the last $\frac{1}{P_n}$ rounds.

Let T(ss) be the threshold value for super nodes, which can be found using P opt is expressed as

$$T(ss) = \begin{cases} \dfrac{P_s}{1 - P_s \cdot \left(r \cdot \bmod \dfrac{1}{P_s}\right)} & if s \cdot G \\ 0 & \end{cases} \quad (24)$$

where r denotes the current round, G represents the super nodes group that never became heads of cluster particularly within the last $\frac{1}{P_s}$ rounds.

VIII. RESULTS AND DISCUSSION

In this section, we deploy CRs and PUs which are distributed uniformly in a specified area sizes as depicted in Table.1. Particularly, EE-CL localization approach is used to calculate estimation of PU around 100 times. With the help of RWP mobility approach the mobile CR manager starts moving, also during the simulation for every step it changes its path. In this scenario we use Matlab software windows operating system with i-7 processor configuration.Generally a mobile CR manager aggregates the samples for every 150ms with the mean value under shadow fading as well as standard deviation σ noise . In order to get the value of standard deviation in a noisy channel environment, samples of RSSD values we collected considers narrow-band IEEE 802.15.4 wireless radios not outside the private area like walls and hindrance, also standard deviation of the noise σ noise we get is equal to 6 dB. Furthermore, path loss exponent value varies between [1.8, 4] [38].

A. Localization result

Here, the root mean square error of PUs location can be

$$\sum_{i=1}^{n \vee \hat{P}-\bar{P}_n} \surd$$

computed as with the help of EE-CL, where P̄ represents the estimated positions on an average over the iterations, P̂ i represents the position estimation and n is the step number varies as per local CR number in every local region. It is be noted that the EE-CL algorithm calculates the position of PU in two steps: localization of mobile CR manager is done first due to its position in the network is not available. Next PU localization is carried out by exploring with the calculation of mobile CR manager position. Therefore, estimation of CR manager position with few errors, may influence to calculate the coordinates of PU. For PU final localization error intensity depends on different reasons by knowing the position of mobile CR manager, lowers localization error of the PU. Fig. 2 represents the localization accuracy of EE-CL approach with two size areas. It ensures accuracy of PU localization where local region CRs number increases with improvement. When local CRs number increases that increases the radius of local region r also sum of CRs number nT in the network. As depicted in Fig. 2 the localization of RMSE in specified large area is more compared to one in the small sized area because communication of local CRs allows large area spacing in a larger way. Hence, distance estimation error and localization error increases.

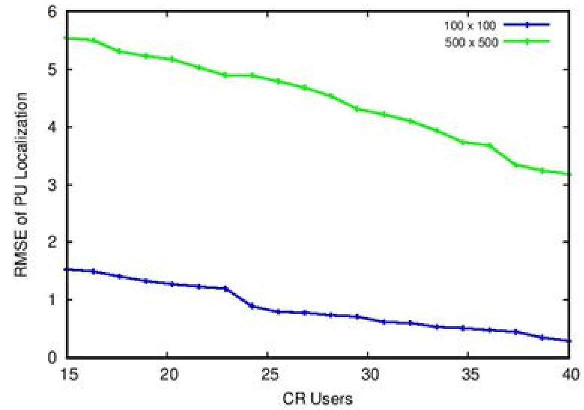
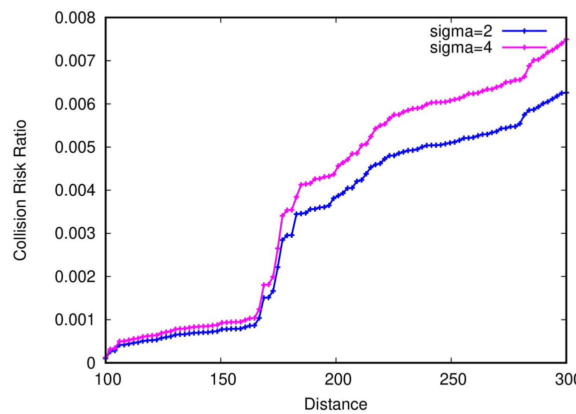


Fig. 2: RMS (m) of localization error vs. local CRs number,

[radius of local region, and CRs count] is [500,100].

Fig. 3: PUs collision risk due to CR users transmission on the chosen route

B. LaCR Routing Performance



It is also evaluated by measuring the PUs collision studied by CR transmissions in a specified locations is analyzed. The PUs collision risk ratio is expressed as the number of colliding transmissions to the number of CR at PUs transmissions. In other words, no perfect localization of PUs information is assumed while collision risk computation under EE-CL routing method. With help of its cooperative nature, the proposed EE-CL localization approach is robust with different channel conditions. Particularly, a noise with σ noise = 2, 8 dB, localization error of standard deviation lowers σ of the happened almost 2 and 4 m respectively. As described in Sec. VI, the EE-CL routing performance is affected by the variance σ 2 of the localization technique. Therefore, EE-CL routing approach benefits from a smaller value of σ. Fig.3 depicts the PU collision risk of EE-CL routing approach with different value σ of the EE-CL. In LaCR approach, we study localization error of the standard deviation. Hence, performance of EE-CL improves with an estimation of PU accuracy. So the proposed EE-CL routing method is evaluated with respect to collision risk at PU.

C. EE-HC routing performance

In order to analyze the EE-HC protocol issue, we consider first order radio model simulation parameters depicted in Table 2. Similarly to investigate the EE-HC performance analysis, for heterogeneous clustered cognitive radio sensor network simulation is applied in the area specified dimension 100m × 150m is shown in Fig. 4, also assumed that count of sensor nodes are n = 100. These super, and normal nodes are distributed non-uniformly over the area specified. Here, we understand that the coordinates of horizontal and vertical positions of all randomly placed sensors chosen between value 0
and specified higher value of the dimension. The sink or base station is at the end and hence, the maximum distance is approximately 150 m between any node to the sink. The message size where nodes send to its hierarchical heads also the message size of that hierarchical head forwards to sink which is assigned with 4000 bits.

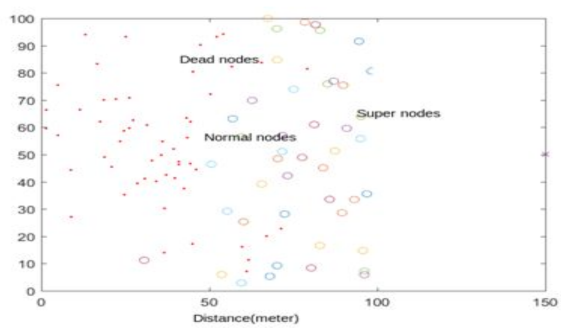


Fig. 4: Dead node presentation

Figure. 5 and 6 depicts a in depth representation of the characterstics which are identified in EE-HC, which illustrates with different settings of heterogeneity. Also, network consist of number of alive nodes indicate the presence for various scenarios. In LEACH, we noticed that the number of nodes die is more compared to EE-HC with the same settings. Normal nodes die very fast and ensures sensing area becomes sparse. In other words, death of super nodes is in sluggish fashion. All the nodes of normal, super nodes are dead where the total average count of hierarchical heads per each round per epoch represents always < 1. It is noticed that no hierarchical head for all the iterations, hence remaining nodes not possible to report its values to sink.In Fig. 7, we observed during the lifetime of network that the received data packets number from cluster heads at sink or BS. Based on the evaluation stable region of EE-HC is evolved in comparision with the LEACH. Furthermore, in the case of unstable region, network lifetime of EE-HC is shorter compared to LEACH. In Fig. 8, obtained result shows the number of clusters increased in EE-HC. With an advent of EE-HC heterogeneity (super nodes with extra energy) offer stable region significantly when compared to LEACH. It is due to beneath EE-HC, super nodes conducting the same process as normal nodes, election of cluster heads in weighted probability causes the consumption of energy in proportion to the nodes initial energy.

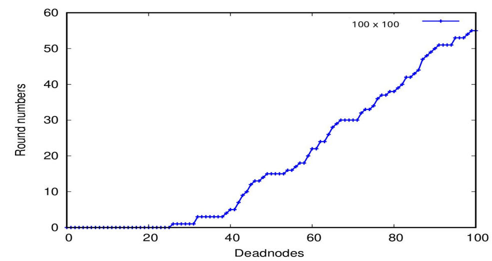


Fig. 5: Dead nodes number per round

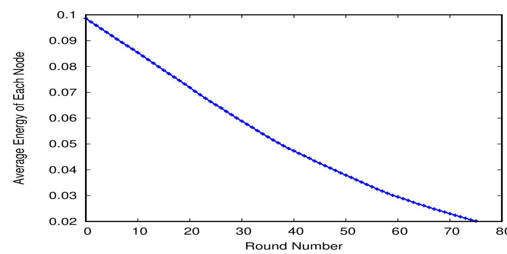


Fig. 6: Average energy of each node vs. round number.

D. Energy consumption result

In order to analyze the energy efficiency of EE-CL approach is evaluated and need to compute the power consumption which takes place in data acquisition stage for an area 500×500 m area.
With the help of energy
consumption opportunistic wakeup model is evaluated by equation (11) with values presented in TABLE I. This energy consumption in TABLE I is associated with spectrum sensing solutions [39].

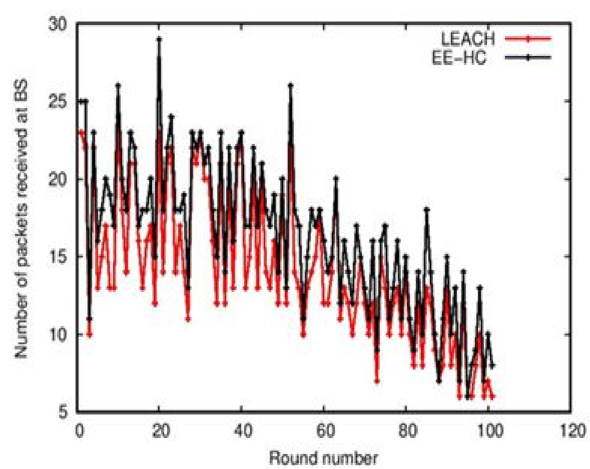


Fig. 7: Data packets received number at BS per round

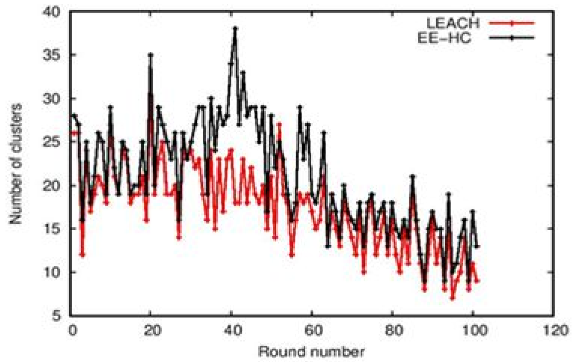


Fig. 8: Number of clusters per round

The CRs average power consumption is covered by each local regions which can be the total power use of the network. Fig. 7 compares the energy utilization of CL and EE-CL approach by changing the CRs number nT. In the CL algorithm, each CRs are active and cooperate to compute the PU position. After that obtained value ensures the wakeup model is energy efficient. Furthermore, result of power utilization does not vary significantly when we increase the count of CRs because of wakeup energy model. Fig. 8 depicts the energy
utilization which is essential for the localization of PU in considering different levels of the localization probability threshold value. The obtained result ensures higher probability, more energy demanding with involvement of large number of CRs which are necesary to wakeup for the PU localization, as well as increases the energy utilization. Nonethless, in the data acquisition stage energy consumption value does not increase with the wake up energy model accordingly.

TABLE 1: Parameter required for Simulation

Parameter	*Symbol*	*Default Value*
Area size	*Square meters*	$100 \times 100 and 500 \times 500$
Path loss exponent	α	[1.3-4]
oise level	σ_{noise}	6dB
CRs number	nT	100,150,20,0,250
Energy consumption	E	146J
Local region radius	r(m)	50,60,65,70
Localization probability threshold	λ	0.8, 0.85, 0.9

TABLE 2: Parameters value required for Transmission

Specification	symbol used	Value considered
Number of nodes in the system	n	100
Energy used by the amplifier for a short distance transmitter	E_{fss}	10 pJ/bit/m^2
Energy used by the amplifier for a longer distance transmitter	E_{emps}	0.0013/pj/bit/m^4
Energy utilized in the electronics circuit for a signak to transmit or receive	E_{bs}	50nJ/bit
Aggregation energy for data	$E_{DA5nJ/bit/report}$	146J5#n#J#/#b#i#t#/ #r#e#p#o#r#t#

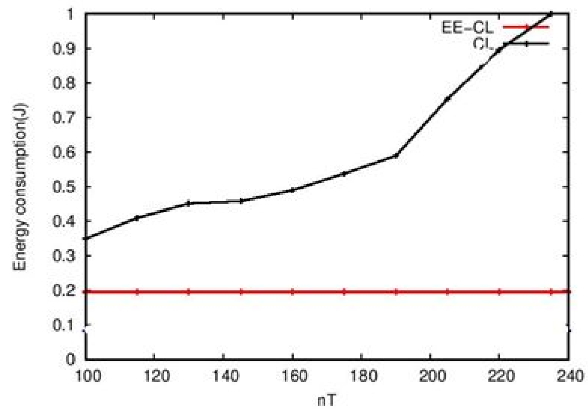


Fig. 9: Comparison between the energy consumption of CL, and EE-CL vs. nT System parameters: localization probability threshold α = 0.8 , local region radius = 150 m, and 200 × 200m^2 area size.

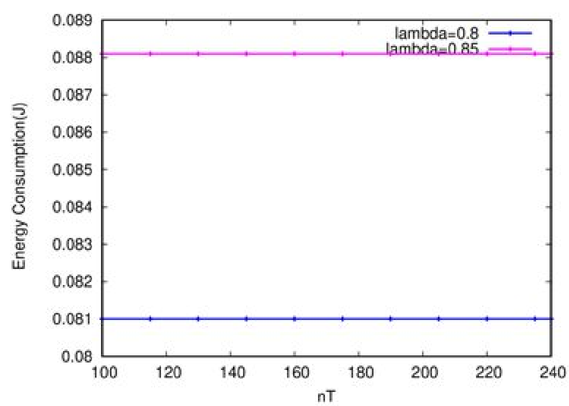


Fig. 10: EE-CL energy utilzation vs. nT for two different values of the considered threshold for localization probability λ Parameters considered: radius of local region = 150, and area size 200 × 200m^2 .

IX. CONCLUSIONS

The cognitive radio networks have been used in various monitoring applications. Energy efficient routing extends the features of managing system stability, location knowledge and lifetime. In this work, we present an energy efficient cooperative localization (EE-CL) technique for cognitive radio network. This EE-CL localization approach ensures energy efficiency compared to cooperative localization (CL) approach. In order to examine the benefits of localization, a LaCR routing approach has been deployed and In addition, allows to deploy the network very easy by energy efficient hierarchical clustering (EE-CL). Hence, reports the election of cluster heads for weighted probability in order to achieve network system lifetime and performance. As per the s imulations the EE-HC has achieved the lifetime by 10%.According to EE-HC many clustering approaches that we need to compare and analyze along with many other factors that affects the lifetime of network system. However, it can be extended to study on clustered sensor networks having more than two level of hierarchy.

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