Energy and Spectral Efficient Cognitive Radio Sensor Networks for Internet of Things

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***Abstract*—Energy and spectral efficient solutions are indispensable to the success of Internet of Things (IoT). The design and development of energy and spectral efficient solutions for IoT are very challenging mainly because of the large-scale deployment of a massive number of sensors and devices. Energy harvesting and cognitive radios (CRs) are considered as promising technologies for energy and spectral efficiency, respectively. In this paper, we propose an energy and spectrum efficient scheme for CR sensor networks (CRSNs). We present an architecture of CRSNs for IoT, in which sensor nodes can access the spectrum opportunistically and harvest energy from ambient radio-frequency sources. We then propose an energy management scheme that consists of: 1) energy-aware mode switching strategy which allows sensor nodes to perform dedicated energy harvesting based on their current energy level and 2) cluster head selection algorithm which considers current and average of past energy levels of sensor nodes to achieve a balance between network performance and lifetime. Furthermore, for reliable intracluster reporting, we propose a channel management strategy to assign the best quality channel to the sensor nodes in terms of stability and reliability. Extensive simulation results demonstrate the effectiveness of the proposed energy and spectrum efficient scheme and show superiority over existing schemes.**

***Index Terms*—Channel allocation, clustering, energy-harvesting, licensed users, sensor networks.**

I. INTRODUCTION

THE INTERNET of Things (IoT) is emerging as an important networking paradigm which enables communication among physical objects. It is anticipated that in near future, offices, industrial, and household devices will have the ability to sense, process the information, and communicate [1]. Thus, the number of wireless devices will continue to increase at an enormous rate, due to which IoT solutions have to face several challenges including energy and spectrum scarcity. These challenges caused by a large number of sensor devices in IoT require spectral and energy efficient methods. Following are the key technologies to develop spectral and energy efficient methods.

1) *Opportunistic spectrum sharing* is a potential solution to achieve spectral efficiency [2]–[4]. It can support a large number of connected devices and diverse range of applications. Cognitive radio (CR) is the key technology for opportunistic spectrum sharing which allows unlicensed devices [secondary users (SUs)] to coexist with a licensed network (primary network) [1], [2], [5]. Primary users (PUs) are those who subscribe to the primary network. CR sensor networks (CRSNs) can use all noncontiguous spectrum which makes it spectrum efficient [6].
2) *Wireless energy harvesting* can provide energy supply from radio-frequency (RF) signals which can enhance energy efficiency and extend network lifetime. In wireless energy harvesting, sensor nodes convert the received RF signal into dc power and use it to perform data transmission and other processing tasks. There can be two possible cases for wireless energy harvesting: a) sensor nodes can harvest energy from ambient RF signals and b) dedicated energy transmitters can be deployed in the vicinity of sensor nodes.

Several research efforts have been devoted to energy-efficient solutions for IoT [7]–[10]. Nishimoto *et al.* [11] introduced a prototype implementation of sensor nodes that are self-empowered by an ambient RF energy. The concept of RF energy harvesting in body area networks is proposed in [12], where energy is harvested from the radio signals of the spectrum band from 3 kHz to 300 GHz. In addition, authors proposed a work-on-demand protocol for energy management. Predominantly, the energy harvesting schemes presented in [13]–[15] prove that harvesting energy from ambient RF signals can meet the energy requirements of sensor nodes and devices. On the other hand, CRSN for IoT can improve spectrum utilization and exploit alternative opportunities for spectrum resources [16]. In [17], a performance comparison of CRSN for IoT is presented, in which different deployment patterns are considered for performance evaluation. Cognition and intelligence is developed and exploited in CRSN to benefit the network efficiency and user requirements [18], [19]. However, sensor nodes in CRSN for IoT require higher energy to perform spectrum sensing and spectrum sharing tasks in addition traditional functionalities [20]. Therefore, energy harvesting can be used in CRSN to improve energy efficiency and address these demands. To incorporate energy harvesting

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in CRSNs, sensor node selection and channel assignment schemes should be redesigned to cater the energy variations (difference between the harvested energy and energy consumption) for better power management and spectral-variations (random PU activity for stable reporting from the source node to sink node).

A. Contributions

In this paper, we investigate energy and spectrum efficient CRSN for IoT. We propose a novel framework that consists of a combination of mode switching, CH selection, and channel allocation that incorporate energy harvesting in CRSNs. The main contributions of this paper are as follows.

1) We propose an energy-aware mode selection strategy with two modes of operation: a) full capability mode (FCM) and b) reduced capability mode (RCM). The sensor nodes switch between FCM and RCM based on their residual energy level.
2) We propose a novel CH selection scheme while considering the current and average energy levels of sensor nodes.
3) We further investigate reliable intracluster channel management scheme (CMS) to assign the best channels in terms of stability and reliability.
4) Extensive simulations are conducted in order to validate the proposed framework for energy and spectrum efficiency and to compare with the existing schemes.

The rest of this paper is organized as follows. Related work is briefly discussed in Section II. System model is given in Section III. The proposed energy and spectrum efficient scheme is presented in Section IV. Simulation results and performance analysis are presented in Section V. Finally, the conclusion is given in Section VI.

II. Related Work

An overview of energy management and associated challenges for IoT is presented in [21]. Authors classify energy management for IoT into two types, i.e., energy-efficient solutions and energy harvesting operations. Energy efficient solutions include optimal scheduling for sleep and idle states, lightweight protocol design, and predictive models for energy consumption. A comprehensive survey of energy harvesting sources, their potential advantages, and applications is presented in [22]. Zhang and Ho [23] introduced two receiver architectures known as time switching and power splitting. The former allows the sensor node to select the received signal either as an information or an energy harvesting source whereas the later separates the received signals into two streams, one for the information receiver and the other for RF energy harvester. Liu *et al.* [24] presented an integrated architecture for spectrum and energy harvesting to deal with the challenges (such as data rate requirement) posed by modern and sophisticated applications.

Energy harvesting has been recently considered for CR networks to deal with energy scarcity. Park *et al.* [25] introduced energy harvesting in CR networks where an optimal spectrum sensing mechanism is proposed to maximize throughput under the constraints of energy causality and collision for spectrum access. Gao *et al.* [26] proposed a cooperative mechanism for wireless energy harvesting and spectrum sharing in 5G networks. An optimization problem is formulated to maximize the throughput of both PUs and SUs with constraints on data rate and energy harvesting. In [27], a channel selection method is proposed for energy harvesting in CR networks in order to obtain the maximal throughput of SUs under energy neutrality constraint and fading channel conditions. A CR system based on slotted mode is proposed in [28], where only SU can harvest energy from the ambient environment and system parameters can be optimized for the "harvesting-sensing-throughput" tradeoff. Lee *et al.* [29] introduced guard and harvesting zones in CR networks. If a node lies inside the harvesting zone then it harvests energy, and if it lies outside the guard zone then it performs data transmission. Although the proposed scheme optimizes throughput, it does not achieve energy balancing. In addition, it does not incorporate the PU behavior in the channel allocation decision.

Various protocols have been investigated for effective energy management in cluster-based CRSNs. In [30], a two level residual energy and channel quality aware sensor node classification scheme and channel pairing scheme are introduced for RF energy harvesting-based CRSN in order to select the best sensor node for reporting process. In [31], an adaptation of low-energy adaptive cluster hierarchy (LEACH) algorithm is introduced for CRSN that elect the cluster head (CH) on a rotational basis to evenly manage energy among different sensor nodes. Although the complexity of this algorithm is low, the irregular distribution of CHs makes it energy inefficient. In [32], a reinforcement learning-based trust and reputation model has been investigated for CH selection in CR networks; however, the focus is to detect malicious SUs. An event-driven spectrum aware clustering is proposed for CRSNs in [33]. First, candidate sensor nodes for CH are determined based on the distance of sensor nodes from the event and sink. Then, CH is selected among the candidate nodes depending on node degree, available channels, and distance from the sink in their neighborhood. In [34] and [35], CH selection strategies are proposed which selects CH based on weight. The weight is determined from residual energy of sensor nodes and average energy of sensors in that cluster. Similarly, an energy-efficient CH selection (EECHS) scheme is proposed in [36] in which CH is randomly selected from inner area nodes of the cluster. Zhu *et al.* [37] used a quantitative location data and binary qualitative connectivity data for clustering in WSNs. Another class of work is confined to incorporate multiple factors (e.g, energy, distance, and signal strength) in the CH selection. The aforementioned schemes improve the life span of the sensor nodes by proper tuning the topology and the CH selection. However, to incorporate the energy harvesting factor in cluster-based CRSNs, significant modifications are required in the protocols, procedures, and system models.

The channel allocation scheme plays a key role in spectral efficiency in CRSNs. Jain and Bohara [38] presented a two-phase protocol for energy harvesting and spectrum sharing in overlay mode for WSNs. The aim is to reduce

TABLE I
SUMMARY OF RELATED WORK IN CRSN FOR IOT

Ref.	Objective	C[a]	E[b]	A[c]	H[d]	Remarks
[21]	Energy management for IoT in smart cities with focus on smart homes	✗	✗	✗	✓	Efficient scheduling of idle and sleep times along with optimal selection of harvesting source
[23]	Concurrent information and power transfer using MIMO technology	✗	✗	✗	✓	Time switching and power splitting architectures are examined and analyzed analytically
[24]	Integrated spectrum and energy management	✗	✗	✓	✓	Energy and throughput optimization using cooperative channel sensing and efficient MAC layer protocols
[25]	Development of an optimal spectrum sensing policy for opportunistic spectrum access in an energy harvesting CR	✗	✓	✗	✓	Under infinite battery capacity investigation of optimal detection threshold for the spectrum sensor under the energy causality constraint and the collision constraint
[26]–[30]	Energy and throughput optimization	✗	✗	✓	✓	Optimal cooperation mechanism for energy and data rate optimization
[31]	CH selection using modified LEACH protocol	✓	✗	✗	✗	Prolonging of network life time by moving CHs to appropriate location
[32]	CH selection considering trust level of nodes	✓	✗	✓	✓	Securing cluster based CR network by selecting secure node as a CH
[33]	CH selection considering energy, channel availability and distance to sink node	✓	✗	✓	✗	Minimize the energy consumption for delay tolerant systems
[34]	Weight based CH selection considering residual energy of the node and average regional energy of all nodes	✓	✗	✓	✗	Prolong network life time by selecting energy rich node as CH
[35]	CH selection considering residual energy of the node	✓	✗	✓	✗	Prolong network life time using energy balancing approach
[36], [37]	Location based CH selection to prolong network life time	✓	✗	✓	✗	Variants of LEACH protocols to make the nodes alive longer
[38]–[40]	Efficient channel scheduling for RF energy harvesting based WSNs	✗	✗	✓	✓	Achieve optimal energy and throughput of the network
[41]–[43]	Efficient channel scheduling for optimized operation	✗	✗	✓	✗	Provides optimal throughput
[44]–[46]	Accurate channel state prediction	✗	✗	✓	✗	Offers smooth operation of users
Proposed	Energy and spectrum efficient solution for IoT	✓	✓	✓	✓	Energy-efficient mode switching, cluster head selection, and spectral efficient spectrum management

[a](C)luster head selection based on current and average energy levels of sensor nodes.
[b](E)nergy-aware mode switching strategy to increase network lifetime.
[c](A)llocation scheme.
[d](H)arvesting energy from RF sources.

the outage probability of PUs and SUs. Zhang *et al.* [39] developed an aggregate utility optimization framework for energy and spectrum management. The algorithm is based on Lyapunov optimization. A dynamic channel selection scheme (DCSS) is presented in [41]. Authors formulate a problem to maximize the total channel utilization for SUs and designed a heuristic greedy algorithm for channel selection. Bhattacharjee *et al.* [42] presented throughput analysis of dynamic random channel selection scheme. Ren *et al.* [43] investigated dynamic channel access to improve the energy efficiency in cluster-based CRSNs. In order to achieve optimal energy efficiency, sequential channel sensing and accessing schemes are proposed for both intracluster and intercluster data transmission in CRSNs. A resource allocation scheme for CRSNs with energy harvesting is proposed in [40]. The proposed solution consists of two algorithms.

1) A scheduling algorithm which allocates channels to spectrum sensors in order to maximize the average detected available time.
2) A resource allocation algorithm to allocate transmission time, power, and channels to data sensors to minimize energy consumption.

The probability-based channel idle time estimation schemes are discussed in [44]–[46]. The authors presented different probabilistic models to estimate the future availability. Although the estimation shows better performance in terms of predictability, the scope of the schemes is limited to the prediction of the idle time only.

In summary given in Table I, existing literature on energy and spectrum efficient CRSN for IoT do not address following cases.

1) CH selection based on current and average energy levels of sensor nodes.
2) Energy-aware mode switching strategy to increase network lifetime.
3) Channel allocation considering the stability and reliability simultaneously.

III. System Model

A. Network Model

We consider a cluster-based CRSN for IoT that consists of C clusters with N sensor nodes in each cluster, M data channels in total, and a control channel in each cluster. It is assumed that sensor nodes are equipped with separate wireless interfaces for data transmission and harvesting. A separate local control channel is used for reliable management of intracluster communication tasks. To account for spectral and energy variations across space and time, we adopt a clustering mechanism in which sensor nodes are partitioned into different groups using K-means clustering algorithm [47]. Clustering reduces transmission power (e.g., shorter distance between transmitter and receiver) which improves overall network lifetime, i.e., the time duration between the deployment and the nonfunctional state of CRSN for IoT. The network is considered as nonfunctional when a certain percentage of sensor nodes die [48], [49]. The K-means clustering algorithm can be described as follows [47]:

$$\Upsilon = \sum_{l=1}^{C} \sum_{i=1}^{N} \partial_{il} \tag{1}$$

where ∂_{il} represents the distance between node i and the center of corresponding cluster l. The parameter Υ depicts the global view of the CRSNs. It is assumed that clusters are nonoverlapping, therefore, the same set of channels is available to each cluster. However, within a cluster, a channel k cannot be assigned to more than one sensor node. This eliminates the possibility of collision among the sensor nodes of the same cluster.

After cluster formation, the next prime task is CH selection. Initially, the CH is selected randomly. This assumption is valid as all sensor nodes have the same energy level (sufficient for initial process) at the beginning. Later on, a CH selection mechanism is applied (see Section IV-A). Each sensor node performs spectrum sensing (detection of vacant channels), reporting (forwarding of sensing results to the corresponding CH), and monitoring (event detection or parameter sensing) tasks in parallel with energy harvesting [4]. Similarly, the CH performs spectrum-sensing, data-reception (receives sensing-reports from sensors nodes), and channel allocation (allocate channels to sensor nodes for reporting). Besides the aforementioned tasks, the CH also performs environment monitoring (detect some phenomenon or measure certain parameters) and data-transmission (report to the sink node) tasks (see Section IV-B).

The architecture of cluster-based CRSN for IoT is presented in Fig. 1. The sensor nodes opportunistically access the spectrum band of the PUs using spectrum sensing and parameter adaptation mechanism of CR technology which allows them to optimize spectral usage and efficiency. The figure shows that after receiving the observed data from sensor nodes, the CH forwards that information to the sink/gateway which directs it to the cloud. The cloud contains protocol stack for the storage and processing of the received information. The network manager can retrieve the desired information from the cloud or it can request sensors for data collection. It is assumed that the sink node lies within the transmission range of CH. The macro view of the cluster highlights different energy harvesting sources and the battery level of sensor nodes. For the sake of simplicity and illustration purpose, we focus on the energy and spectrum management within an intracluster environment. Due to the distributed nature of operations, the same scheme is applicable to all clusters and hence we can achieve energy and spectral efficiency across the entire network.

B. Frame Structure

The time-slotted frame structure of CRSN for IoT is shown in Fig. 2. Each frame is comprised of a control slot and functional slots. Since it is assumed that sensor nodes are equipped with a separate wireless interface for energy harvesting, the sensor nodes can harvest energy for the entire frame duration. The CH is selected for the specific number of frames known as CH tenure T_{CH}. For example, if the ith sensor node is selected as CH for $T_{\text{CH}} = 10$ in frame index $r = 11$, then it can act as CH from frame indexes $r = 11$–20. At the beginning of frame index 20, all sensor nodes in the cluster forward their current and average energy levels to CH. The CH then performs the CH selection algorithm for next tenure (see Section IV-A for details).

C. Energy Harvesting Model

We consider that sensor nodes can harvest energy from nearby ambient RF sources. The amount of energy harvested by sensor nodes depends on the transmit power of RF source, harvesting circuit, and propagation properties of the environment. In terrestrial environment, the energy harvested $E_{H_{i,u}}$ by the ith sensor node from uth RF source is [50]

$$E_{H_{i,u}} = \Gamma P_u \frac{G_u G_i \lambda_u^{\alpha}}{4\pi d_{i,u}^{\alpha}} h_t \tag{2}$$

where G_u and G_i are the antenna gains for uth energy harvesting source and ith sensor node, respectively. P_u is the transmit power of signal transmitted by uth energy harvesting source, $d_{i,u}$ is the distance between ith sensor node and u harvesting source, α is the path-loss exponent, Γ is the harvesting-efficiency, h_t is the harvesting duration, and λ is the wavelength of RF signal.

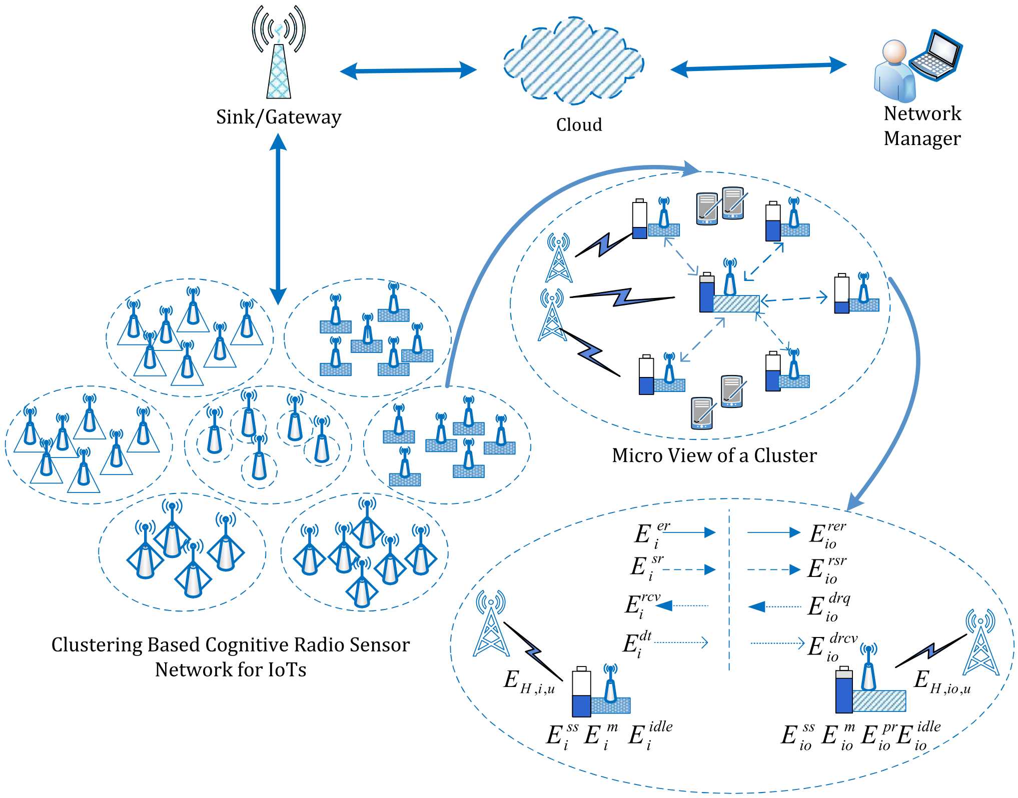


Fig. 1. Proposed energy and spectral efficient CRSN architecture for IoT.

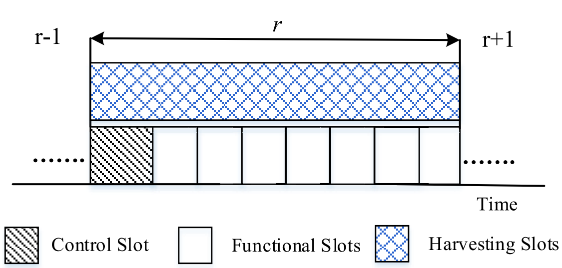


Fig. 2. Time-slotted frame structure of CRSN for IoT.

D. Energy Consumption Model

The different tasks performed by sensor nodes and CH are shown in Fig. 3. Initially, each node sends an energy-information packet (EIP) to CH which contains node ID and current and average energy levels. In this way, CH will have information of current and average energy levels of all nodes. The ith sensor node consumes energy E_i^{er} to transmit EIP. We name this energy information transmission as *energy-reporting process*. After sending EIP, each node performs the spectrum-sensing task and reports its observation to CH over a local control channel. Energy consumed by ith sensor node for spectrum sensing and reporting is E_i^{ss} and E_i^{sr}, respectively. The sensor node then performs the environmental monitoring task (such as crowd behavior detection, surveillance, etc.) that consumes E_i^m energy. On receiving the reporting request from CH, the ith sensor node transmits monitoring results to the CH. The energy expenditure in receiving the reporting request from CH and transmitting the monitored data to CH are E_i^{rcv} and E_i^{dt}, respectively. Based on this model, the overall energy consumed by ith sensor node (E_i^{cons}) during one frame is given as

$$E_i^{\text{cons}} = E_i^{\text{er}} + E_i^{\text{ss}} + E_i^{\text{sr}} + E_i^{m} + E_i^{\text{rcv}} + E_i^{\text{dt}} + E_i^{\text{idle}} \tag{3}$$

where E_i^{idle} is the energy consumed by ith sensor node in idle state. Without loss of generality and for simplification, we assume that within a cluster c_l, sensor nodes are homogeneous in nature. Therefore, all nodes consume the same amount of energy during spectrum sensing and environmental monitoring tasks.

From the perspective of CH, the energy consumed by i_0th CH ($E_{i_0}^{\text{cons}}$) during one frame can be written as follows:

$$\begin{aligned} E_{i_0}^{\text{cons}} &= E_{i_0}^{\text{rer}} + E_{i_0}^{\text{ss}} + E_{i_0}^{\text{rsr}} + E_{i_0}^{\text{pr}} + E_{i_0}^{m} \\ &\quad + E_{i_0}^{\text{drq}} + E_{i_0}^{\text{drcv}} + E_{i_0}^{\text{idle/snkr}} \end{aligned} \tag{4}$$

where $E_{i_0}^{\text{rer}}$, $E_{i_0}^{\text{ss}}$, and $E_{i_0}^{\text{rsr}}$ are the energies consumed by the CH i_0 for receiving the EIP packets, performing the spectrum sensing tasks, and collecting the spectrum-sensing results from other sensor nodes, respectively. Further, the energy consumed by i_0th CH to process the spectrum-sensing reports, field monitoring, data request, and data reception tasks are given by $E_{i_0}^{\text{pr}}$, $E_{i_0}^{m}$, $E_{i_0}^{\text{drq}}$, and $E_{i_0}^{\text{drcv}}$, respectively. Since the CH forwards the data to sink node on request. If the request arrives the CH forwards data to sink and consume energy $E_{i_0}^{\text{snkr}}$ otherwise it consume $E_{i_0}^{\text{idle}}$ in the idle state.

A list of symbols and their description used in the model is provided in Table II.

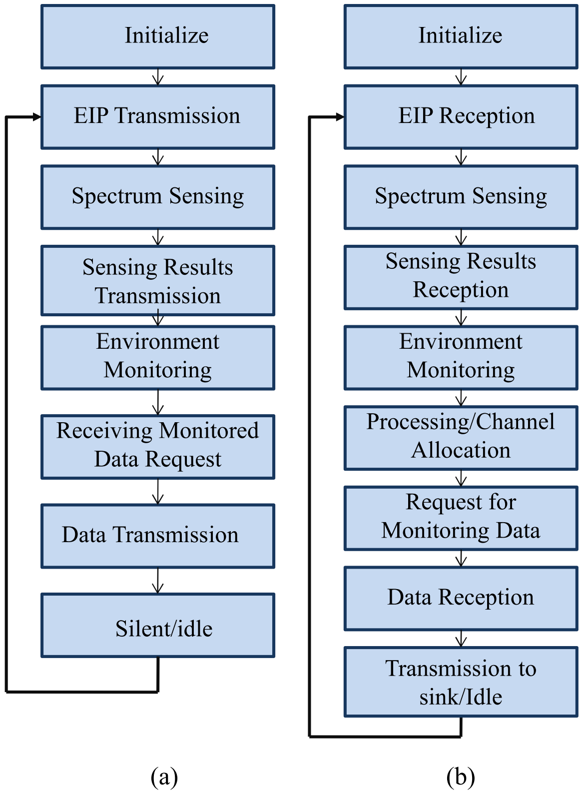


Fig. 3. Different energy consuming tasks for (a) sensor node and (b) CH.

IV. Energy and Spectrum Management Framework for IoT

We propose a novel energy management scheme (EMS) and an innovative CMS for IoT-based on CRSNs. We now describe the detailed operations for both EMS and CMS.

A. Energy Management Scheme

The EMS comprise of an energy-aware mode switching strategy and a CH selection scheme which are the key aspects of energy management in CRSN for IoT.

1) Energy-Aware Mode Switching Strategy: Energy-aware mode switching strategy allows sensor nodes to select their operational mode according to their current energy level. Let $E_{i,c}$ denote current energy level of ith sensor node. Fig. 4 depicts the operational modes for ith sensor node. In mode 1 (FCM), the sensor node performs energy harvesting, environment monitoring tasks for sensor nodes, and other supporting tasks associated with CRSN such as spectrum sensing, reporting, transmission, etc. It is assumed that in FCM, the total harvested energy of the sensor node is always less than or equal to the energy consumption of the node in a given frame. This argument is practically valid as the harvesting efficiency of RF-to-dc conversion is typically 30 to 70% [25], [51]. In mode 2 (RCM), the node performs only the energy harvesting task. The ith sensor node checks its energy-level $E_{i,c}$ at the beginning of each frame and switches from FCM to RCM when $E_{i,c}$ falls below a certain threshold E_{th}. The switching behavior can

TABLE II
Description of Symbols Used in This Paper

Symbol	Description
N	Number of sensor nodes
M	Number of channels
C	Number of clusters
r	Frame index
i	Sensor node index
i_0	CH index
R	Total number of frames
T_{CH}	Cluster head tenure
Γ	Harvesting efficiency
h_t	Harvesting duration
α	Path loss exponent
$E_{Hi,u}$	Energy harvested by *i-th* sensor node from *u-th* RF source
$d_{i,u}$	Distance between *i-th* sensor and *u-th* RF source
E_i^{cons}	Energy consumed by *i-th* sensor node during one frame
$E_{i_0}^{cons}$	Energy consumed by i_0-*th* CH during one frame
$E_{i,c}$	Current energy level of *i-th* sensor node
E_{th}	Energy threshold for mode switching
$E_{i,a}$	Average energy during CH selection frame
V	Number of history samples of PU activities
S	Number of regions for channel state history samples
$\Phi_{k,r}^s$	Weight for *s-th* region for channel k
γ_k	Average PU index of channel k
$Q_{r,k}$	Reliability of *k-th* channel during frame r
$\beta_{i,k}$	BER of *i-th* sensor node on channel k
W	Tolerable PU index limit

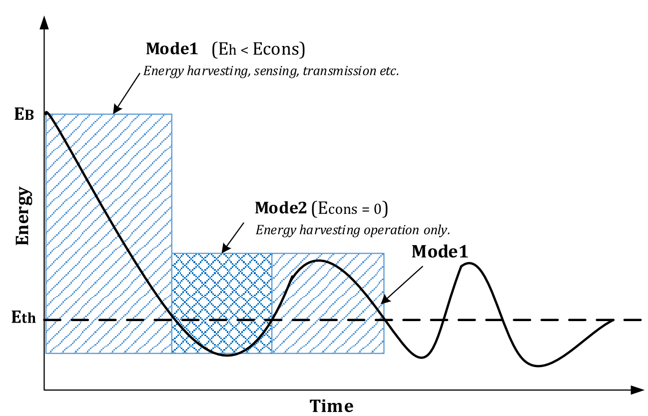


Fig. 4. Energy-aware mode switching strategy for sensor nodes in CRSNs for IoT.

be described as follows:

$$E_{i,c} \underset{\text{RCM}}{\overset{\text{FCM}}{\gtrless}} E_{\text{th}}. \tag{5}$$

Considering RCM and FCM, two additional modes are introduced known as: 1) dynamic operation mode (DOM) and

2) fixed operation mode (FOM). In DOM, a sensor node can switch between FCM and RCM whereas in FOM sensor node can only operate in FCM. The network can remain active for much longer time by operating in DOM as compared to FOM.

2) Cluster Head Selection Scheme: The CH selection scheme achieves energy balancing by selecting the energy-rich nodes as CH on rotational basis. To account variations of energy arrival (e.g., energy harvesting) and energy departure (e.g., due to data transmission), a new selection criterion is introduced which incorporates current as well as past energy levels of sensor nodes. A sensor node may have high residual energy at a certain time instant by staying longer in RCM. However, the sensor node can quickly deplete its energy due to its low energy-arrival rate and higher energy-departure rate. Therefore, by incorporating the average energy level of sensor nodes, the proposed scheme selects a sensor node with higher energy harvesting and lower energy consumption rates as a CH.

The CH selection algorithm is physically performed on the earlier selected CH, i.e., if the CH selection is to be made for frame r then the CH during frame r-T_{CH} to frame r-1 is called earlier selected CH. After applying CH selection mechanism, if the current CH shows high energy-level then it will continue its leadership role for the next tenure. Otherwise, it will handover the authority to another energy-rich node. The CH selection mechanism can be described as follows.

1) Each sensor node forwards EIP to the earlier selected CH on a local control-channel that contains: node ID, current energy-level $E_{i,c}$, and average energy-level $E_{i,a}$ during CH selection frame.
2) After receiving EIP from all sensor nodes, the earlier selected CH maximizes $E_{i,c}/E_{i,a}$ in order to select the new CH. The CH selection problem can be formulated as

$$\begin{aligned}&\underset{1\le i\le N}{\text{argmax}} \quad \frac{E_{i,c}}{E_{i,a}}\\ &\text{subject to} : E_{i,c} \ge E_{\text{th}} \quad \forall i \in \{1, 2, \dots, N\}.\end{aligned} \tag{6}$$

The ith sensor node with current energy-level $E_{i,c} \le E_{\text{th}}$ moves to RCM. Therefore, the constraint ensures that the selected CH have sufficient energy to perform a leader role for the given tenure T_{CH}.
3) The sensor nodes update their current and average energy-levels as follows:

$$E_{i,a}(r+1) = \begin{cases} (1-\mu)E_{i,a}(r) + \mu E_{i,c}(r), & i = i_0 \\ (1-\mu)E_{i,c}(r), & i \ne i_0 \end{cases} \tag{7}$$

$$E_{i,c}(r+1) = \begin{cases} \big(E_{i,c}(r) + E_{Hi,u}(r)\big) & \\ \quad - E_{i_0}^{\text{cons}}(r), & i = i_0 \\ \big(E_{i,c}(r) + E_{Hi,u}(r)\big) & \\ \quad - E_{i}^{\text{cons}}(r), & i \ne i_0 \end{cases} \tag{8}$$

where μ is a small positive constant to control amount of adaptation at each step. The case $i = i_0$ means ith sensor node is acting as CH i_0.

Algorithm 1 provides step by step working operation of EMS. Equations (6) and (8) depict node selection criteria inspired by the past and current energy level of the nodes. By selecting a CH considering only its current energy level may result in quick energy depletion. By incorporating both current and average energy level, indirectly we are exploring the history of sensor node's energy in the decision process.

Algorithm 1 EMS

```
Require:  • Number of nodes in the cluster N
  • Tenure duration of CH T_CH
  • Current energy-level E_{i,c}, ∀i ∈ {1, 2, ..., N}
  • Average energy-level Ei, a, ∀i ∈ {1, 2, ..., N}
Ensure: 1. Selected leader or CH
        2. Nodes in RCM
        3. Nodes in FCM
  for Frame index r: 1 to R do
    for Node index i: 1 to N do
      if f % T_CH == 0 then
        Select CH using (6)
      end if
      if i == i_0 then
        Update E_{i,a} using (7) Case-1
        Update E_{i,c} using (8) Case-1
      else
        Update E_{i,a} using (7) Case-2
        Update E_{i,c} using (8) Case-2
      end if
      if E_i^c ≤ E_th then
        RCM ← i
      else
        FCM ← i
      end if
    end for
  end for
```

B. Channel Management Scheme

Here, we provide a CMS that a CH employs to select best quality channels in terms of stability and reliability. The CH initiates the reporting process by requesting sensor nodes to transmit monitored data. As a response, the sensor nodes forward the desired data to CH on designated channel. The CH is responsible for forming the optimal sharing patterns using CMS. Sensor nodes are equipped with CR technology, thus, they can operate opportunistically in available channels to send their environment monitoring data to CH during the reporting process.

The PUs can either be static or mobile with noticeably higher transmission power. It is assumed that primary networks follow a slotted structure. The transmission of PUs follows a random process where the channel state varies randomly for each slot duration [20]. Based on the sensing reports collected from different sensor nodes, the CH characterizes each channel based on the PU index. The CH stores V recent PU activities (on–off) over different channels. We model the PU behavior using a two-state model: ON state (occupied) and OFF state (available for transmission). Let history-samples V be partitioned into S regions each having weight $\Phi_{k,r}^{s}$. The weights are assigned in such a way that recent history samples have higher weights compared to old samples. This is due to the fact that recent samples provide the latest information about the behavior of PU. The average PU index for channel k over R frames can be computed as follows:

$$\gamma_k = \frac{1}{R}\sum_{r=1}^{R}\sum_{s=1}^{S}\Phi^s_{k,r}\theta^s_{k,r} \tag{9}$$

where $\theta^s_{k,r}$ indicates the number of consecutive busy states ($\mathcal{H}_1$) of channel k in certain history-region s. It is obvious that smaller value of γ_k indicates that the channel is highly stable. It is work to note that the average PU index incorporates the PU history. There might be a situation in which a channel is detected to be idle and available; however, when PU arrival on that channel may cause severe QoS degradation to the sensor nodes. In summary, the rationale behind the history-based node and channel selection provide a wider view about the energy of sensor node and stability of the channel.

The reliability $Q_{r,k}$ of kth channel during frame r can be computed as follows:

$$Q_{r,k} = \frac{1}{\beta_{i,k}} \tag{10}$$

where $\beta_{i,k}$ is the bit error rate (BER) of ith sensor node on channel k. It is assumed that ith sensor node is using binary phase shift keying and BER can be estimated as $\beta_{i,k} = (1/2)e^{-\xi_{b,k}}$ ($\xi_{b,k}$ is the energy per bit to noise power spectral density) [50].

For channel allocation process, our objective is to maximize the reliability of channels while average PU index must be ensured for all selected channels. The CMS is invoked according to the requirement of data transfer by sensor nodes. The reliability maximization problem can be formulated as

$$\begin{aligned} &\max \quad \sum_{k=1}^{M} m_k Q_{r,k} \\ &\text{subject to}: \gamma_k \le W \quad \forall k \in \{1, 2, \ldots, M\} \\ &m_k = \{0, 1\} \end{aligned} \tag{11}$$

where binary variable m_k denotes whether channel k is occupied or not by sensor nodes. W denotes tolerable PU index limit above which the channel is not stable. Since sensor nodes are utilizing the channels in an opportunistic manner, we should select channels with average PU index (γ_k) less than W for higher stability, i.e., sensor nodes are allowed to transmit on channels with low PU arrival rate.

The problem formulated in (11) is a knapsack problem (which is problem in combinatorial optimization). There are a number of possible ways to get the solution of this problem. One way is to enumerate over all possible combinations of k, which is computationally expensive and unrealistic for a large number of channels. Therefore, we consider dynamic programming method to solve problem in (11) which is depicted in Algorithm 2.

The main steps of dynamic programming to solve the knapsack problem in (11) are as follows [52]. Let $V[k, w]$ be an array for tracking channels, where k and w are the integers satisfying $1 \le k \le M$ and $0 \le w \le W$, respectively. Each entry of $V[k, w] = \max(V[k-1, w], Q_k + V[k-1, w-\gamma_k]), \forall w \ge 0$ and $V[k, w] = -\infty, \forall\ w < 0$. $Q_{f,k}$ and γ_k are the objective function and average PU index of channel k, respectively. Each entry of V holds the collected sum of objective function for the selected channels where overall PU activity is lower than w. Array $V[k, w]$ does not track selected channels. Therefore, to track the selected channels $M* \subseteq M$, a Keep[k, w] array is introduced that holds binary values for channels, where the value 1 indicates the selection of channel k. Using a backtracking approach, we determine M*. The backtracking is a recursive process starting with $k = M$ and $w = W$. During backtracking, if the value of Keep[k, w] is 1 then the channel k becomes the element of set M*. For this case, the value of w is updated by $w-\gamma_k$. By repeating the same process for entire set of channels, an optimal solution of (11) is achieved. The computational complexity of the proposed CMS is $O(M \times W)$.

Algorithm 2 Dynamic Programming Algorithm for CMS

Require:
- Number of available channels M
- Maximum tolerable PU activity W
- Reliability factor Q_1 *to* Q_M
- Average PU index of channels γ_1 *to* γ_M
- Keep Array for tracking channels

Ensure: Resource allocation $s^* = V[M, W]$

```
for (w: 1 to W) do
  V[1, w]←0
end for
for channel index k: 1 to M do
  for keep array index (w: 1 to W) do
    if γk > w then
      V[k, w]← V[k-1, w]
      Keep[k, w]←0
    else
      V[k, w] ← max(V[k-1, w], Qk + V[k-1, w-γk])
      if Qk + V[k-1, w - γk] > V[k-1, w] then
        Keep[k, w]←1
      else
        Keep[k, w]←0
      end if
    end if
  end for
end for
Z←W
for channel index k: M to 1 do
  Keep[k,w]←1
  if Keep[k, Z]==1 then
    Ouput k
    Z ←Z - γk
  end if
end for
return V[|M|,W]
```

V. Simulation Results

In this section, we evaluate the performance of proposed energy and spectrum efficient framework. A slotted CRSN architecture for IoT is considered in which each sensor node

TABLE III
SIMULATION PARAMETERS

Parameter	Value
Sensor nodes (N)	20
Channels (M)	$10 \sim 50$
RF harvesting bands	(900,1800) MHz
Harvesting time per frame (h_t)	1 sec
Antenna Gains (G_i, G_u)	(1,1)
Distance to RF-source $(d_{i,u})$	1 to 100 m
EH efficiency (Γ)	30 %
Modulation scheme	DBPSK
Modulation index (Δ)	2
Total slots of frame (f)	8
Slot duration	0.125 sec
Functional slots (Z)	7
Harvesting slots	8
Sensor initial energy	100 J
Sensing power (P^{ss})	0.01 watts
Sensing time (T^{ss})	0.125 sec
Processing power (P^{pr})	0.01 watts
Processing time (T^{pr})	0.0625 sec
Sensor initial energy	100 J
Energy consumption in transmitter or receiver circuitry (E_{elec})	50 (nJ/bit)
Energy dissipation for intra-cluster communication (ε_{fs})	10 (pJ/bit/m2)
Energy dissipation for CH to sink communication (ε_{amp})	0.0013 (pJ/bit/m2)
Path loss exponent$_1$ (α_1)	2.0
Path loss exponent$_2$ (α_2)	3.5
Size of EIP (K^{er})	0.5 Kb
Size of sensing data (K^{ss})	1 Kb
Size of monitoring data (K^{dt})	300 Kb
PU arrival rate $(idle \rightarrow busy)$	0.05-0.35

is equipped with separate wireless interface for data transmission and harvesting circuit. We consider 100 sensor nodes uniformly distributed in an area of size 500 m $\times$500 m. Each cluster is assumed to have same number of sensor nodes, i.e., $N = 20$. Here, we present results for lth cluster. The position of two RF sources are $u_1 = (100, 100)$ and $u_2 = (350, 250)$, respectively. PU traffic is modeled using on and off states with PU arrival rate from 0.05 to 0.35. To compute PU index, the PU history is maintained for V=30 slots which are divided into S=3 regions with 10 slots in each of them. We assigned weight $\Phi^1 = 0.6$ to the region with most recent history samples, $\Phi^2 = 0.4$ to the second region, and $\Phi^3 = 0.2$ to the region with old samples. The detailed list of simulation parameters is given in Table III. The performance metrics used for evaluation are: 1) average residual energy; 2) number of functional nodes; 3) stability; 4) reliability; and 5) PU activity.

A. Performance Evaluation of EMS

We compare the performance of proposed EMS with current and average energy level-based CH selection (CAECHS) scheme [34], energy aware CH selection (EACHS) scheme [35], and EECHS scheme [36]. As mentioned in Section II, CAECHS scheme consider the current and average energy of sensor nodes whereas EACHS scheme consider only residual energy for CH selection. EECHS scheme select CH randomly from inner area nodes of the cluster. We apply CAECHS scheme and EACHS scheme in CRSNs for IoT with RF energy harvesting, i.e., energy harvesting networks (EHNs) where sensor nodes can harvest energy based on their residual energy (similar to proposed EMS). However, EECHS scheme is not based on EHNs.

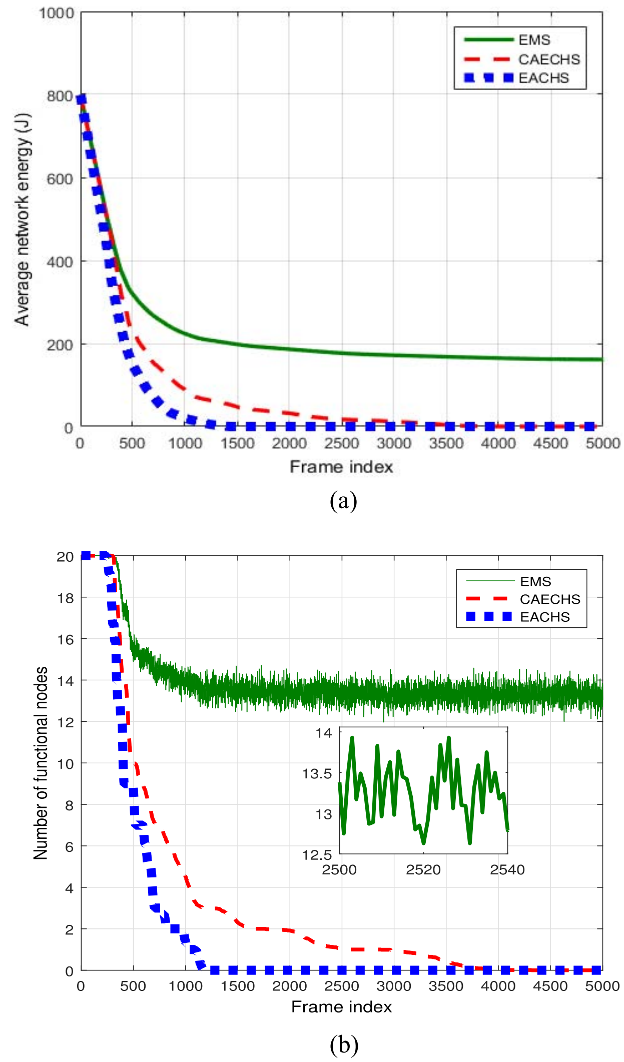


Fig. 5. Performance comparison of EMS with existing schemes in terms of (a) residual energy and (b) number of functional nodes for different frame indexes ($N = 20$).

Fig. 5(a) illustrates the residual energy versus frame index for EMS and compared with CAECHS, EACHS, and EECHS schemes. It is clearly visible that the proposed EMS have long lifetime when compared to the existing schemes. For example, the EECHS in non-EHNs depletes its entire energy in just 228 frames whereas the proposed EMS-based EHNs perform perpetual operation and show significantly higher residual energy. This is due to the EACHS and energy-aware

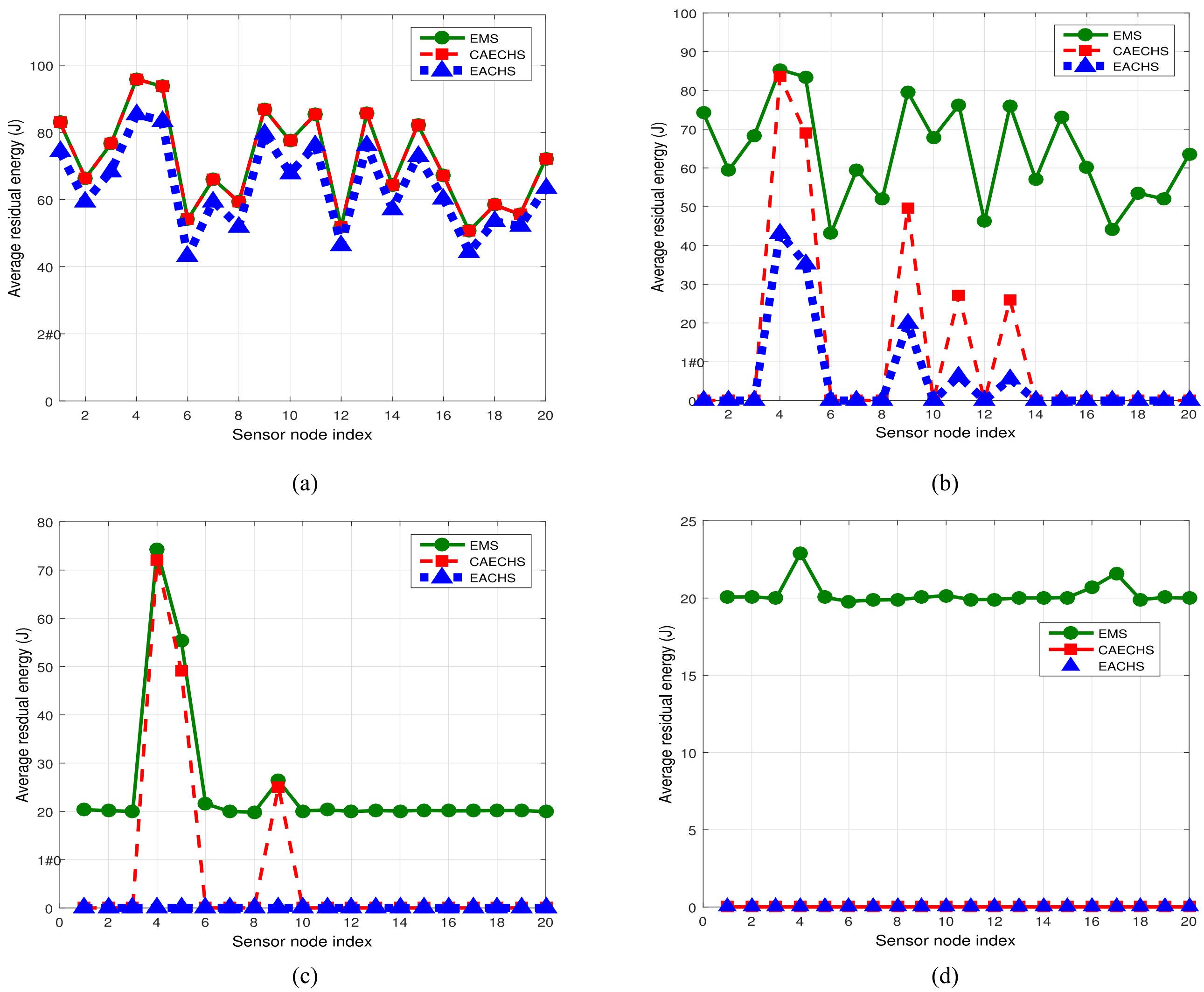


Fig. 6. Average residual energy versus different sensor nodes for EMS and existing schemes at different frame indices (a) 200, (b) 1000, (c) 1500, and (d) 4500.

mode switching mechanism that helps to achieve energy balancing and longer sustainability. We further compare proposed EMS with CAECHS and EACHS schemes in EHNs to explicitly highlight the advantages of the energy-aware switching mechanism. In EMS, the sensor nodes can perform perpetual operations and thus network energy never approaches the dead level (zero joules). However, the EHNs that employ CAECHS and EACHS deplete their energy at 1192 and 4316 frame indexes, respectively. Fig. 5(b) illustrates the number of functional nodes across different frame indices to evaluate energy balancing. A sensor node is considered to be functional if it performs both energy harvesting and other tasks. The proposed EMS shows a significantly large number of functional nodes for the given frame index compared to other aforementioned schemes. For example, at frame index 500, the EMS shows 35.48% and 45.16% higher functional nodes compared to CAECHS and EACHS schemes, respectively. Hence, the proposed EMS achieves better energy balancing as it shows a higher number of functional nodes.

Fig. 6(a)–(d) shows the average residual energy versus number of sensor nodes for different frame indices, i.e., 200, 1000, 1500, and 4500, respectively. The EMS shows higher average residual energy of nodes compared to CAECHS and EACHS schemes. Initially, sensor nodes have higher energy levels, therefore, we can observe only a small difference in the performance of the EMS compared with other schemes that are based on EHNs in Fig. 6(a). However, it is clear from the Fig. 6(b) that the EECHS-based non-EHN quickly depletes its entire energy and all the nodes become nonfunctional at 1000 frame index. As mentioned earlier, a functional node performs both energy harvesting and other associated tasks. The node will be nonfunctional if the residual energy is less than the 40% of the initial energy. Using CAECHS scheme, there are only seven functional nodes at frame index 1000 whereas five nodes remain functional when EACHS is employed. Compared to these schemes, the EMS shows higher network energy, i.e., 13 functional nodes. Similarly, for the other two cases (i.e., frame indices 1500 and 4500), the EMS also shows the higher residual energy of sensor nodes. Hence, with EMS, the sensor nodes remain functional (i.e., sensor node performs both energy harvesting and other tasks) for a longer time which improves energy-efficiency of CRSNs for IoT. Since nodes are at certain

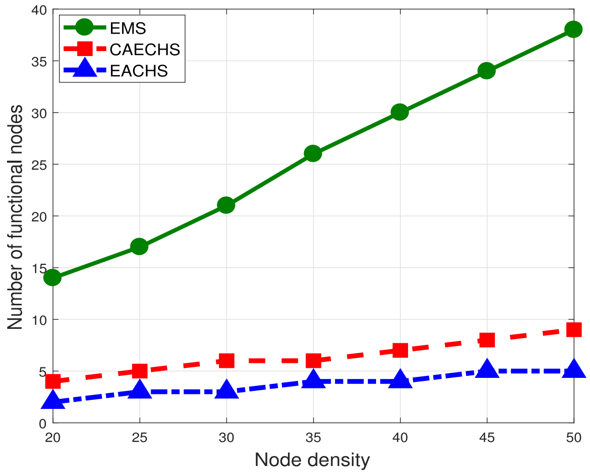


Fig. 7. Number of functional nodes versus node density for frame index $r = 1000$.

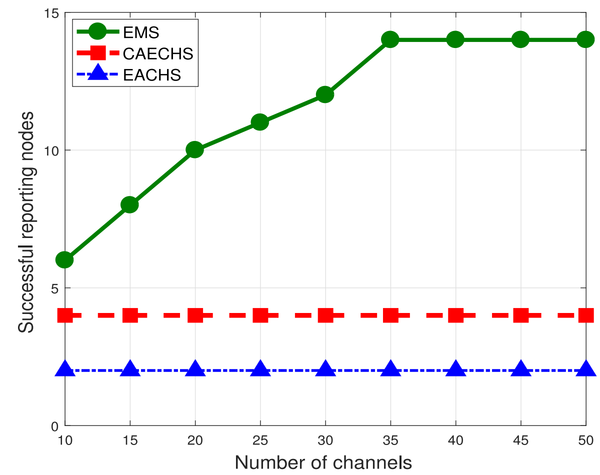


Fig. 8. Successful reporting nodes versus number of channels for $N = 20$ and frame index $r = 1000$.

distance from RF energy harvesting source. Therefore, average residual energy of each node varies based on their consumption and harvesting. The nodes which are close to harvesting source will have more residual energy as compared to others.

Fig. 7 highlights the performance gain of the proposed EMS scheme over existing schemes in terms of the functional node at frame index $r = 1000$ across different node densities varying from $N = 20 - -50$. The EMS shows up to 4- and 9.5-times higher functional nodes compared to CAECHS and EACHS, respectively. These higher numbers are due to the mode switching capability of EMS which makes the nodes to perform switching between different operational mode based on their residual energy. Further, the RF EH allows the node to harvest energy for longer existence and operations.

Similarly, Fig. 8 depicts the performance gain of EMS in terms of successful reporting nodes. The reporting is considered successful if current energy of the node is greater than the given threshold (i.e., $E_{i,c} > E_{\text{th}}$) and it gets the channel that can fulfill its transmission requirements. For Fig. 8, we consider $N = 20$ and plotted the number of nodes which successfully report their data to CH during frame $r = 1000$. Since EMS allow nodes to remain alive longer and CMS allocates best quality channels, more nodes succeed in reporting. The performance gain of EMS is drastically increased with the increase in the number of available channels. For example, at $M = 30$, the EMS shows 3- and 6-times higher reporting nodes compared to CAECHS and EACHS, respectively. There are only four and two alive nodes in CAECHS and EACHS, respectively. All alive nodes get the channel for reporting as the number of alive nodes are less in number than the available channels. Hence, the EMS scheme is quite effective to provide energy and spectrum efficiency to sensor nodes.

B. Performance Evaluation of CMS

We compare the performance of the proposed CMS with DCSS [41] and dynamic random channel selection scheme (DRCSS) [42]. DCSS is based on a heuristic greedy algorithm for channel selection whereas DRCSS selects channel randomly.

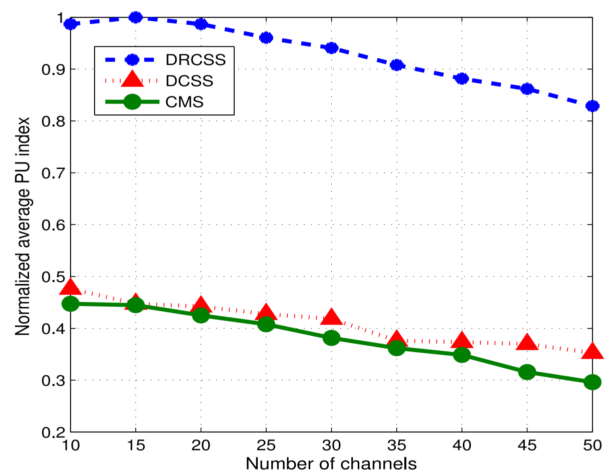
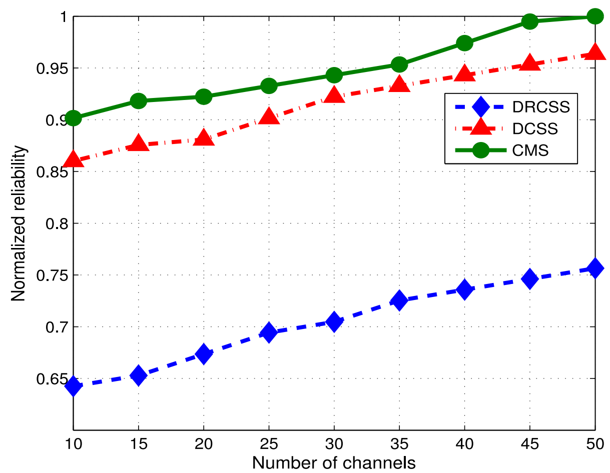


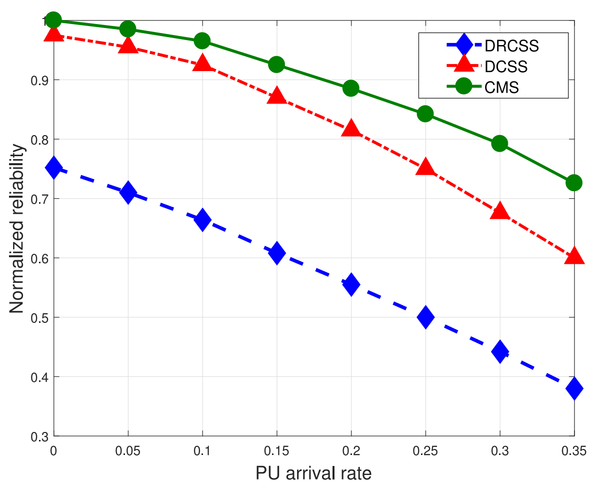
Fig. 9. Normalized PU index versus number of channels for CMS and existing schemes.

Fig. 9 shows normalized PU index (which represents stability of channels) versus number of channels for CMS, DCSS, and DRCSS. After selection, the channels are marked as assigned and they are removed from the availability list. The same procedure is repeated for other channels until the given tolerable PU activity limit W is violated. It is evident that the proposed CMS has better performance than DRCSS. This is due to the fact that CMS allocates channels by minimizing the overall PU activity. Similarly, the CMS shows lower PU index (i.e., higher chances of transmission to the sensor node) compared to the DCSS. For example, when compared DCSS for the cases with 30 and 45 available channels, the CMS shows 8.7% and 14.57% lower PU index of selected channels, respectively. Similarly, the CMS shows 59.48% and 63.35% lower PU index than the DRCSS for the cases with 30 and 45 available channels, respectively. Hence, the proposed CMS is quite efficient to cater the random PU activity.

Fig. 10(a) shows the normalized reliability index [which is the reliability of channel given in (10) divided by maximum reliability of channel within a cluster] versus number of channels for CMS, DCSS, and DRCSS. The CMS outperforms



(a)



(b)

Fig. 10. Performance comparison of CMS with existing schemes in terms of normalized reliability versus (a) number of channels with existing schemes and (b) PU arrival rate.

DCSS and DRCSS across different number of available channels. For instance, when there are 30 available channels, the CMS shows 4.5% and 26.96% higher reliability index than the DCSS and DRCSS, respectively. Hence, by employing CMS, the CH allocates highly stable and reliable channels to sensor nodes for reporting their monitored data.

Fig. 10(b) illustrates the performance gain of the CMS over DRCSS and DCSS in terms of normalized reliability for different PU arrival rates. It is evident from the result that CMS effectively caters the PU arrival activity due to the history-based PU arrival prediction and channel management. For example, when PU arrival rate is 0.15, the CMS shows 17% and 78.7% better reliability index compared to DRCSS and DCSS, respectively. Hence, the proposed CMS is quite effective in tackling random PU activity and offer better channel utilization for alive nodes.

Fig. 11 shows channel rewarded to sensor nodes versus tolerable PU limit W for CMS, DCSS, and DRCSS. By following the total tolerable PU activity limit, the best-quality channels are selected from the pool of available channels. It is clearly visible that CMS rewards more channels to sensor nodes for reporting their monitoring data to the CH. For example, at tolerable PU limit of 0.3, the proposed CMS rewards 47.21% and 17.65% higher number of channels to sensor nodes compared to the DRCSS and DCSS, respectively. Similarly, CMS rewards 34.05% and 9.45% more channels to sensor nodes at tolerable PU limit $W = 0.5$ when compared with DRCSS and DCSS, respectively. Hence, the CMS provides a better transmission capacity to sensor nodes.

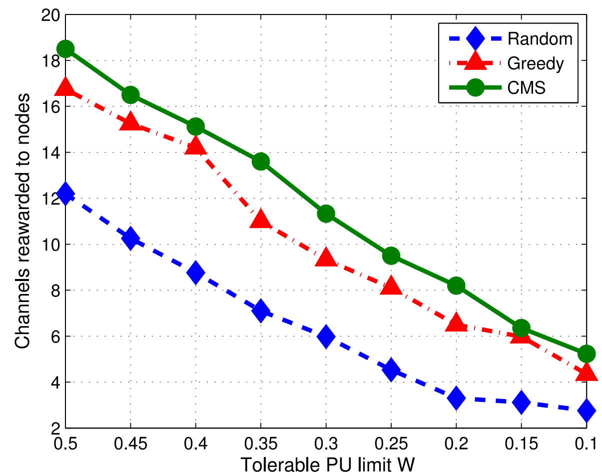


Fig. 11. Number of channels rewarded to sensor nodes versus tolerable PU limit for CMS and existing schemes.

VI. Conclusion

This paper addresses two main challenges to the CRSNs for IoT: 1) energy management and 2) channel management. An energy-aware mode switching strategy and CH selection algorithm are introduced for better energy management. Energy-aware mode switching strategy allows sensor nodes to switch between different operational modes (FOM and DOM) and CH is selected based on the current and average of past energy levels of sensor nodes to attain a balance between network lifetime and performance. Simulation results demonstrate the effectiveness of proposed energy and spectrum efficient framework for CRSNs in terms of functional nodes and residual energy of the network. Furthermore, the proposed EMS shows 35.48% and 45.15% higher functional nodes compared to energy harvesting-based CAECHS and EACHS schemes, respectively. The computational complexity of proposed EMS is higher than CAECHS and EACHS; however, modern day devices are capable to solve EMS effectively. From channel allocation perspective, the proposed CMS allocates the best-quality channels in terms of reliability and stability. Simulation results demonstrate that the proposed CMS provides 14.57% and 63.35% higher stability channels compared to the DCSS and DRCSS. Findings also highlight that CMS allocates 4.5% and 26.96% better reliability indexed channels compared to the DCSS and DRCSS. In addition, the proposed scheme reward more channels to sensor nodes for reporting their observations to CH. In future, this paper can be extended to incorporate node heterogeneity within a cluster and shifting the processing of clustering mechanism at the cloud. Furthermore, the sink to cluster communication can be incorporated within energy calculations of the sensor nodes.

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