Egyptian Informatics Journal 23 (2022) 315–327

Contents lists available at ScienceDirect

Egyptian Informatics Journal

journal homepage: www.sciencedirect.com

Game theory based node clustering for cognitive radio wireless sensor networks

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ARTICLE INFO

Article history:
Received 4 September 2021
Revised 1 February 2022
Accepted 11 February 2022
Available online 23 February 2022

Keywords:
Cognitive radio wireless sensor networks
Primary user
Cognitive user
Node clustering

ABSTRACT

Cognitive radio wireless sensor networks (CRWSN) is a promising technology for developing bandwidth constrained applications. Future Internet of Things (IoT) applications may extensively use CRWSN. CRWSN consists of cognitive radio enabled sensor nodes which are energy constrained, in general. Hierarchical cluster based approach for overall network management is suitable for network stability and scalability. Thus node clustering is an important problem in CRWSN setup. Objective of this work is to develop a suitable node clustering algorithm for CRWSN, in which nodes are expected to be mobile. A node clustering protocol for CRWSN has been proposed in this paper. The proposed clustering protocol is based on evolutionary game theory (EGT). Initial clusters are formed through a simple partitioning approach. Eventually, initial clusters are merged to form the final clusters. After forming the clusters by the resourceful sink node, the cluster head nodes for respective clusters are determined. The sink node runs the EGT based algorithm to identify the most capable node as the cluster head. The strength of this approach is that while identifying the cluster head node, various parameters such as residual energy level, geographic location, mobility, and the probability of primary user (PU) arrival are considered. The clusters and therefore, the cluster head nodes are distributed uniformly in the geographical area. The proposed clustering protocol has been compared with LEACH, RARE and the spectrum aware clustering algorithm. The simulation results show that the proposed clustering protocol outperforms all these similar node clustering protocols. On average, the proposed protocol outperforms the benchmarks protocols by 25% in terms of number of high energy nodes selected as cluster head, by 37% in terms of uniform geographical distribution of cluster head nodes, by 23% in terms of total energy consumed during the simulation time, and by 27% in terms of network lifetime. The future scope of the work has been outlined.

1. Introduction

Cognitive radio networks have opened up the possibilities for opportunistic usage of the available spectrum. In Cognitive Radio Wireless Sensor Networks (CRWSN), the sensor nodes are expected to be cognitive radio enabled. The licensed users are known as Primary Users (PU) and the opportunistic users (i.e., unlicensed) are known as Secondary Users (SU). In a CRWSN setup, the sensor nodes are resource-constrained in terms of low computing power, low available memory capacity, limited available communication bandwidth, and also limited on-board battery power. However, CRWSN is expected to resolve the issues like highly growing wireless network traffic due to extensive usage of handheld and other mobile devices connected to the Internet, and spectrum scarcity [24]. Even the CRWSN has capabilities to meet the stringent user requirements in terms of Quality of Services (QoS) if the available spectrum is used optimally [25].

Wireless sensor networks are nowadays integrated with the Internet of Things (IoT) [26]. Thus, production processes are optimized, operational efficiencies in the enterprises are improved,

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Peer review under responsibility of Faculty of Computers and Information, Cairo University.

Production and hosting by Elsevier

https://doi.org/10.1016/j.eij.2022.02.003
1110-8665/

and delivery of high-quality services is now possible. Various types of devices are getting connected to the Internet and it is estimated that 10 billion different devices used in industries are now connected to the Internet. CRWSN is going to play a vital role in the Industrial Internet of Things (IIoT), in the days to come. Moreover, research and development in the area of wireless sensor networks for various research issues such as energy efficiency, load balancing, congestion control, etc are still ongoing and recent publications are available [33,34].

Routing is an important task in any network including CRWSN. Such a network is always energy-constrained, and therefore, hierarchical routing or cluster-based routing is considered to be an energy-efficient approach. Cluster formation in a CRWSN setup, considering the geographically closed nodes together inside one cluster, is again a computationally challenging task. When the sensor nodes are mobile, the situation becomes even more complex. Still, communications can effectively be managed in distributed wireless systems through clustering [27]. Properly designed clustering protocols can improve network performance, can ensure stable operations, and also can handle network scaling issues. Clustering is highly important for CRWSN considering the dynamics involved in such networks. Node mobility, unpredictable arrival of PUs, availability of channels in cognitive radio environment (which is highly dynamic), and unavailability of sensor nodes (which are SUs) due to various reasons like untimely depletion of battery power, etc., make CRWSN highly dynamic. To exploit the advantages of clustering in network operation, the clustering protocol must take care of these aspects. Therefore, the design of an appropriate node clustering protocol for CRWSN is a problem that has attracted researchers in recent times.

Clustering of points is a well-studied problem in statistics as well as in the context of data mining. Let us consider a set of n patterns X, where X = $\{x_1, x_2, x_3, \ldots, x_n\}$; here x_i is a vector with N dimensions in given space of features. Clustering essentially means the grouping of the patterns in such a way that patterns belonging to one group are more similar to each other than the patterns belonging to other distinct groups. Similarity may be measured in terms of distance. In the context of sensor networks, clustering also means the grouping of the sensor nodes into clusters considering similarities concerning different parameters as applicable. Clustering of nodes in the network setup is necessary because it enables better management of the network in terms of routing and other dimensions. There are various clustering approaches used for cognitive radio sensor networks. For example, the Bayesian method for channel clustering was adopted in [30]. This method is based on unsupervised clustering methodology, and it outperforms the K-means clustering algorithm. In [29], an enhanced version of LEACH (Low Energy Adaptive Clustering Hierarchy) named CogLEACH which a spectrum-aware clustering protocol for cognitive radio networks was proposed. This protocol performs better than LEACH but does not take care of issues related to topology and channel quality properly. Clustering is essential for taking care of the issues like energy expenditure optimization and scalability.

Game theory is a theory of decision-making. It was developed by John Von Neumann, who is a Hungarian-born American mathematician, in the year 1944 [32]. In the present scenario, it has been increasingly used in network research. There are few papers recently published that explore the application of game theory in cognitive radio networks [3–5]. Evolutionary game theory is an enhancement over the classical game theory that can handle the dynamics of a system where population change over time. Traditional game theory is more static. This mathematical extension to traditional game theory has recently been explored for solving issues in different engineering systems. There are few papers recently published in which evolutionary game theory has been applied for solving some of the issues in wireless sensor networks [6,12,14].

In this paper, a node clustering protocol for CRWSN has been proposed. During the design process, evolutionary game theory has been applied. Various characteristics of CRWSN such as node mobility, dynamically available communication channels, the residual energy level of nodes, and geographic locations of the nodes are considered as input parameters to the clustering algorithm.

1.1. Motivation

The sensor networks are resource constrained. Topology is highly dynamic and when mobility is added to the sensor nodes, the issue of managing the network with limited energy in the nodes becomes more complex. Thus, energy efficiency is an essential requirement for the longer lifetime of such networks. Cluster-based management of the network reduces the communication overhead, and therefore, is more energy-efficient. Moreover, cluster-based hierarchy-based management of the network makes it more scalable. In a cognitive radio network setup, PU arrivals make the network unstable in the sense that the SUs are compelled to leave their ongoing transmissions. Again, mobility of the nodes creates a highly dynamic topology.

Considering these aspects, providing a proper cluster-based stable network management approach for cognitive radio wireless sensor networks is the motivation behind this work. The first requirement in this direction is to develop a node clustering scheme that is spectrum aware, node mobility aware, and also energy aware.

1.2. The contributions made in this paper are as mentioned below:

A node clustering algorithm for CRWSN has been proposed. The proposed clustering algorithm considers mobility, available energy, and also channel availability in terms of the probability of PU arrival while selecting cluster head nodes.

- A game theory (evolutionary) based node clustering protocol for CRWSN has been proposed. The proposed protocol involves minimum message exchange (communication).
- The proposed node clustering algorithm can also select geographically uniformly distributed cluster head nodes.
- The node clustering algorithm that involves minimum computation in the resource-constrained sensor nodes is the major contribution in this work; moreover, the proposed algorithm is energy efficient.
- A theoretical analysis of the proposed node clustering approach is also provided in this study.

The rest of the paper is organized as follows. Section 2 presents the related work along with a background of this work. The system model is highlighted in section 3. The proposed protocol is presented in section 4 followed by a theoretical analysis of the protocol presented in section 5. Simulation results related to the performance evaluation of the proposed protocol are presented in section 6. The paper is concluded in section 7.

2. Related work and background

There are several papers published in the area of node clustering and cluster-based routing in wireless sensor networks [19–21]. The energy efficiency issue in the context of resource-constrained wireless sensor networks has been extensively studied. Relevant protocols for different layers of the protocol stack including the network layer have been developed [22,23]. Moreover, node clustering protocol and medium access control protocol for cognitive radio ad hoc networks is proposed in [35]. In this section, a few papers in the line of game theory-based node clustering for wireless sensor networks, and CRWSN are highlighted.

A game theory-cluster-based routing protocol for wireless sensor networks is proposed in [1]. Energy efficiency is the major concern in this paper. Evolutionary game theory has been used in clustering the nodes in the WSN setup. In this work, node mobility is not considered, and the cognitive radio (CR) aspect is out of scope. However, the performance of the proposed protocol is compared with LEACH [2], and LEACH-C [2]. The proposed game theory-based protocol shows improved performance.

A game theory-based distributed clustering approach for wireless sensor networks is proposed in [3]. A non-cooperative game theory-based algorithm is proposed in this work to control the sensor node's energy consumption in the network. The work shows that it is better in terms of energy consumption, and therefore, network lifetime to use game theory-based protocols than protocols without game theory. This approach does not consider the mobility of nodes as well as the CR aspect of the sensor network.

A game theory-based clustering algorithm for wireless sensor networks is proposed in [4]. The proposed approach is based on LEACH [2] and CROSS [5], and a game-theoretic approach is considered during the selection of cluster heads. The proposed work achieves an even distribution of cluster heads and uniform energy consumption across the network. However, the proposed approach does not consider the mobility of the nodes and the CR aspect of the network.

Evolutionary game-based routing protocol for wireless multimedia sensor networks is proposed in [6]. After cluster formation in the network, the cluster head node for each cluster is elected by using the evolutionary game. The proposed approach shows improved performance in terms of energy efficiency, end-to-end delay, packet delivery ratio, network lifetime, and cluster formation time.

A spectrum-aware version of LEACH was proposed in [7] that is applicable for CRWSN. The proposed protocol was named CogLEACH. In this enhanced version, the number of free channels was considered as a weight in computing the probability of each sensor node for becoming cluster head. CogLEACH outperformed LEACH. However, the issues of network topology, mobility of nodes, and channel quality were not properly considered in the design.

A spectrum-aware clustering approach was proposed in [8] for CRWSN. In this work, network topology and spectrum availability were represented jointly through an undirected bipartite graph. Spectrum aware clusters were formed by constructing bicliques of maximum size from the bipartite graph. This protocol does not consider the residual energy of the nodes and incurs heavy computational loads. Node mobility was also not considered.

A cluster formation approach was introduced in [9] considering various weighted clustering metrics such as temporal-spatial correlation, confidence level, and residual energy level that are applicable for CRWSN. The assumptions made in this work were very firm, for example, the Euclidean distance between any two nodes is known and it does not change. Channel state was also not considered.

Network Stability Aware Clustering protocol (NSAC) has recently been proposed in [10] for CRWSN. This protocol considers power consumption and spectrum dynamics simultaneously. Channel quality has been considered as a metric while cluster head nodes were selected. A modified version of NSAC applicable for CRWSN has very recently been proposed in [11]. However, both protocols do not consider node mobility in CRWSN.

In [15], a node clustering approach for heterogeneous cognitive radio wireless sensor networks has been proposed. The scheme aims at energy saving. However, node mobility is not considered in the network.

Thus, there is a research gap considering the issue of node clustering in CRWSN in which a solution handles node mobility, spectrum availability, and energy availability simultaneously. In this work, all these above-mentioned three dimensions are considered while clusters are being formed in a given CRWSN setup.

In the following part of this section, a brief introduction to Evolutionary Game Theory (EGT) is presented. The EGT concept was first introduced in 1973 by John Maynard Smith and G. R. Price [12,13]. In recent times, game theory has widely been used in the area of computer networks. The biological evolution with organism and mutation process has been included in the concept of EGT and it is different from the classical Game Theory. In EGT, each player is interacting with other players, and they learn and adapt from each other's strategies. In EGT, players are known as a *population* that consists of individual players, and the expected payoff is known as the *fitness* of individuals. Therefore, in EGT, an individual can observe the activities of other individuals and learn from these observations, and subsequently adapt its strategy so that the entire population reaches equilibrium. EGT helps to understand the dynamics of interactions among individuals in a population [14]. Also, when the entire population is using the same strategy, there can be a small group of invaders within the population using a different strategy. However, these invaders will eventually die off over multiple generations as they learn from other individuals and adapt to the best strategy.

There are two basic concepts involved in EGT, i.e., evolutionary stable strategy (ESS) and replicator dynamics.

i) Evolutionary Stable Strategy (ESS): A strategy S is an ESS if there is a (small) positive number y such that when any other strategy T invades S at any level $x < y$, the fitness of an organism playing S is strictly greater than the fitness of an organism playing T. For all the strategy $T(S{\neq}T)$, then ESS is given by such that

$$U(S, xT + (1-x)S) > U(T, xT + (1-x)S) \tag{1}$$

where $x \in (0, y)$, y is invasion bound, which is a constant associated with strategy T, and$xT + (1-x)S$ is computed from groups that select the ESS and groups that adopt a mutation strategy.

ii) Replicator Dynamics: It is used to analyse the behaviour of the entire population based on the "survival of the fittest" principle of evolution theory. The equation that determines population behaviour is given as

$$X(t) = \frac{dx}{dt} = X_i(t)\left[U_i(t) - \overline{U}(t)\right] \tag{2}$$

where $X_i(t)$ represents the group in the population choosing strategy i at time$t$, $U_i(t)$ represents the payoff of individuals in the group who select strategy i at time t, and $\overline{U}(t)$ is the average payoff received by each individual in the group at time t [12]. It indicates that the group with better fitness will grow whereas the group having less fitness will be diminishing in size slowly.

3. System model

In this section, the entire system model adopted in this work has been detailed.

Network model: The sensor nodes are cognitive radio enabled. The sensor nodes are distributed randomly in the sensor field. The cognitive radio sensor nodes are resource-constrained, and the nodes are mobile with low speed, 2–4 m/min. The sink node is located outside the sensor field. The sink node is static. It has been assumed that the PUs who are licensed users arrive in the system following the Poison Arrival process. Cognitive radio-enabled sensor nodes are opportunistic users and are also known as the SUs. The SUs are going to form the clusters and finally, the communication shall take place through a cluster-based hierarchical approach among the SUs considering the sink as the destination. Fig. 1 shows this network model.

The nodes are deployed randomly in inaccessible environments. The sensor field is unattended and also of hostile nature. The nodes are deployed by uncontrolled means, for example, from helicopter or airplane. It has been assumed that as per the above consideration, the deployment of nodes follows poison distribution. Thus, the probability that there are m nodes within area s is given by the following expression [28].

$$P(m) = \frac{(\lambda s)^m}{m!} e^{-\lambda s} \tag{3}$$

Channel model: It is considered that there are Nchannels available to be accessed by the SUs opportunistically. Each of these N channels is licensed to the PUs. All the channels can be modelled as Rayleigh fading channels. Based on the proximity of the communicating nodes, there can be interference among the SUs. The terms SU node and CR node are used interchangeably. Fig. 2 shows how the CR nodes (i.e., nodes numbered as 1,2,3, & 4) can interfere with each other. The figure also shows how the CR nodes can interfere with the PU even. It is assumed that the interference radius is double the communication radius.

Energy model: In CRWSN, the CR nodes apart from data transmission and reception perform additional tasks of spectrum sensing and switching. Hence, the energy consumption is more in CRWSN as compared to traditional WSN. So, while designing the energy consumption model all four tasks have to be considered. Assume, E_{ss} to be the energy consumed during spectrum sensing, E_{sw} to be the energy consumed during spectrum switching. The energy consumed by i^{th} SU during data transmission of $\mathscr{L}$ bits is expressed as mentioned below [15,31].

$$E_{tx,i}(\mathscr{L}) = \begin{cases} \left(e_{RF} + e_{amp} d^2\right) \times L, d < d_0 \\ \left(e_{RF} + e'_{amp} d^4\right) \times L, d \geq d_0 \end{cases} \tag{4}$$

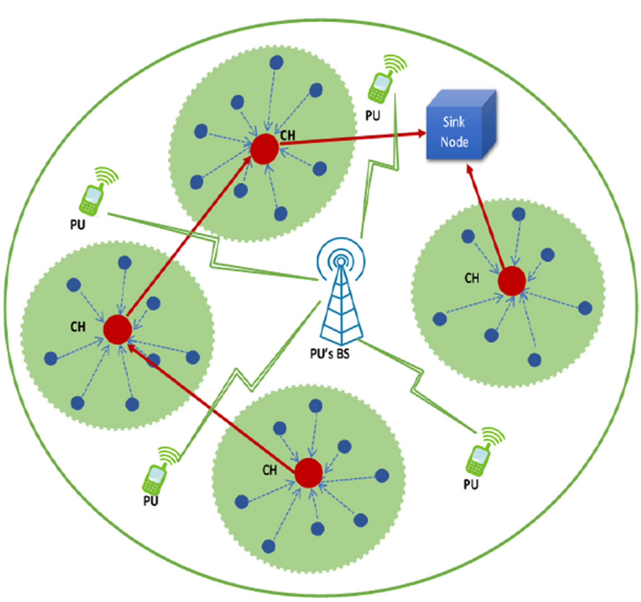

Fig. 1. Cluster-based hierarchical communication among the SUs.

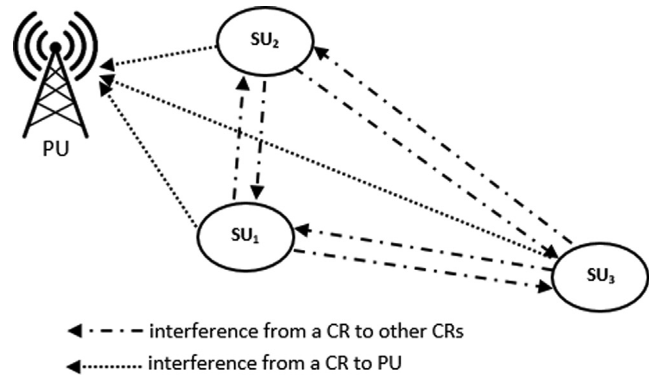

Fig. 2. Interference in different channels by different entities.

where e_{RF} is the energy consumed by the radio frequency circuit to receive and transmit the signal,e_{amp} and e'_{amp} are the amplifier energy related to path loss model used, d is the distance between transmitter node to receiver node, and d_0 is the distance threshold used to differentiate path loss model where $d_0 = \sqrt{e_{amp}/e'_{amp}}$ [16].

Considering the i^{th} SU receives $\mathscr{L}$ bits of data, the energy consumed during the reception mode is

$$E_{rx,i}(\mathscr{L}) = e_{RF} \times \mathscr{L} \tag{5}$$

Mobility model: The objective behind this work is to achieve stable clusters. Therefore, the cluster head nodes are expected to be the nodes with relatively low mobility. To characterize the instantaneous nodal mobility M_i, the following expression is used [17,18].

$$M_i = \frac{1}{T} \sum_{t=1}^{T} \sqrt{(x_t - x_{t-1})^2 + (y_t - y_{t-1})^2} \tag{6}$$

where (x_t, y_t) and (x_{t-1}, y_{t-1}) are coordinates of a node n_i at time instants t and $t-1$ respectively. Again, T is the period for which this parameter is going to be estimated. It is also assumed that the nodes move following the random waypoint mobility model.

M_i is defined to be the movement profile of a node i, and is computed by using (6).

4. Proposed clustering approach

In this section, a node clustering algorithm for cognitive radio wireless sensor networks is proposed. The majority of the computing burdens have been shifted to the sink as the sink is considered to be a resourceful node.

Assumptions. *There are a few assumptions made concerning the characteristics of the nodes. It is assumed that the sensor nodes (i.e., the PU or CR nodes) know their residual energy level and geographic location. Movement profile as per (6) is also computed by each node. Moreover, it has been assumed that each node is aware of the probability of PU arrival at its proximity that can be interfered with by itself. The phenomenon of interference is shown in Fig. 2.*

The entire process of node clustering may be presented in terms of various stages as mentioned below.

Stage 1: In this stage, the sink collects data from the participating nodes. The important parameters collected from the nodes are *node_id, residual energy level, geographic location, PU arrival probability, and the movement profile.*

Stage 2: The sink node creates the topology of the cognitive radio sensor network. This topology is created based on the geographic location and movement profiles of the sensor nodes.
Stage 3: The sink node forms the clusters after forming virtual grids across the sensor field. Grids are merged based on the necessity to form clusters.
Stage 4: The sink node classifies the participating nodes inside each cluster, into two classes as eligible (E_{CH}) and ineligible (NE_{CH}).
Stage 5: The sink node runs Evolutionary Game Theory-based computations and selects the respective cluster head nodes inside each cluster.

The advantage of this approach is that as the computational overhead is shifted toward the sink, and communication overhead is minimized, the sensor nodes save energy. Moreover, the cluster head nodes selected are always the nodes having a balanced cumulative value among various parameters such as residual energy level, mobility, PU arrival probability, and geographic locations. Therefore, the cluster head nodes tend to be geographically uniformly distributed. The entire process of cluster formation and cluster head selection has been depicted in Fig. 3.

Details of the stages are mentioned below.

In **stage 1**, the sink node collects the following five different parameters from each of the nodes: <*node_id, residual energy level, geographic location, PU arrival probability, and the movement profile* > .

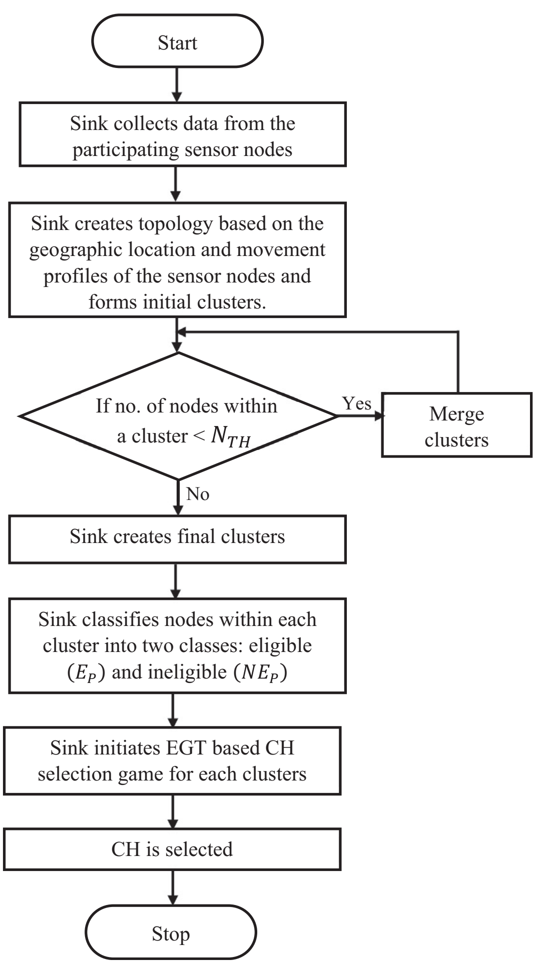

Fig. 3. Cluster formation and cluster head selection process.

In **stage 2**, once the sink node gathers the information from all the sensor nodes, it creates the topology of the cognitive radio sensor network. This initial topology is created based on the geographic locations, and the movement profiles of the sensor nodes.

In **stage 3**, the sink node forms various clusters covering the entire sensor field. Depending on the location of the nodes, the sink node forms the initial cluster by dividing the deployed area into *nbyn* grids. Each grid is initially considered as a cluster. Then the number of nodes within each cluster is examined. Each cluster should have a minimum threshold number of nodes. For example, a minimum of 10% of the total nodes deployed in the field may be considered as the threshold, to determine the minimum number of nodes required inside each cluster. The clusters are scanned from left to right and top to bottom, as given below:

a. The sink node divides the deployed are into *nbyn* equal virtual grids. Each grid forms one cluster. Therefore, there will be n^2 clusters initially.
b. A minimum number of nodes that each cluster should have is pre-decided, and a threshold value, N_{TH}, is set; for example, $N_{TH} = 10\% of Total number of nodes deployed$.
c. The sink node scans each cluster (from left to right in the entire grid set) and checks the number of nodes present in the cluster. If the cluster i has less then N_{TH} then it checks its neighbour clusters horizontally, and the nodes within cluster i are assigned to its neighbour (the cluster on the right side). The maximum number of merge operations that are permitted to occur in a horizontal row of the initial grid set is $n/2 + 1$. And thus, the minimum number of individual clusters that can form in a given row isn/2
d. Step c is repeated until all the clusters are scanned. Therefore, from the initial n^2 clusters, the final clusters are formed; and this final number of clusters is generally less than n^2. This is due to the merging of initial clusters for the low density of the nodes inside initial clusters.
e. The sink classifies all the nodes into different final clusters.

[Note: if after the maximum number of permitted merge operations, some clusters in a row, are left with less than the threshold number of sensor nodes, then it is left as it is; vertical merging is not attempted in this work.]

Fig. 4 depicts the process of cluster formation. Initially, virtual grids are formed. The scan happens from left to right and top to bottom. Initially, each grid is a cluster. Due to the fewer number of nodes inside each initial cluster, the adjacent clusters are merged. For example, cluster (1,1) and (1,2) are merged. Similarly, the remaining three initial clusters in the same row are merged and one cluster is formed. The black solid arrow indicates the merging of initial clusters.

In **stage 4**, nodes are classified as eligible (E_{CH}) and ineligible (NE_{CH}) respectively.

The sink node collects various node information during stage 1. Various information collected from the nodes are as mentioned below: < *node_id, residual energy level, geographic location, PU arrival probability, and the movement profile* > . These parameters are processed by the sink node and the sensor nodes inside each cluster are classified into two sets: eligible (E_{CH}) and ineligible (NE_{CH}).

Three main parameters contribute the maximum in selecting the elements for the above mentioned two sets E_{CH} and NE_{CH}. The parameters are *residual energy level, PU arrival probability, and the movement profile*. Ideally, the node with higher *residual energy*, having lower *PU arrival probability*, and being relatively a more stable one, although all the nodes are mobile, is the most suitable node for the cluster head role.

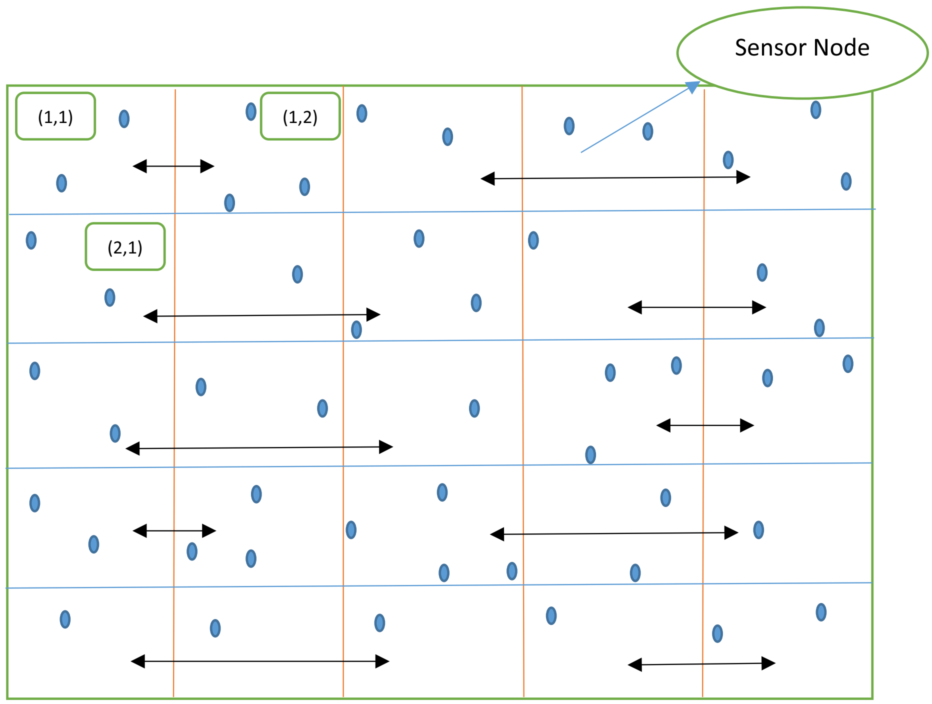

Fig. 4. Schematic diagram demonstrating the process of clustering.

Then a weighted cumulative value for each node i (denoted as W_i), considering these three parameters is computed.

$W_{i=}$ W_1 (residual energy level) + W_2 /(PU arrival probability) + W_3 /(mobility in terms of movement profile)

$$W_i = W_1 \times E_i + \frac{W_2}{P_i} + \frac{W_3}{M_i} \quad (7)$$

where $W_1 + W_2 + W_3 = 1$ and $0 \leq P_i \leq 1$; M_i is computed using (6).

Thus, the nodes having the "W_i" value above a threshold (W_{TH}), become members of E_{CH} set, and the remaining nodes become members of NE_{CH} set.

$$E_{CH} = \left\{ n_i | n_i is the i^{th} sensor node and W_i \geq W_{TH} \right\} \quad (8a)$$

$$NE_{CH} = \left\{ n_j | n_j is the j^{th} sensor node and W_j < W_{TH} \right\} \quad (8b)$$

Moreover, $E_{CH} \cup NE_{CH} = N_s$, where N_s is the set of all the cognitive radio sensor nodes deployed in the field.

The nodes in the E_{CH} set shall compete for the cluster head role and the nodes in the NE_{CH} set shall remain as ordinary cluster member nodes.

In **stage 5**, the sink node does the necessary computation, as mentioned below, to select the most suitable nodes, as respective cluster head nodes for each of the clusters.

A game is designed for the selection of cluster heads based on evolutionary game theory inspired by the work presented in [6]. Let the cluster head selection game be denoted by $CHSG < P, S, U >$ where P represents the player set, S represents the strategy set that will be used by the players, and U represents the utility or payoff earned while playing a certain strategy.

The sink node classifies the sensor nodes within each cluster into two classes i.e., eligible (E_P) and ineligible (NE_P) as mentioned in stage 4. It is worth mentioning that eligible (E_P) and ineligible (NE_P) node sets are equivalent to eligible (E_{CH}) and ineligible (NE_{CH}) node-set mentioned in stage 4, respectively; the reason behind the symbol p being used instead of CH is that, in stage 5, the nodes are now players (p) as per the game theory under consideration.

If a node has a residual energy percentage greater than a certain energy threshold percentage (RE_T) then it is grouped into E_P otherwise into NE_P. Therefore, the player set $P = E_P \cup NE_P$. The strategy that the players can choose is either to become a cluster head (s_{CH}) or not be a cluster head (s_{NCH}). Therefore, the strategy set is given as

$$S = \{s_{CH}, s_{NCH}\} \quad (9)$$

Depending on the strategy selected by a node i within a cluster, the utility function of node i is defined as

$$U_i = R_i - P_i \quad (10)$$

where R_i denotes the reward earned and P_i denotes the penalty imposed for the strategy selected during the game. The reward and penalty are essential because there should be some incentive for performing the role of cluster head and penalty for escaping to be a cluster head. The cluster head nodes have to perform additional tasks therefore, the energy depletion will be higher compared to normal nodes and many nodes can act selfishly to conserve their energy. So, we consider that the reward gained for becoming a cluster head by a node $\in E_P$ is θ and the reward gained by nodes $\in NE_P$ is ω. Also, a step of incentive or disincentive (represented by δ) for becoming a cluster head is assumed.

In evolutionary game theory, it is very important to formulate the ESS. An ESS is a state in the game that ensures that different species in a population co-exist together and do not threaten each other by increasing the extinction probability through a selfish choice of strategies. For this *CHSG* (Cluster Head Selection Game) game, the ESS is the nodes in E_P subset should select the strategy s_{CH} and the nodes in NE_P subset should select the strategy, s_{NCH}.

Suppose we consider that the nodes belonging to E_P subset selects the strategy s_{CH} with the probability p then the probability for selecting the strategy s_{NCH} will be $(1-p)$. Similarly, for the nodes belonging to the subset NE_P, the probability of choosing the strategy s_{CH} is q then the probability for selecting the strategy

s_{NCH} will be $(1-q)$. Using these probabilities and rewards, a payoff matrix can be formulated as shown in Fig. 5.

Using the payoff matrix, the expected utility or payoff earned by nodes in E_P set by choosing the strategy to become cluster head i.e., s_{CH} is

$$U_{E_P(s_{CH})} = q\theta + (1-q)(\theta + 2\delta) = \theta + 2\delta - 2\delta q \quad (11)$$

The expected utility or payoff earned by nodes in E_P set by choosing the strategy not to become cluster head i.e., s_{NCH} is

$$U_{E_P(s_{NCH})} = q(\theta - \delta) + (1-q)(-\delta) = q\theta - \delta \quad (12)$$

Therefore, the total reward for nodes in E_P set will be

$$\overline{U_{E_P}} = p(\theta + 2\delta - 2\delta q) + (1-p)(q\theta - \delta) \quad (13)$$

Similarly, the expected utility or payoff earned by nodes in NE_P set is formulated as

$$U_{NE_P(s_{CH})} = p\omega + (1-p)(\omega + \delta) = \omega + \delta - \delta p \quad (14)$$

$$U_{NE_P(s_{NCH})} = p(\omega + 2\delta) + (1-p)(-\delta) = \omega p + 3\delta p - \delta \quad (15)$$

Therefore, the total reward for nodes in NE_P set will be

$$\overline{U_{NE_P}} = q(\omega + \delta - \delta p) + (1-q)(\omega p + 3\delta p - \delta) \quad (16)$$

Using eq. (11) and (14), the utility of each node within a cluster is calculated. The node having the highest utility value is elected as cluster head and other nodes act as cluster members.

Interpretations of various symbols used in the above mathematical framework (eq. 9–16) are given in Table 1.

Finally, the sink node sends a < cluster_info > message to all the nodes, which contains the information about the cluster to which a node belongs. The message format will contain < *node_id, cluster_id, clusterhead_id* > .

Following are the various data structures necessary to be used in the proposed approach (Table 2):

5. Analysis of the proposed clustering approach

In this section, an analysis of the presented clustering approach is presented.

5.1. Theoretical analysis

Lemma 1. *Formed clusters are mutually exclusive.*

Proof: The sink node forms the clusters. The sensor field is geographically virtually partitioned into the grids. In the process of forming the final clusters, initial clusters are merged sometimes, if the total number of nodes inside a cluster does not reach at least the threshold number. Thus, there is no chance that a sensor node can become a member of more than one cluster. As the sensor node does not choose a cluster head node, rather it is the sink node that forms the clusters and also selects the cluster head nodes, the formed clusters are always mutually exclusive.

		q	$(1-q)$
	E_P \ NE_P	s_{CH}	s_{NCH}
p	s_{CH}	θ, ω	$\theta + 2\delta, \omega + 2\delta$
$(1-p)$	s_{NCH}	$\theta - \delta, \omega + \delta$	$-\delta, -\delta$

Fig. 5. Payoff matrix.

Table 1
Interpretation of various symbols used in the mathematical framework.

Symbol	Interpretation	Symbol	Interpretation
P	Player set	q	The probability that nodes belonging to NE_P subset selects the strategy s_{CH}
S	Strategy Set	δ	A step of incentive or disincentive for becoming a cluster head
U_i	Utility function for node i	$U_{E_P(s_{CH})}$	The expected utility or payoff earned by nodes $\in E_P$ to become cluster head by selecting the strategy s_{CH}
R_i	Reward earned for node i	$U_{E_P(s_{NCH})}$	The expected utility or payoff earned by nodes $\in E_P$ choosing strategy s_{NCH} i.e., not to become cluster head
P_i	Penalty imposed for node i	$\overline{U_{E_P}}$	The total payoff for nodes in E_P
θ	The reward gained for becoming a cluster head by a node $\in E_P$	$U_{NE_P(s_{CH})}$	The expected utility or payoff earned by nodes $\in NE_P$ to become cluster head by selecting the strategy s_{CH}
ω	The reward gained for becoming a cluster head by nodes $\in NE_P$	$U_{NE_P(s_{NCH})}$	The expected utility or payoff earned by nodes $\in NE_P$ choosing strategy s_{NCH} i.e., not to become cluster head
p	The probability that nodes belonging to E_P subset selects the strategy s_{CH}	$\overline{U_{NE_P}}$	The total payoff for nodes in N E_P

Theorem 1. *The number of clusters to be formed* (N) *satisfies the condition* $n/2 \le N \le n^2$ *where n is the initial number of grids in a row after partitioning the sensor field into* $n \times n$ *grids.*

Proof: During the initial stage of the clustering process, the sensor field is logically partitioned into n $\times$ n grids. At this stage, the number of clusters N_{TH}. Then the grids are scanned from left to right and top to bottom. Considering the geographic locations of the sensor nodes, if the number of sensor nodes inside a cluster is less than a threshold value (N_{TH}), then horizontally adjacent grids are merged one by one to form a new cluster; this process continues till the number of nodes inside each cluster $> N_{TH}$. Thus, depending on the geographic distribution of the sensor nodes, and the value of N_{TH}, the largest possible number of clusters is n^2. On the other hand, the merging of grids in a particular row can continue for a maximum of n/2 times. Thus, the number of clusters in each row can never be lesser than $n/2$, provided each grid contains at least one sensor node. And it has been assumed that although the sensor nodes are deployed randomly, each virtual grid contains at least one sensor node.

Theorem 2. *Uniform geographic distribution of the cluster heads is ensured.*

***Proof*:** The cluster head nodes are selected after the formation of the clusters. Again, the clusters are either the initially formed grids or merged grids. Due to the virtual partitions created in the sensor field in terms of grids, and the process of conditional merging of grids, the final clusters are geographically uniformly distributed. Cluster head nodes are selected in such a way that the most suitable node in terms of parameters such as < *noterid, residual energy level, geographic location, PU arrival probability, and the movement profile* > becomes the cluster head for the respective cluster. Thus, the cluster head nodes are uniformly geographically distributed.

Table 2
Data Structures used.

Available channel list for the cognitive nodes (i.e., the sensor nodes)
List of cluster head nodes
List of cluster members for the cluster c_i
List of common channels between any two cognitive nodes
Residual energy levels of the cognitive nodes
Movement profile/mobility of the cognitive nodes
PU arrival probability against each available channel for cognitive nodes.

Theorem 3. *Communication overhead is minimized.*

Proof: The process of cluster formation involves the broadcasting of only one packet originated by each node containing the parameters mentioned as < *nomeid, residual energy level, geographic location, PU arrival probability, and the movement profile*>. Although the intermediate nodes in the sensor field may have to forward other packets as well, originated elsewhere, as per the broadcast policy. Then the sink node creates clusters and also selects the cluster head node for each cluster. Then each cluster head node advertises its role, and subsequently, cluster member nodes join the respective cluster just by sending one < ack > message. Therefore, it is evident that the number of communications involved in the process of cluster formation, cluster head selection, and joining the clusters by member nodes is the minimum, and the communication complexity is O (1).

Theorem 4. *Unique clusters are formed.*

Proof: The process of cluster head node selection is based on evolutionary game theory and inspired by the process depicted in [6]. However, the outcome of our protocol in terms of cluster formation is different and unique. This is so because the way sensor nodes are classified into eligible, and ineligible is unique, and different from that of [6].

Theorem 5. *In the event of executing the cluster formation protocol, every sensor node receives a role either cluster member or cluster head.*

Proof: The sink node is responsible for forming the clusters and also for identifying one cluster head node per cluster. After the formation of the clusters, the sink node classifies all the sensor nodes belonging to each cluster into two sets, namely, eligible (E_{CH}) and ineligible (NE_{CH}) set of nodes (stage 4 of the procedure). Eventually the most suitable node from the eligible (E_{CH}) set receives the role of cluster head. The remaining nodes of the eligible (E_{CH}) set, and all the elements of the ineligible (NE_{CH}) set become cluster members. It is already stated that $E_{CH} \cup NE_{CH} = N_s$, where N_s is the set of all the nodes deployed in the field. Therefore, every node deployed in the field receives a role either cluster member or cluster head.

Theorem 6. *The cluster formation and cluster head selection algorithms terminate.*

Proof: The sink node collects various node information initially. This data collection happens for a suitable period. The movement profile also includes the direction of movement, apart from relative speed. Once preliminary data collection is over, the rest is only a matter of processing. Being the sink node a resourceful one, it can form the clusters and also select the cluster head nodes by running appropriate algorithms as discussed. Since the processing of initial data takes place in the sink, and this processing does not need any more intermediate data from the sensor nodes, the formation of clusters and the selection of cluster head nodes eventually come to an end within a finite time. Had there been any necessity of data from the sensor nodes, in the middle of the computation, there could have been a situation under which the algorithms would have gone into loops. The collected movement profile of a node is sufficient to estimate the location of the node at a different instance of time, then the time of data collection.

6. Performance evaluation

The proposed clustering scheme is simulated for its performance evaluation. A cognitive radio wireless sensor network setup consisting of wireless sensor nodes enabled with cognitive radio has been considered. The simulation has been carried out in MATLAB 7.1. The sensor nodes are considered to be deployed randomly. The sink node is located outside the sensor field. The sensor nodes have mobility; however, the sink node is considered to be static. Each simulation ran for 1800 s. There were six rounds each of 250 s, in each simulation. During one round, the cluster setup was considered to be the same. Various essential parameters considered for simulation are presented in Table 3. The presented values of different parameters are an average of six different simulations taken repeatedly.

In this section, various results showing the performance of the proposed clustering scheme are presented.

As mentioned earlier, the sensor nodes are deployed randomly. Fig. 6 depicts initial random node deployment across the sensor field.

Fig. 7 shows the initial cluster formation as per the proposed clustering protocol. At this stage, the merging of clusters considering the number of nodes inside each cluster has not taken place. Different colours are used to show unique clusters.

Fig. 8 shows the final cluster formation as per the proposed protocol. At this stage, the merging of initial clusters formed has taken place. The clusters are geographically uniformly distributed. Since the nodes are mobile, the presented scenario is valid for a duration t only. Figs. 6, 7, and 8 represent the snapshots at appropriate instants, during the entire simulation duration.

Fig. 9 presents the status regarding energy consumption during cluster formation. This energy consumption is due to necessary communication by the nodes as per the clustering protocol and required computation. The blue-coloured portion represents the total initial energy in the entire system of a varying number of

Table 3
Simulation setup.

Parameter	Value
Node deployment area	200 m × 200 m
Sink position	(250, 100)
Number of sensor nodes deployed	200
Number of primary users	5
Number of available channels	5
Initial energy of the sensor nodes	0.5 J
e_{RF}	50 nJ/bit
e_{amp}	10 pJ/bit/m^2
e'_{amp}	0.0013 pJ/bit/m^2
d_0	87 m
Data packet size	50 bytes
Control packet size	20 bytes

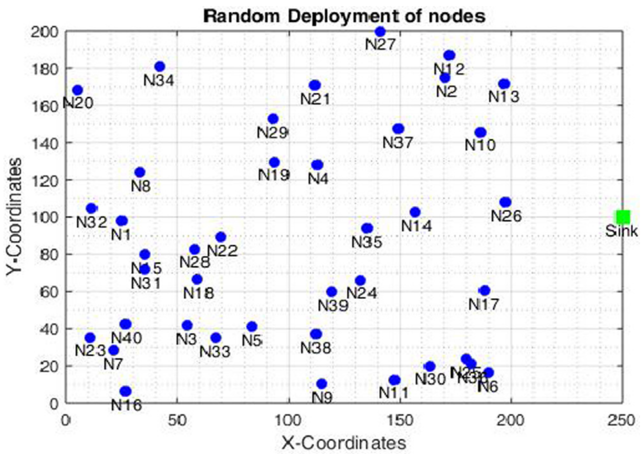

Fig. 6. Random deployment of 40 nodes.

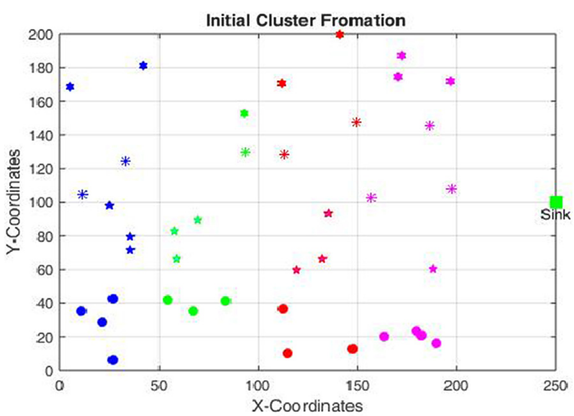

Fig. 7. Initial cluster formation.

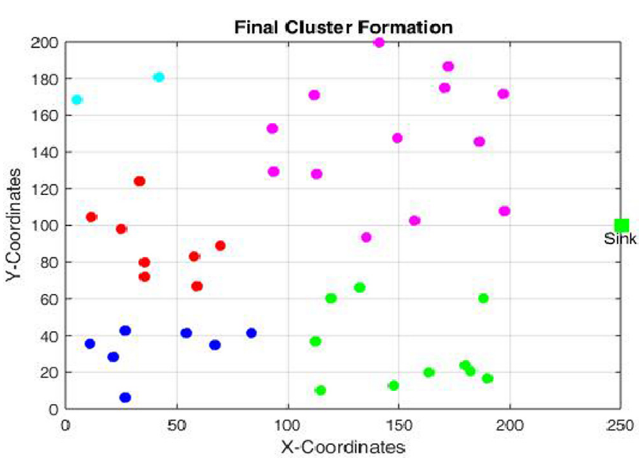

Fig. 8. Final cluster formation.

nodes, whereas the red portion represents the average energy spent in the entire system, due to cluster formation. It is observed that the average energy spent in the system decreases as the number of nodes increases. This is because, with the growth in the number of nodes, the network becomes dense. As a result, the physical distance between two nodes that need to be traversed reduces, and this incurs less energy as per the energy model considered (eq. (4)) in this work.

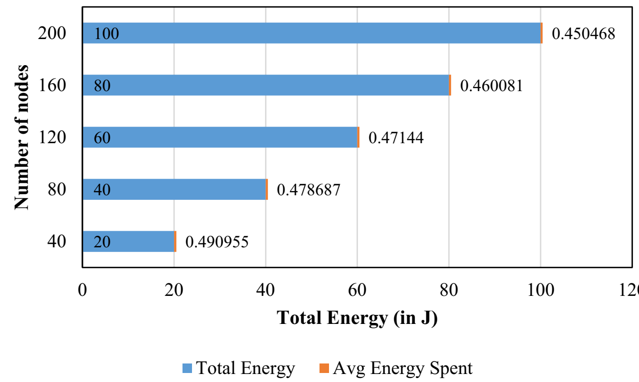

Fig. 9. Energy consumption against cluster formation.

Fig. 10 presents the rate of energy depletion during cluster formation. The rate of energy depletion is calculated as per the expression given in (17). The rate of energy depletion during cluster formation varies along with the number of nodes in the system. The rate declines along with the increase in the number of deployed nodes. This is because, as the number of nodes increases, the sensor field becomes denser, and the relative distances between the nodes decrease. As a result, the energy requirements for communication are reduced proportionally.

$$Rateofenergydepletion = \frac{InitialTotalEnergy - RemainingTotalEnergy}{InitialTotalEnergy} \times 100\% \tag{17}$$

Energy expenditure that occurred during the process of cluster head selection is shown in Fig. 11. Again, the blue-coloured potion represents the total energy available in the network system considering all the sensor nodes, whereas the red portion represents the average energy spent during the cluster head node selection. The average energy spent during cluster head node selection increases along with the increase in the number of nodes in the system. This is because as the number of nodes increases the number of cluster head (CH) nodes also increase. However, the energy spent is quite less as compared to the cluster formation process, because as per the protocol the sink nodes select the CH nodes based on the initial information collected. Thus, processing happens in the sink node only. Finally, the sink node informs all other nodes about the selected cluster head nodes. Thus, the sensor nodes spend energy

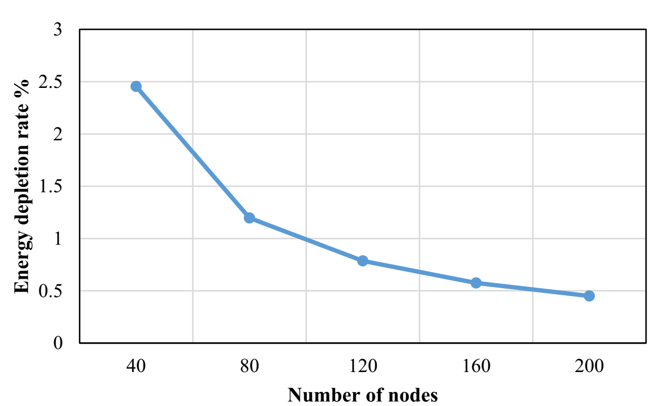

Fig. 10. Rate of energy depletion during cluster formation.

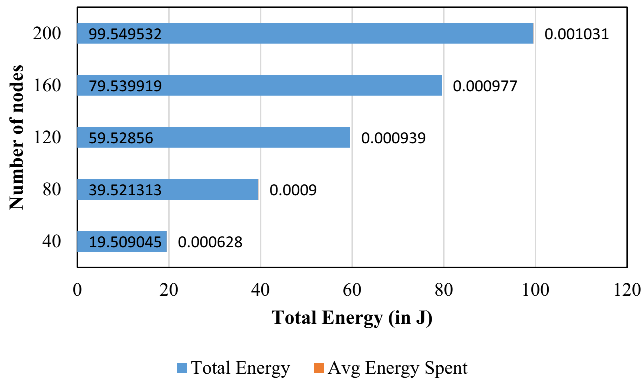

Fig. 11. Energy consumption in selecting CH.

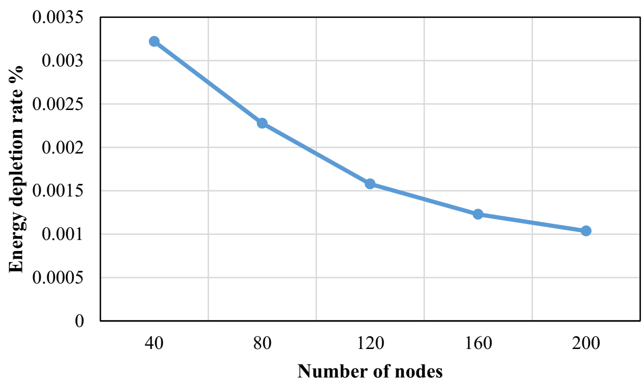

Fig. 12. Rate of energy depletion during CH selection.

in receiving such messages sent by the sink. As a result, the energy consumption is very less in the process of CH selection, and increases proportionally, as the number of nodes increase.

As per eq. (17), the energy depletion rate during the process of cluster head selection is computed. Fig. 12 represents this energy depletion rate. This energy depletion is due to the necessary communications between the sensor nodes and the sink node. Here, this parameter represents the rate of reduction or depletion of energy levels in the nodes during the cluster head selection. The rate declines along with the increase in the number of deployed nodes. However, the rate of increase is very low because as the number of nodes increases, the total energy of the network increases. It is also observed that the rate of energy depletion is lower during CH selection as compared to cluster formation.

The performance of the proposed clustering protocol in terms of the quality of the selected CH node has been compared with the protocol proposed in [9], RARE [35] and LEACH [2]. Here, the quality of the selected cluster head node indicates two parameters. The first one is the *percentage of high-energy sensor nodes* that has got selected as cluster head. High energy indicates that the residual energy level of the selected cluster head node is above a certain threshold. Here this threshold has been considered as 75% of the initial energy level. The second parameter is the *geographical distribution* of the selected cluster head nodes. The way, the selected cluster head nodes are geographically uniformly distributed in the parameter under consideration. No two selected cluster head nodes are expected to be geographically close to each other. Although this term “close” is qualitative, intuition has been considered in judging the uniform distribution of the cluster head nodes in terms of geographic location. Since the simulated system is relatively smaller in terms of the number of deployed nodes, this was quite possible to determine without any hassle.

Fig. 13 shows the percentage of high-energy nodes that have been selected as cluster head nodes, during the entire simulation duration. This parameter is calculated under the influence of the proposed protocol, LEACH [2], RARE [35] and the protocol reported in [9].

It is observed that the proposed protocol outperforms protocol in [9] by 23%, LEACH by 26%, and RARE by 28%. This is because the residual energy in the nodes has been considered as a parameter while selecting the nodes suitable as candidate nodes for the cluster head role.

Fig. 14 presents the geographic distribution of the selected cluster head nodes under the influence of the proposed protocol, LEACH, RARE and the protocol reported in [9].

It is observed that the proposed protocol outperforms the protocol in [9] by 28%, LEACH by 40%, and RARE by 43%. This is because, the way grids are formed in the sensor field, and the way grids are merged to form the final clusters, naturally lead toward the uniform geographic distribution of the cluster head nodes.

Fig. 15 presents the total energy consumed in the system due to packet transfer under the influence of various protocols over the simulation span.

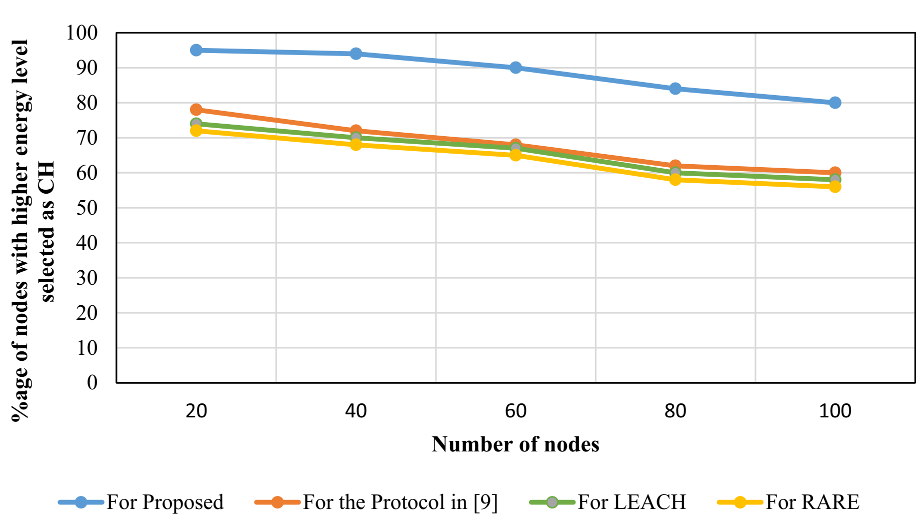

Fig. 13. Energy levels of the CH nodes.

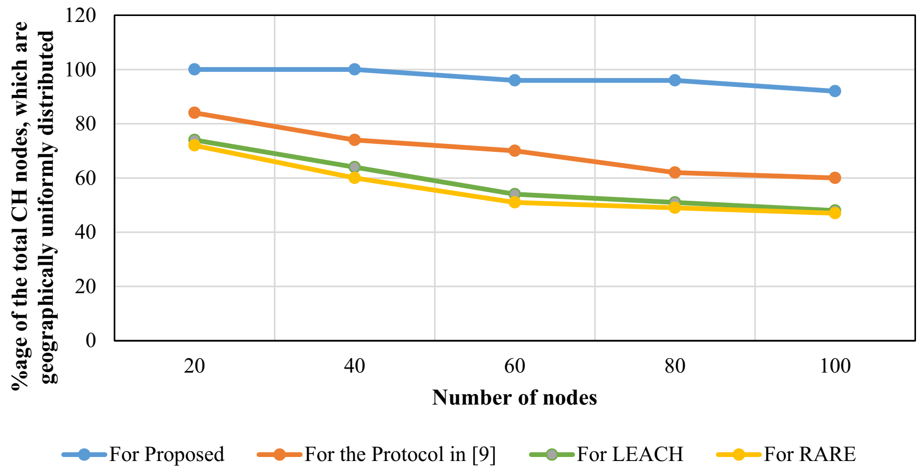

Fig. 14. Uniformity in the geographical distribution of the CH nodes.

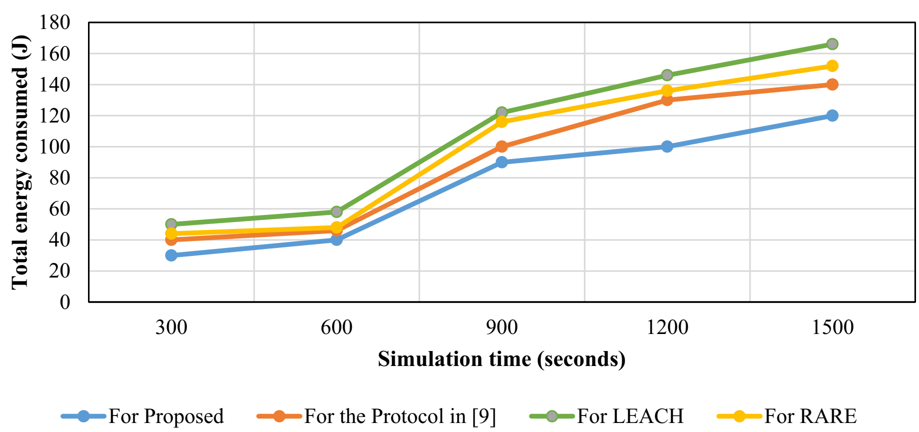

Fig. 15. Energy consumption versus simulation time.

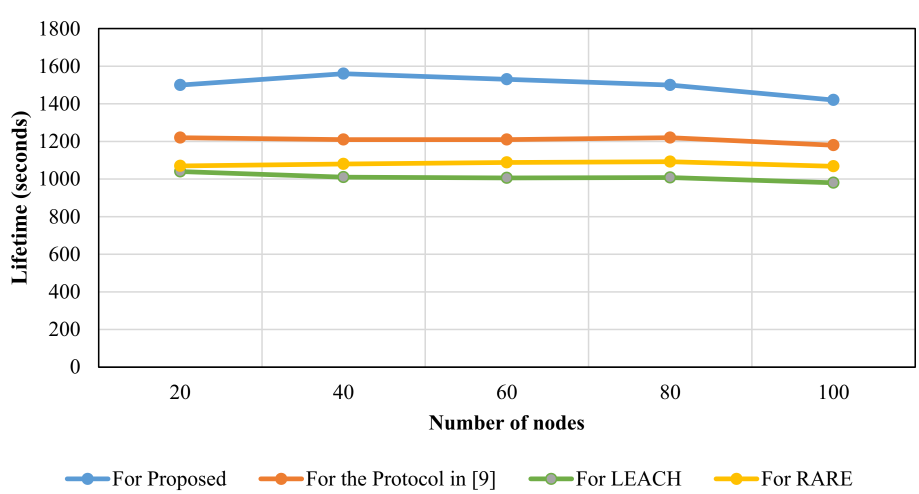

Fig. 16. Number of nodes versus network lifetime.

It is observed that the proposed protocol reduces energy consumption by 17% as compared to the protocol in [9], by 31% as compared to LEACH, and by 23% as compared to RARE.

This is mainly because of the geographically uniform distribution of the cluster head nodes under the influence of the proposed protocol.

Fig. 16 presents the network lifetime analysis under the influence of various protocols. Lifetime is considered to be the time duration elapsed, till the death of 50% of the nodes deployed in the field.

It is observed that the proposed protocol increases the network lifetime by 20% as compared to the protocol in [9], by 33% as compared to LEACH, and 28% as compared to RARE.This is again due to the energy saving in the system and most of the energy saved under the influence of the proposed protocol is mainly due to uniform geographic distribution of the cluster head nodes, and lesser PU arrival in the channels of the CH nodes.

7. Conclusion and future work

In this paper, a node clustering protocol for CRWSN has been proposed. The sensor nodes are considered to be mobile. The proposed protocol is based on EGT. The sensor field is virtually partitioned into a suitable number of grids. Then grids are subsequently merged to form an optimal number of clusters depending on the geographical locations of the nodes. The sensor nodes are classified into two sets as {eligible}, and {ineligible} containing the identity of the nodes that are suitable to become cluster head, and not suitable to become cluster head, respectively. Once classification is done, the most suitable candidate node is selected as the CH for a particular cluster. This selection procedure is based on EGT. Moreover, as an outcome of this protocol, the most suitable candidate node inside each cluster, in terms of residual energy, geographic location, and movement profile, is selected as the CH node. The entire computing burden is shifted to the sink node. The proposed protocol outperforms the similar protocol proposed in [9], RARE [35] and also LEACH [2]. The performance of the proposed protocol was analysed in terms of the parameters like the number of high energy nodes selected as CH node, the percentage of uniform geographical distribution of CH nodes, the total energy consumed during the simulation time, and also the network lifetime. Shifting of computational load from the sensor nodes to the sink node is highly essential since the sink node is resourceful and it also possible to refuel the sink node. Moreover, uniform geographical distribution of the CH nodes is also important considering the uniform coverage of the sensor field and also to minimize the energy expenditure due to communication. Again, sensor nodes with higher level of residual energy should be selected as the CH nodes as it helps in prolonging the network lifetime by avoiding the necessity of frequent re-clustering.

As a future scope of the work, a hierarchical routing protocol for CRWSN may be designed that can use the clustering protocol proposed in this paper, to create clusters and select CH nodes.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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