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Article

Energy-Efficient Scheduling for a Cognitive IoT-Based Early Warning System

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Abstract: Flash floods are deemed the most fatal and disastrous natural hazards globally due to their prompt onset that requires a short prime time for emergency response. Cognitive Internet of things (CIoT) technologies including inherent characteristics of cognitive radio (CR) are potential candidates to develop a monitoring and early warning system (MEWS) that helps in efficiently utilizing the short response time to save lives during flash floods. However, most CIoT devices are battery-limited and thus, it reduces the lifetime of the MEWS. To tackle these problems, we propose a CIoT-based MEWS to slash the fatalities of flash floods. To extend the lifetime of the MEWS by conserving the limited battery energy of CIoT sensors, we formulate a resource assignment problem for maximizing energy efficiency. To solve the problem, at first, we devise a polynomial-time heuristic energy-efficient scheduler (EES-1). However, its performance can be unsatisfactory since it requires an exhaustive search to find local optimum values without consideration of the overall network energy efficiency. To enhance the energy efficiency of the proposed EES-1 scheme, we additionally formulate an optimization problem based on a maximum weight matching bipartite graph. Then, we additionally propose a Hungarian algorithm-based energy-efficient scheduler (EES-2), solvable in polynomial time. The simulation results show that the proposed EES-2 scheme achieves considerably high energy efficiency in the CIoT-based MEWS, leading to the extended lifetime of the MEWS without loss of throughput performance.

Keywords: Flash floods; internet of things; cognitive radio; early warning system; network lifetime; energy efficiency

1 Introduction

Global warming at alarming levels is stimulating a wide variety of factors that cause flash floods [1]. Flash floods are considered the most fatal types of floods due to their high mortality rate as shown in Tab. 1. Excessive rainfall, dam failure, or a sudden release of water held by glacier jam may result in a flash flood. Rapidly rising water can reach heights of 30 feet or more. Flash floods can roll rocks, tear out trees, obliterate structures and overpasses, and scrub out new water channels. Furthermore, flash flood-producing rains may incite catastrophic mudslides. Occasionally, the floating debris or ice accumulates at a natural or man-made barricade, resulting in the rise of water level upstream. On the abrupt release of the obstruction, the wreckage carried by an excessive volume of water triggers astringent damage to the life and property downstream. In such situations, there is a fleeting time to caution the populace aboutsudden floods.

Table 1: Major flash floods that caused huge fatalities [2]

Year	Area	Description	Mortalities
1979	India	Machchhu-2 (Machu River) busted after heavy rainfall	25,000
1989	US	South Fork Dam (Little Conemaugh River) broke after heavy rainfall	2,209
2010	Pakistan	Heavy rains fall caused huge flooding in the Indus River basin	1,480
1967	Portugal	Severe flooding rampaged the city of Lisbon	464
2006	Ethiopia	Heavy rain caused flash floods in eastern Ethiopia,	350
1982	Japan	Infrastructure collapses due to heavy rains in Nagayo, Nagasaki	299
1903	US	Heppner Flood, Oregon, killed almost a quarter of the town's residents	247

The characteristics of cognitive radio (CR) and the Internet of things (IoT) can be exploited to achieve a short response time during flash floods. The IoT is a technological revolution that brings us into a new era of pervasive connectivity, computing, and communication. The evolved idea of IoT is to develop intelligent physical objects to sense, communicate, process, and act for concerted decisions, entailing a new paradigm named cognitive Internet of Things (CIoT) [3]. The IoT devices and networks are anticipated for reliability, quality, and time enduring availability. Connectivity is considered the most critical component in the realization of the concept of IoT. Wireless communication technologies emerge as a cost-effective solution to provide essential inter-connectivity among IoT devices and accessibility to remote users [4,5].

Radio spectrum scarcity has emerged as one of the major challenges due to the unprecedented growth of IoT devices [4,6,7]. The studies reveal that incorporation of the CR capability into IoT devices and networks substantially improves spectral efficiency by using dynamic spectrum access (DSA) and opportunistic transmission capabilities [3,4,6]. They also suggest that the benefits of IoT without cognitive functionalities such as CR and intelligence techniques are limited [4]. Moreover, the integration of CR into IoT can provide advanced information processing capabilities.

On the other hand, CR requires a powerful energy source to perform its functionalities. However, the current battery technologies cannot meet the higher power requirements related to the flow of data generated by CIoT devices, due to slower progress in battery technologies compared to semiconductor technologies [8]. Hence, efficient utilization of the CIoT network to develop an early warning system for flash floods becomes vital to save lives and reduce the devastating impacts of natural hazards [9]. Consequently, flash flood monitoring requires a CIoT network deployment over a wide range of geographical areas without frequent battery replacement. In addition, efficient utilization of battery energy for CIoT devices is crucial in network design. It can provide cost-effectiveness and extended network lifetime as well as reduced environmental concerns.

1.1 Related Work

The international strategy for disaster reduction (ISDR) has laid down outlines to devise measures for minimizing the damages caused by floods and other disasters. These measures are classified as: 1) structural and 2) non-structural [10,11]. The structural measures include the engineering construction design of physical structures to reduce potential impacts of hazards such as protection, retention, and drainage systems involving huge time and economic resources [10]. On the other hand, the non-structural measures employ data or policies to reduce the risk [10–12]. These are further classified as passive and active measures.

The active measures promote direct interactions with people such as training, early warning systems (EWSs) for people, and public information, among others. The passive measures involve policies, building codes and standards, and land use regulations. In this paper, we consider the non-structural passive measures for our proposed CIoT-based EWS. A summary of the non-structural studies related to IoT-enabled disaster management is listed in Tab. 2. However, these previous studies generally take into account legacy wireless sensor networks at an abstract level. Moreover, they do not aim to extend the network lifetime through efficient utilization of the limited battery energy.

Table 2: Summary of the studies for disaster management and flood monitoring

Category	Core Area	Ref.
	Pre-Disaster Caution	
WSN-based EWS for geo-hazards	Geo-location data transmission to the monitoring station	[10]
WSN-based EWS, water level monitoring	Development of WSN-based data collection/transmission	[11,13,14]
IoT-based in disaster management	Real-time awareness of the situation	[15,16]
WSN-based EWS, water level monitoring	Development of WSN-based data collection and GSM-based transmission	[17]
Comparison of various EWSs presented in the literature for pluvial flash floods	Identification of flaws in existing WSN-based schemes to suggest a more efficient EWS in pluvial flash floods	[18]

(Continued)

Table 2: Continued

Category	Core Area	Ref.
	Pre-Disaster Caution	
Water drainage detection from a reservoir	ZigBee-based WSN was developed for surface drainage detection using ultrasonic sensors.	[19]
Development of an energy-efficient algorithm for WSN-based flood monitoring	Optimization of energy consumption by trading off between accuracy and power consumption	[20]
Data-driven machine learning-based flood prediction	Dam data and supportive vector machine based flood prediction	[21]
Design stages for automatic water level recorder sensor system	automatic water level recorder sensor-based water level monitoring	[22]
	Post-Disaster Relief	
IoT-based identification for post-disaster needs	IoT-based data collection for planning a relief operation	[12]
Cognitive Internet of vehicles (CIoV)-based disaster management and recovery system	CIoV entities are equipped with cognition and intelligence to learn, understand, and respond without human interaction to serve, to manage disasters, and earlier recovery	[23]
Situational awareness in disaster management	Collaborated sensing, topology-aware routing, accurate resource localization to optimize data collection and energy use	[24]
Data-driven analysis of flash floods hazards to suggest a relief strategy	Spatial and temporal flash flood data assessment to suggest mitigation strategy for future	[25]

The implementation of state-of-the-art technologies such as CR and IoT have been investigated to mitigate the vulnerabilities of flash floods [12–14,22]. The state-of-the-art CIoT networks are expected to operate multiple cognitive and intelligent functionalities to minimize the loss of lives and assets under disastrous situations and higher power requirements. However, since the CIoT networks involve several battery-limited devices, efficient energy utilization is required and it has three main objectives: 1) cost-effectiveness, 2) longer battery lifetime, and 3) environmental concerns.

The energy efficiency in resource allocation is well investigated in the literature. Kim et al. studied the scheduling for IoT devices to enter them into sleep and active modes to prolong the network lifetime while satisfying the report accuracy and timely-update requirements for environmental monitoring applications at higher network levels [26]. Sarangi et al. proposed several schemes to minimize the energy consumption between neighboring IoT nodes and servers at the network layer [27]. In [28], Bui et al. proposed a scheduling scheme for software updates of IoT devices to minimize total energy consumption while satisfying the deadline constraint for updating all the IoT devices. In [29], Afzal et al. presented a context-aware traffic scheduling algorithm to allocate resources to multi-hop IoT devices and reduce their total awake time by employing adaptive duty cycling at a higher network layer. Yu et al. [30] formulated an energy consumption minimization problem considering offloading, user association, and small base station sleeping for network-wide devices and components. Kaur et al. [31] proposed a deep-reinforcement-learning (DRL)-based intelligent routing scheme for a clustered divided IoT-enabled wireless sensor network (WSN) to reduce the network delay and increase network lifetime. However, the previous work mainly focuses on the energy consumption minimization at the network layer, e.g., routing. Most recently, In [32], Verma et al. investigated the energy efficiency of a clustered IoT-based WSN to save battery energy through scheduling the selection of a cluster head and controlling the sleep mode of IoT sensor devices.

1.2 Contribution and Organization

Contrary to the studies mentioned above, in this paper, we propose CIoT-based monitoring and early warning system (MEWS) to reduce the devastation of flash floods. The proposed system model considers the characteristics of CR to develop a clustered CIoT sensor network over a wide range of geographical areas. The network lifetime of the MEWS can be increased through a suitable selection of communication channels for reporting the data collected by the CIoT sensors. To save the limited battery energy of CIoT devices, we formulate an energy efficiency maximization problem based on nonlinear integer programming (NLP). To solve this problem, we propose two polynomial-time heuristic scheduling schemes.

The rest of this paper is organized as follows. Section 2 introduces the CIoT-based system model considered in this paper. The optimization problem formulation and the proposed heuristic scheduling algorithms are presented in Section 3. The performance of the proposed scheduling schemes is evaluated in terms of energy consumption, normalized energy efficiency, the average number of available reports, and network throughput in Section 4. Discussions and conclusions are presented in Section 5 with the intended future work.

2 System Model and Background

Fig. 1 shows the bi-level MEWS. At Level-1, CIoT sensors are deployed in water channels and canyons to measure different flood-related parameters, such as water level, intensity, pressure, temperature, etc. The CIoT sensors report their observations as fixed-size packets to the smart base station (SBS) after getting the channel allocation map from SBS. At Level-2, the SBS forwards the collected data to the flood management system on a high-speed link. The flood management system employed at the disaster management center (DMC), analyzes the data to take preventive measures while a flash flood is detected. The SBS plays a role as the cluster gateway and is responsible for allocating sub-channels to the CIoT sensors.

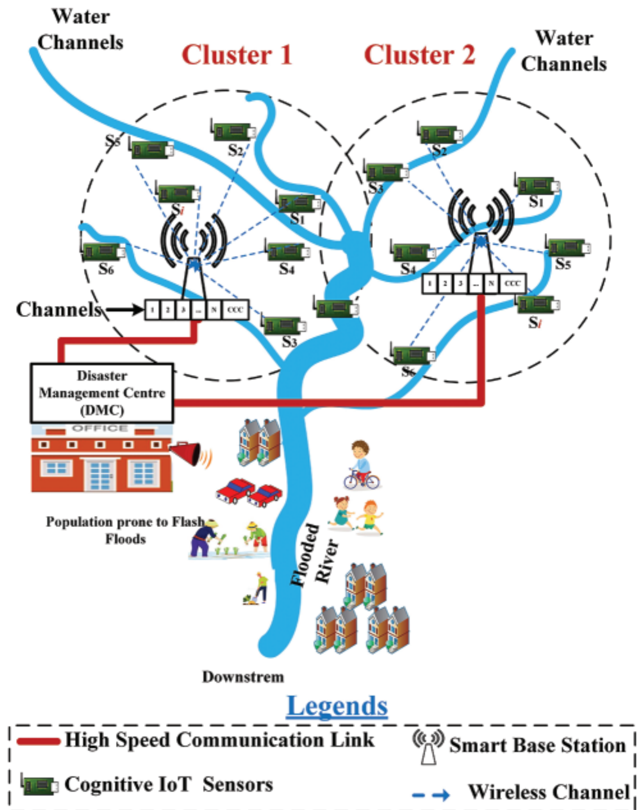


Figure 1: CIoT-based flash flood monitoring and early warning system

We consider a clustered architecture serving M CIoT sensors ($i = 1, 2, \ldots, M$), where a central entity SBS acts as the cluster head and CIoT sensors are the members of the cluster. There can be 20 to 50 CIoT sensors in a cluster. The clusters are constructed considering the distance between each CIoT sensor and the SBS. The primary network (PN) has N non-overlapping orthogonal sub-channels. The channel occupancy is modeled as a two-state Markov chain.

In this paper, spectrum sensing is not performed, assuming that the spectrum occupancy of primary users (PUs) is obtained by the SBS from a white space database which is fully synchronized with the PN [33]. Such database-based CR systems have attained notable attention due to their immense potential for transmuting CRs into functional networks [33,34]. The channel idle probability is denoted as p_{idle}. The SBS allocates j idle sub-channels to M CIoT sensors in a cluster, where $j = 1, 2, \ldots, N$. The frame architecture of the proposed scheduling schemes are shown in Fig. 2. In a cluster, at the beginning of each frame, the SBS disseminates the idle channel information to all CIoT sensors on a common control channel. As acknowledgment, each CIoT sensor sends a small packet back to the SBS on different idle sub-channels. Each CIoT sensor also shares its residual battery energy level, E_i, with the SBS on the common control channel. Exchange of these messages is performed within the control message duration, T_{ctr}, for every frame. We assume that the control message duration is significantly shorter, compared to the other time durations of the frame. As the whole information is gathered at the SBS, the SBS perform an assignment policy and broadcast the channel scheduling information to all the CIoT sensors. After that, each CIoT sensor can be either in transmission mode or idle mode. Figs. 2a and 2b illustrate the frame structures in transmission and idle modes, respectively.

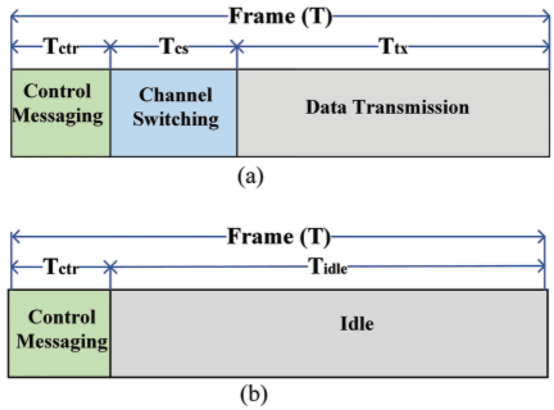


Figure 2: Frame structure of the proposed scheduling schemes: (a) frame structure of CIoT sensors when the sub-channels are allocated by the SBS, (b) frame structure of CIoT sensors when the sub-channels are not allocated by the SBS

2.1 Channel Capacity Modeling

The maximum number of bits that a single CIoT sensor can transmit in a frame over the channel depends on three factors: 1) bandwidth of the channel, W, 2) signal-to-noise-ratio (SNR), and 3) channel switching delay. The switching delay T_{cs}, is defined as the time duration spent for tuning the i-th CIoT sensors' radio frequency front-end from the previously used channel $j^{/}$ to the newly assigned channel j, which is named channel switching latency in the literature [35–37] and given as:

$$T_{cs}^{\,i,j\rightarrow j^{/}} = \tau_{cs}|j^{/} - j| \text{ seconds,} \tag{1}$$

where τ_{cs} is the hard switch delay for switching unit bandwidth. Let $C_{i,j}$ be the channel capacity for the i-th CIoT sensor and the j-th sub-channel. Using the Shannon-Hartley equation, it is expressed as:

$$C_{i,j} = W\log_2\left(1 + \frac{|h_{i,j}|^2 P_{Tx}^{i,j}}{N_0}\right) \text{ bits/second,} \tag{2}$$

where $|h_{i,j}|$, N_0, and $P_{Tx}^{\max}$ are the channel gain from the i-th CIoT sensor to the SBS in the j-th sub-channel, the normalized noise power, and the maximum transmission power, respectively. The actual throughput of a single sub-channel is defined as the maximum number of bits that can be transmitted by a single CIoT sensor on a single sub-channel during a frame dration. Let $M_{i,j}$ denote the actual throughput of the j-th sub-channel when the i-th CIoT sensor transmits information over this channel, which is obtained by

$$M_{i,j} = C_{i,j}(T - T_{ctr} - T_{cs}^{i,j}) \text{ bits,} \tag{3}$$

where T,T_{ctr}, and $T_{cs}^{i,j}$ are the total frame duration, the control message duration when the CIoT sensor is in transmission mode, and the time consumed by the i-th CIoT sensor in switching the sub-channel when the j-th sub-channel is assigned, respectively. Therefore, the total throughput R of the CIoT sensors network can be expressed as

$$R = \sum_{i=1}^{M} \sum_{j=1}^{N} D_{i,j} M_{i,j} \text{ bits,} \tag{4}$$

where $D_{i,j}$ is the binary decision variable that represents the assignment status for the i-th CIoT sensor on the j-th sub-channel. If $D_{i,j} = 1$, a sub-channel is assigned to the i-th CIoT sensor, and otherwise, $D_{i,j} = 0$, which implies no channel assignment to the i-th CIoT sensor.

2.1.1 Transmission Mode—Energy Consumption Modeling

Let $\mathbb{S}$ denotes the set of CIoT sensors assigned with the sub-channels by the SBS. The frame structure in Fig. 2a shows that if a CIoT sensor is assigned to a sub-channel (i.e., $i \in \mathbb{S}$) by the SBS, it switches its radio frequency chain to the assigned channel during the channel switching period and it transmits data during the transmission period. We refer to this scenario as the transmission mode scenario. On the other hand, Fig. 2b illustrates that if a CIoT sensor is not assigned to a channel (i.e., $i \notin \mathbb{S}$), it stays idle after the control messaging period till the end of the frame. We refer to this scenario as the idle mode scenario. Accordingly, we model the energy consumption for both scenarios as follows.

In this subsection, we derive the energy consumption of a CIoT sensor during different time durations in a single frame. At the beginning of the frame, each CIoT sensor sends its state to the SBS during the control messasing period, consuming the amount of energy E_{ctr}^{Tx} for transmitting a control message. The energy consumed by the i-th CIoT sensor during the control messaging period is calculated as follows:

$$E_{ctr}^{Tx} = P_{Tx}^{\max} T_{ctr} \text{ Joules.} \tag{5}$$

We assume that the CIoT sensors use maximum transmission power $P_{\max Tx}$ during the control message duration. After the control message, the sensors that are assigned different idle sub-channels by the SBS, switch to the assigned sub-channels by consuming channel switching energy E^{cs}. Channel switching energy consumption by the i-th CIoT sensor on the j-th assigned sub-channel is calculated as follows:

$$E_{cs}^{i,j} = P_{cs} T_{cs}^{i,j/\to j} \text{ Joules,} \tag{6}$$

where P_{cs} is the power dissipation for channel switching by a CIoT sensor. $T_{cs}^{i,j/\to j}$ is the channel swiching delay at the i-th CIoT sensor to change its sub-channel from $j^{/}$ to j, given in (6). Finally, the CIoT sensors start transmitting the collected data on the assigned sub-channels, consuming energy E_{data}. In this paper, we consider adaptive transmission power control in which the transmission power during data transmission period is adaptively assigned to the CIoT sensors according to the assigned channel condition.

Transmission energy consumption is proportional to the transmission time duration and the assigned transmission power $P_{Tx}^{i,j}$. The transmission time duration $\tau_{data}^{i,j}$ of the i-th CIoT sensors on the j-th sub-channel is obtained by

$$\tau_{data}^{i,j} = \frac{M_{i,j}}{C_{i,j}} \text{ seconds.} \tag{7}$$

Accordingly, the energy consumption during data transmission for the *i*-th CIoT sensor on the *j*-th sub-channel can be calculated as follows:

$$E_{data}^{Tx} = |h_{i,j}|^2 P_{Tx}^{i,j} \tau_{data}^{i,j} \quad \text{Joules.} \tag{8}$$

The power consumed by the electric circuitry within the CIoT sensor in transmission mode, named circuit power, is defined as P_C. It is a constant value, which is not dependent on transmission rate. The amount of energy consumed by the electric circuitry for the *i*-th CIoT sensor on the *j*-th sub-channel is expressed as

$$E_C^{i,j} = P_C \tau_{data}^{i,j} \quad \text{Joules.} \tag{9}$$

Eventually, the total energy consumption for the *i*-th CIoT sensor on the j-th sub-channel in the transmission mode scenario is obtained by adding Eqs. (5), (6), (8), and (9) as follows:

$$E_{tot}^{i,j} = (P_{Tx}^{\max} T_{ctr}) + (P_{cs} T_{cs}^{i,j/\to j}) + (|h_{i,j}|^2 P_{Tx}^{i,j} \tau_{data}^{i,j}) + (P_C \tau_{data}^{i,j}) \text{ Joules.} \tag{10}$$

2.2 Idle Mode–Energy Consumption Modeling

If no sub-channel is assigned to a CIoT sensor by the SBS in a frame, the corresponding CIoT sensor goes into the idle state after the control messaging time duration. Energy consumption for the idle CIoT sensor is the sum of the amount of energy consumed in control messaging and consumed during idle period. The length of the idle period is $T_{idle} = T - T_{ctr}$. Therefore, the energy consumption during the idle period is expressed as

$$E_{idle} = P_{Tx}^{\max} T_{ctr} + P_{idle} T_{idle} \text{ Joules.} \tag{11}$$

Consequently, the total energy consumption for a single frame in a CIoT sensor network is derived by

$$E = \sum_{i \in \mathbb{S}} \sum_{j=1}^{N} E_{tol}^{i,j} D_{i,j} + \sum_{i \notin \mathbb{S}} E_{idle} \text{ Joules.} \tag{12}$$

In Eq. (12), the first term represents the energy consumptions by active CIoT sensors, while the second term denotes those by idle CIoT sensors in the network.

3 Problem Formulation and Proposed Scheduling Schemes

Energy efficiency can be defined as the throughput achieved per unit energy consumed in a given frame time duration, T, as bits per joule [38]. Dividing Eq. (4) by Eq. (12), we obtain the energy efficiency of a CIoT sensor network as follows:

$$\eta = \frac{R}{E} \quad \text{bits/Joule.} \tag{13}$$

Subsequently, we formulate an energy efficiency maximization problem as follows:

$$\max_{\vec{d}} \eta \tag{14}$$

$$s.t. \sum_{j=1}^{N} D_{i,j} \leq 1, i \in \{1, 2, \ldots, M\}, \tag{15}$$

$$\sum_{i=1}^{M} D_{i,j} \leq 1, j \in \{1, 2, \ldots, N\}, \tag{16}$$

$$D_{i,j} \in \{0, 1\}, \tag{17}$$

where $\vec{d} = [D_{i,j}], \forall i, j$, is the channel assignment vector where each element is a binary integer value

$D_{i,j} \in \{0, 1\}$. The first constraint (15) confirms that each CIoT sensor is assigned to a single sub-channel maximally assuming that each CIoT sensor is equipped with a single antenna. The second constraint (16) ensures that only a single CIoT sensor can transmit on a certain sub-channel in a given time slot assuming that simultaneous transmissions on a single sub-channel are not allowed. The last constraint (17) means that $D_{i,j}$ is a binary integer variable. The problem at hand contains a nonlinear objective function and thus, it is so complicated to find the solution. For instance, if the CIoT sensor network has $N = 10$ idle sub-channels and $M = 15$ CIoT sensors to transmit the data in a frame, the search space considering all the possible assignments is composed of $\sum_{j=0}^{N} \left(\frac{N!}{j!(N-j)!}\right) \left(\frac{M!}{(M-j)!}\right)$ elements.

At the beginning of each frame, it is required that the SBS solves the problem and disseminates the assignment decision to all the CIoT sensors. Then, the CIoT sensors start to transmit the collected data over the assigned sub-channels. Since the SBS determines the channel assignment at the beginning of each frame, an efficient scheduling scheme is needed in the perspective of energy consumption and complexity. In this paper, the optimal solution can be found for only a small number of available idle sub-channels and CIoT sensors through exhaustive search. However, in general, since several CIoT sensors and available idle sub-channels exist in the CIoT network, a more efficient and tractable scheduling scheme is required. In the next subsections, we propose two energy-efficient scheduling schemes: energy-efficient scheduler-1 (EES-1) and energy-efficient scheduler-2 (EES-2).

3.1 Proposed Energy Efficient Scheduler-1

Fig. 3 shows the flowchart of the proposed EES-1 scheme. It greedily assigns an idle sub-channel to a CIoT sensor so that it maximizes the energy efficiency on the sub-channel. The energy efficiency matrix is calculated using Eq. (12). If the available number of idle sub-channels is larger than the number of CIoT sensors, the proposed EES-1 scheduler searches for the best CIoT sensor for a given sub-channel to maximize the energy efficiency value. Afterward, the CIoT sensor and the assigned sub-channel are removed from the search space in the energy efficiency matrix and placed in the assignment matrix. The loop continues until all the available idle sub-channels are assigned to the CIoT sensors. On the other hand, if the number of CIoT sensors is larger than the number of available idle sub-channels, the proposed EES-1 scheduler searches for the best sub-channel for a given CIoT sensor to maximize the energy efficiency. Afterward, the selected CIoT sensor and the assigned sub-channel are removed from the energy efficiency matrix and placed in the assignment matrix. The same procedure is iteratively performed until all the CIoT sensors are assigned to the idle sub-channels.

The proposed EES-1 scheme operates in polynomial time for a certain number of available idle sub-channels. More specifically, its complexity is given by the order of $O(MN)$. The performance of the proposed EES-1 scheme can be limited since the solution is often able to be local optimum. Therefore, we proposed the EES-2 scheme as an alternative scheduling scheme in the next subsection.

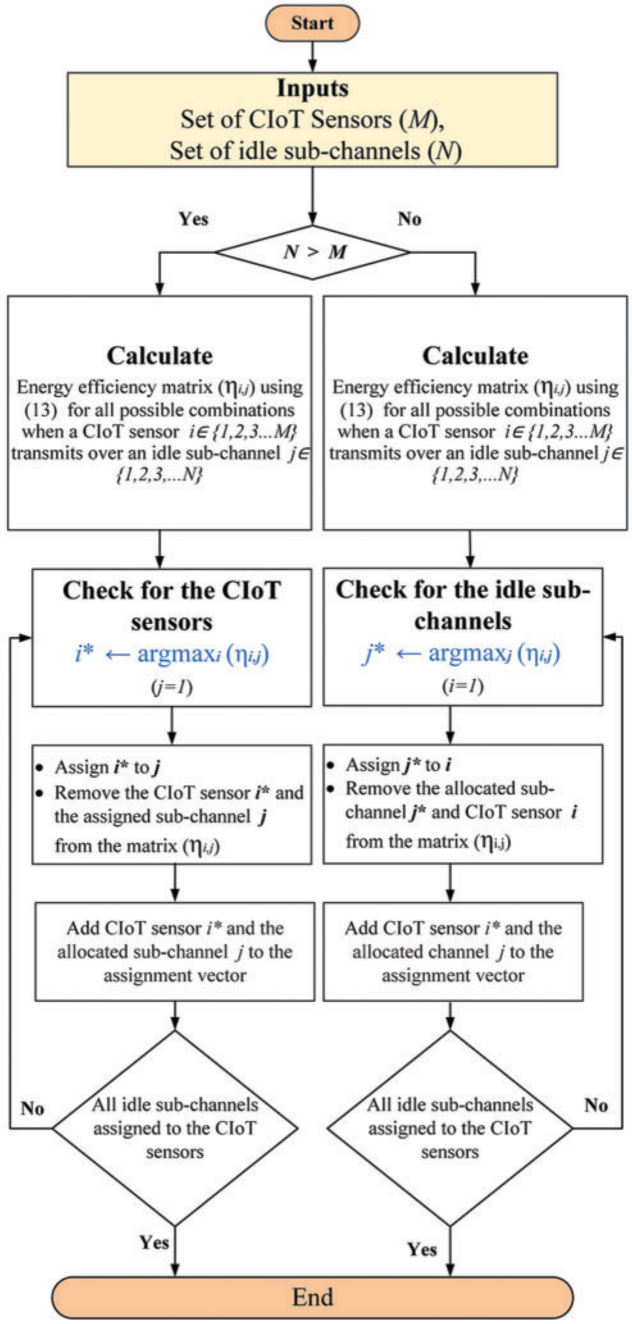


Figure 3: Flowchart of the proposed EES-1 scheme

3.2 Proposed Energy Efficient Scheduler-2

We model the channel assignment problem using a weighted bipartite graph by placing the CIoT sensors in a group of vertices, V_1, and the idle sub-channels in the other group of vertices, V_2, such that $V_1 \cap V_2 = \phi$ and $\eta_{i,j}$ (i.e., the energy efficiency for the i-th CIoT sensor and the j-th sub-channel) implies the weight factor for the corresponding edge. The bipartite graph representation of the problem is shown in Fig. 4. Accordingly, the energy efficiency maximization corresponds to a maximum weight matching problem, which is solvable using the Hungarian algorithm. Therefore, we propose the EES-2 scheme based on the Hungarian algorithm to solve the problem at hand. The flowchart of the proposed EES-2 scheme is shown in Fig. 5. The Hungarian algorithm attempts to minimize the objective function. However, our objective is to find the scheduling policy that maximizes energy efficiency. To this end, we first modify the energy efficiency matrix by subtracting each element of the initial energy efficiency matrix from the corresponding element of the maximum valued matrix. Next, we apply the Hungarian algorithm for the modified energy efficiency matrix to obtain the channel assignment result. Finally, we find the optimized energy efficiency value from the initial energy efficiency matrix for each frame by applying the channel assignment result. Since the Hungarian algorithm is a combinatorial optimization approach that solves the assignment problem in polynomial time, the complexity of our proposed EES-2 scheme is given by $O(N^3)$ [39].

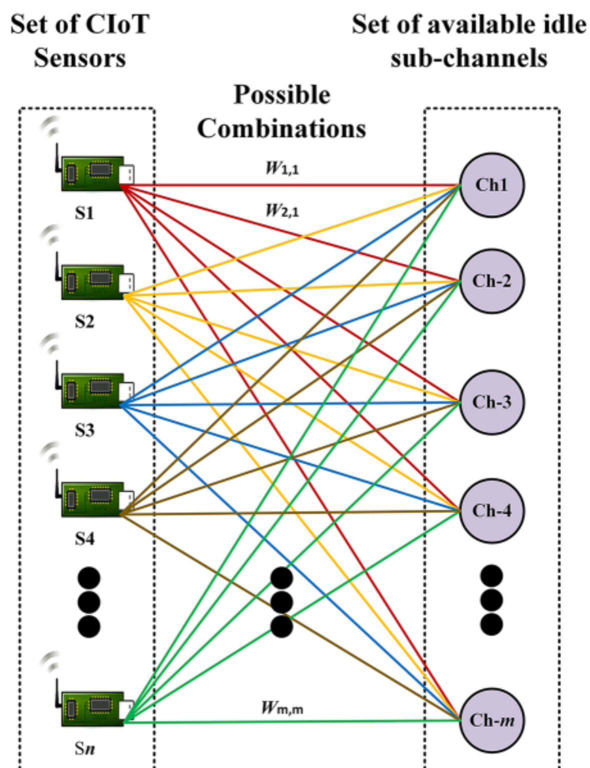


Figure 4: Bipartite graph representation for the energy efficiency maximization problem

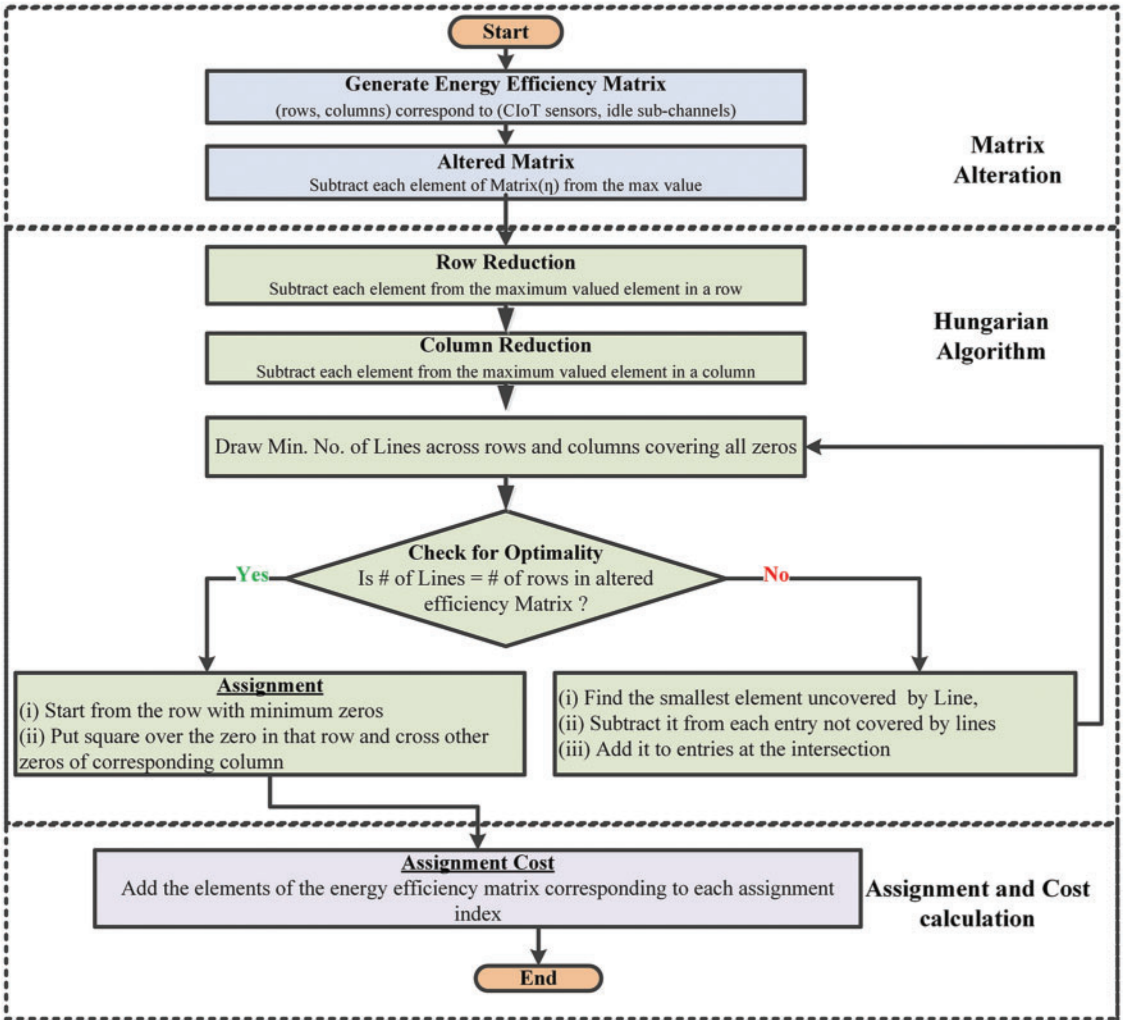


Figure 5: Flow chart of the proposed EES-2 scheme

4 Performance Evaluation

4.1 Simulation Setup

In this section, we evaluate the proposed EES-1 and EES-2 schemes through extensive simulations. As the basic performance metrics, we consider energy consumption, the average number of available reports, normalized energy efficiency, and network throughput. A random scheduler (RS), in which the idle sub-channels are randomly assigned to the CIoT sensors, is taken into account as a benchmark scheme. For simplification of the analysis, we consider a contiguous spectrum scenario with sub-channels, each of which has equally spaced bandwidth. We set the number of iterations to 30 and consider 300 frames for each iteration. In addition, each CIoT sensor transmits 200 bits of data per frame when a certain sub-channel is allocated to the CIoT sensor. It is assumed that the channel follows an independent and identically distributed (i.i.d.) Gaussian distribution and the average SNR is set to 3.5 dB. The relationship among the power values is such that $P^d < P^{cs} < P_{\max Tx}$. More specifically, the power consumption profile for a wireless local area network (WLAN) interface [38] is used in our simulation setup. Transmission power during the data transmission period is determined according to the assigned channel gain but not exceeding the maximum power level $P_{Tx}^{\max}$. The detailed simulation parameters are listed in Tab. 3.

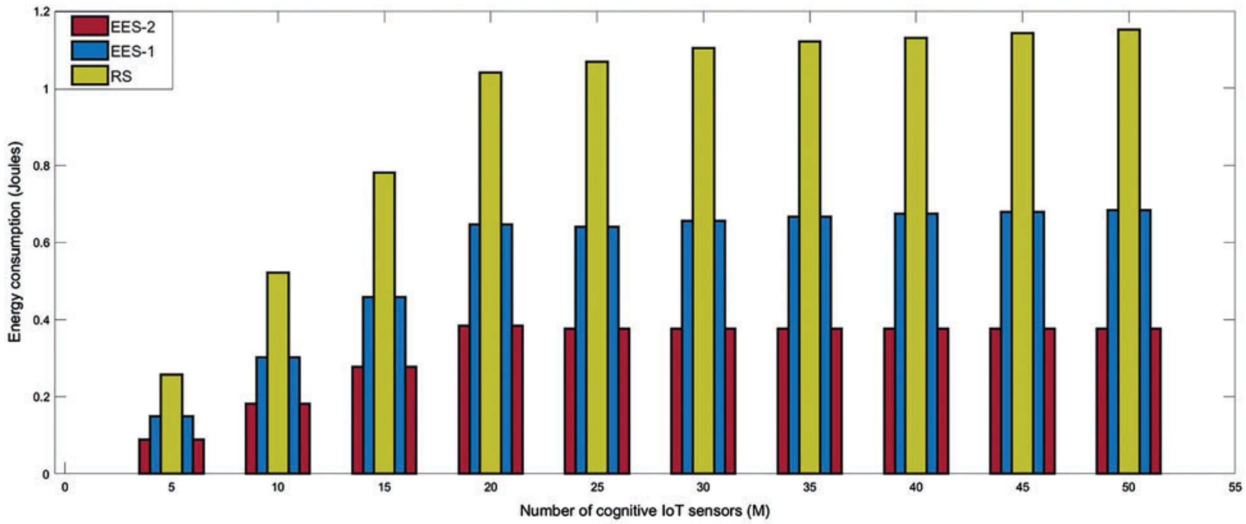
Table 3: Simulation parameters

Symbol	Description	Value
$D_{i,j}$	Binary decision variable indicating the assignment; $D_{i,j} = 1$ if a channel is assigned; else zero	$\{0, 1\}$
T	Frame duration	$10\ ms$
T_{ctr}	Control messaging time duration	$50\ \mu s$
τ_{cs}	Hard switching time	$1\ \mu s$
W	Channel bandwidth	6 MHz
$P_{Tx}^{\max}$	Maximum transmission power	$1980\,mW$
P_{CS}	Channel switching power	$1000\,mW$
P_C	Circuity power	$210\,mW$
P_{idle}	Idling power	$990\,mW$
N	Number of sub-channels	[5 : 50]
M	Number of CIoT sensors	[5 : 50]

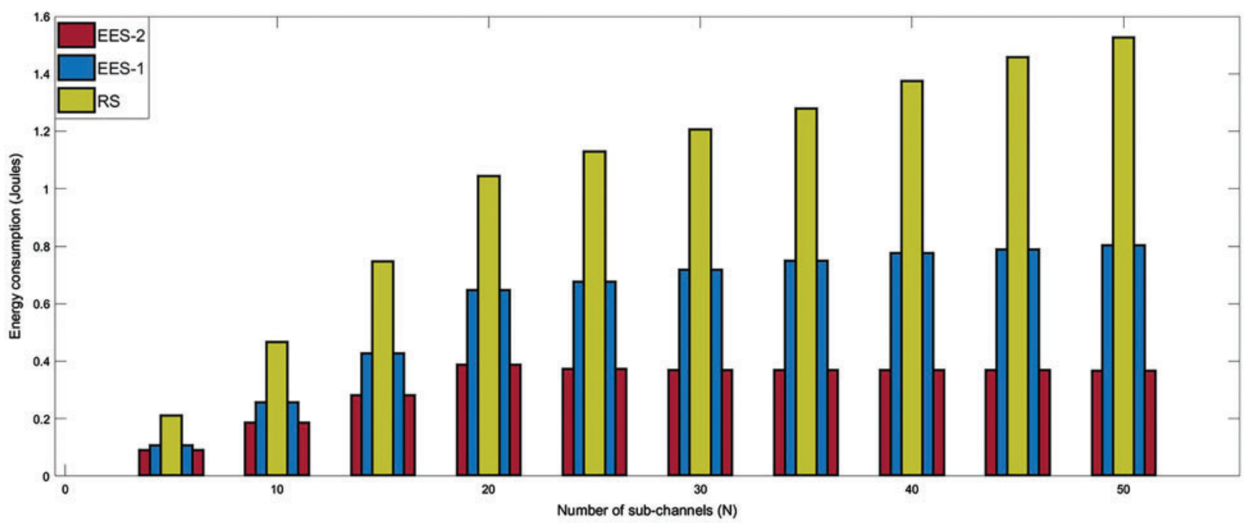
4.2 Energy Consumption

Fig. 6a shows the effect of the number of CIoT sensors on the energy consumption of the conventional and proposed scheduling schemes when the number of sub-channels is set to 20 (i.e., $N = 20$). It is clear that the proposed EES-2 scheme is the most efficient in energy consumption. The energy consumption rises as the number of CIoT sensors increases since more CIoT sensors are involved in data transmission. After a point (e.g., $N = 20$), the energy consumption of the proposed EES-2 scheme decreases and is saturated to a certain level. The proposed EES-2 scheme searches for more suitable sub-channels out of available sub-channels, leading it to consume less energy. On the contrary, the energy consumption in the proposed EES-1 and the conventional RS schemes is not reduced significantly as the number of CIoT sensors increases. The proposed EES-1 scheme greedily assigns the sub-channel providing higher energy efficiency to a CIoT sensor without considering the overall energy efficiency of the CIoT network. Similarly, the conventional RS scheme randomly chooses the channels and assigns them to any CIoT sensors. Thus, it causes more energy consumption which is linearly increasing as the number of CIoT sensors increases.

Fig. 6b illustrates the effect of the number of sub-channels on the energy consumption when the number of CIoT sensors is set to (i.e., $M = 20$). In the figure, it is shown that the proposed EES-2 scheme achieves the lowest energy consumption. The proposed EES-2 scheme searches for the best assignment for all the CIoT sensors consuming less energy overall, while the proposed EES-1 scheme tries to allocate the best sub-channel to one of the CIoT sensors only satisfying the constraints, without considering the energy efficiency in the whole CIoT network. Since the RS scheme randomly chooses the CIoT sensors for the idle sub-channel without taking the energy efficiency into account, it consumes the most amount of energy, compared to the other proposed schemes.



(a) Energy consumption vs. number of CIoT sensors



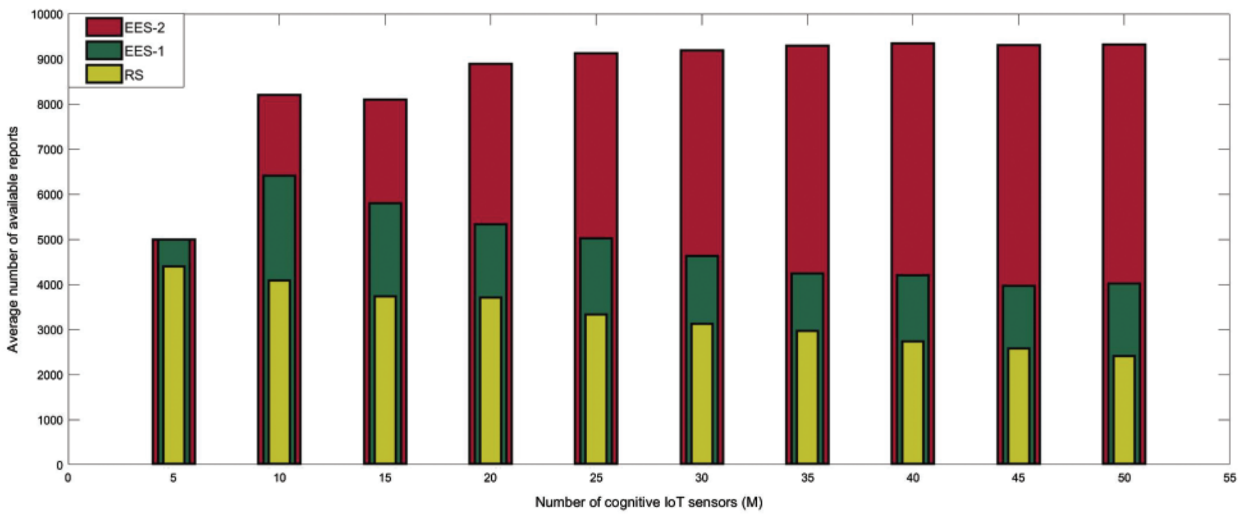
(b) Energy consumption vs. number of sub-channels

Figure 6: Energy consumption: (a) Effect of the number of CIoT sensors and (b) Effect of the number of sub-channels

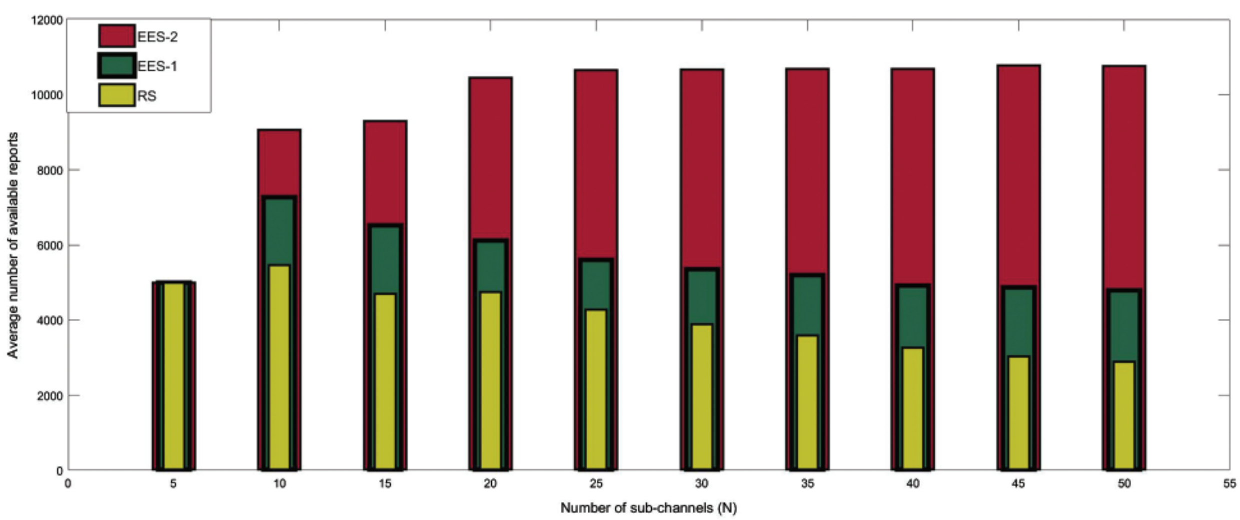
4.3 Average Number of Available Reports

The lifetime of a CIoT network can be defined as the average number of available reports in an assignment before the first depleted CIoT sensor in battery energy occurs in the network [40]. To validate the effectiveness of the proposed EES-1 and EES-2 schemes, we set the initial battery capacity of each CIoT sensor in the network to 15 mAh. The battery threshold level to decide the depletion of battery energy is set to 5 mAh and 10,000 consecutive frames are considered in the simulations.

Fig. 7 shows the average number of available reports for varying the number of CIoT sensors and the number of sub-channels. From Fig. 7a, it is clear that the proposed EES-2 scheme achieves a large average number of available reports before the first CIoT sensor reaches the battery threshold level. The average number of available increases with increasing the number of CIoT sensors. It is saturated to a certain level after a particular point since the fixed number of CIoT sensors only participate in data transmission effectively. On the other hand, the average number of available reports of the proposed EES-1 scheme rather decreases as the number of CIoT sensors increases. This is because in the proposed EES-1 scheme, due to being a greedy scheme, some of the CIoT sensors may transmit with higher energy on the assigned channel so that their batteries are more quickly depleted. Consequently, it consumes more energy in the assignments, resulting in a fast battery energy decay. Similarly, in Fig. 7b, it is shown that the proposed EES-2 scheme also outperforms the other schemes in terms of the average number of available reports. The average numbers of available reports of the conventional RS and proposed EES-1 schemes rather decrease as the number of sub-channels increases when it is larger than 10, while that of the proposed EES-2 scheme is increased and saturated to a certain level. Therefore, the proposed EES-2 scheme is the most efficient in the perspective of network lifetime.



(a) The average number of available reports vs. number of CIoT sensors



(b) The average number of available reports vs. number of sub-channels

Figure 7: Average number of available reports: (a) Effect of the number of CIoT sensors and (b) Effect of the number of sub-channels

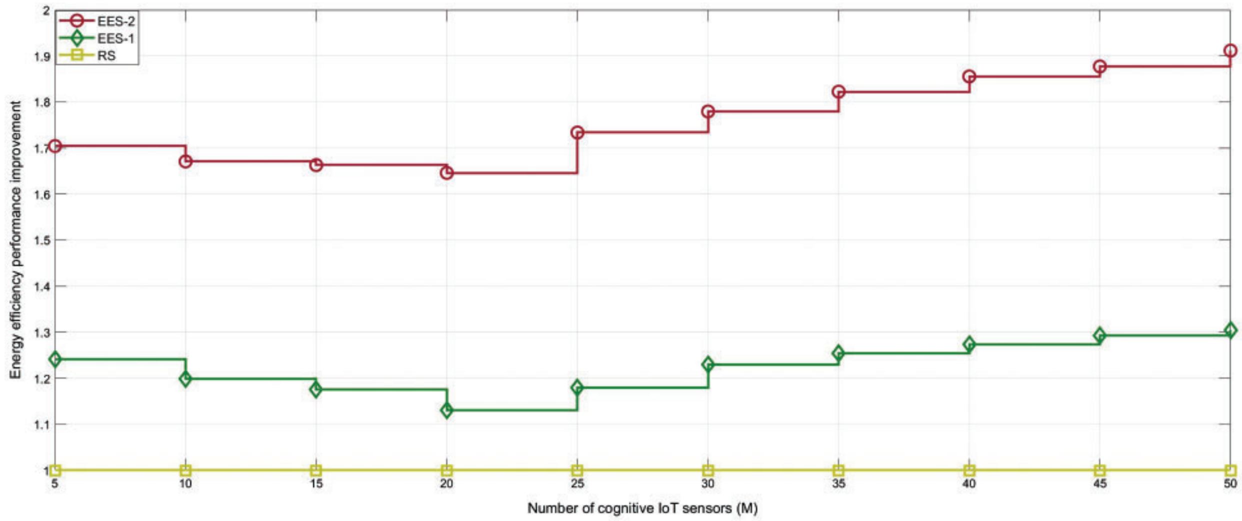
4.4 Normalised Energy Efficiency

In this subsection, we present the performance improvement in the normalized energy efficiency achieved by the proposed schemes over the conventional RS scheme. We consider the conventional RS scheme as a yardstick to show the relative effectiveness of the proposed schemes.

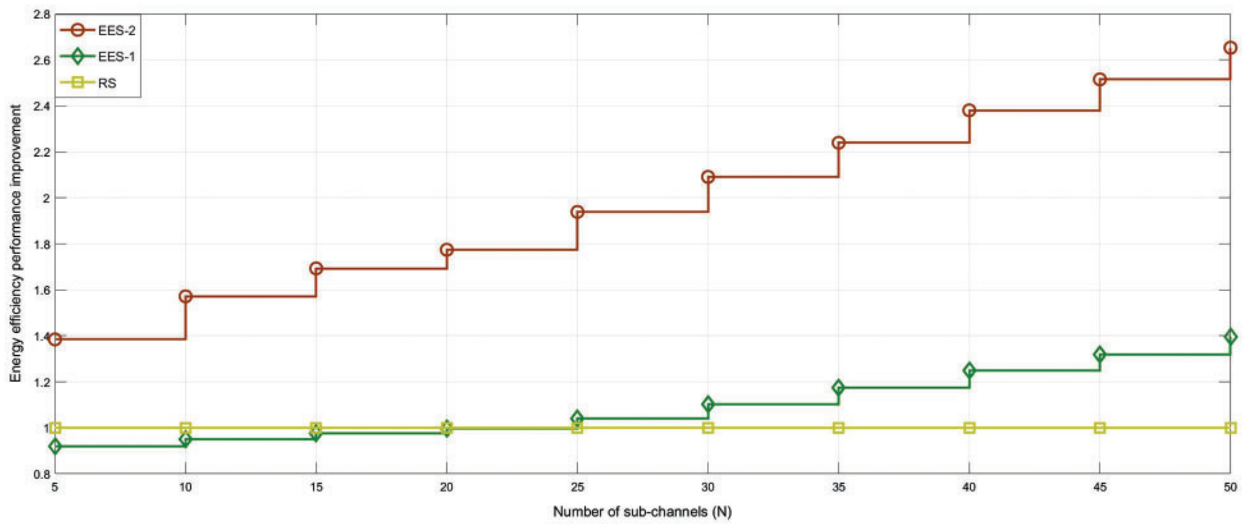
Fig. 8 shows the normalized energy efficiency for varying the number of CIoT sensors and the number of sub-channels. In Fig. 8a, when $N=20$, as the number of CIoT sensors increases, the proposed EES-2 always outperforms the proposed EES-1 and the conventional RS schemes. Especially, it significantly improves the energy efficiency for a typical operation region, i.e., $N \geq 20$. The reason is that the proposed EES-2 scheme can transmit more collected data with less energy consumption. On the contrary, the proposed EES-1 and the conventional RS schemes consume higher energy for data transmissions. Similarly, Fig. 8b shows the normalized energy efficiency for varying the number of sub-channels when $M = 20$. It is clear that the proposed EES-2 outperforms the proposed ESS-1 and the conventional RS schemes as the number of idle sub-channels increases. The reason is that the proposed EES-2 scheme searches for the best sub-channels considering the overall energy efficiency of the network. On the contrary, the proposed EES-1 searches for the subject sensor only thus consuming higher energy for data transmissions.

4.5 Network Throughput

Fig. 9 shows the network throughput achieved by the proposed and conventional schemes for varying the number of CIoT sensors and the number of sub-channels. In Fig. 9a, the impact of the number of CIoT sensors on the network throughput in the network is illustrated when $N = 20$. It is obvious that the proposed EES-2 scheme achieves the highest network throughput followed by the proposed EES-1 and the conventional RS schemes. As the number of sub-channels increases, the network throughput proportionally increases since more CIoT sensors are involved in data transmissions. If there exist sufficient idle sub-channels, the proposed EES-2 scheme searches for more suitable channels to allocate each CIoT sensor. As a result, more CIoT sensors can transmit their own collected data with more available sub-channels, resulting in achieving a higher network throughput. On the other hand, the network throughputs of the proposed EES-1 and the conventional RS schemes rather decrease as the number of CIoT sensors increases. The proposed EES-1 scheme greedily assigns a sub-channel providing higher energy efficiency to the best CIoT sensor without taking the overall energy efficiency of the CIoT network into consideration. In addition, since the conventional RS scheme randomly selects the sub-channels for assignment to the CIoT sensors, it achieves the lowest network throughput. Similarly, in Fig. 9b, it is shown that the proposed EES-2 scheme outperforms the other schemes, and its network throughput increases as the number of sub-channels increases. On the contrary, those of the proposed ESS-1 and the conventional RS schemes have an opposite trend, where the network throughput is reduced with increasing the number of sub-channels.

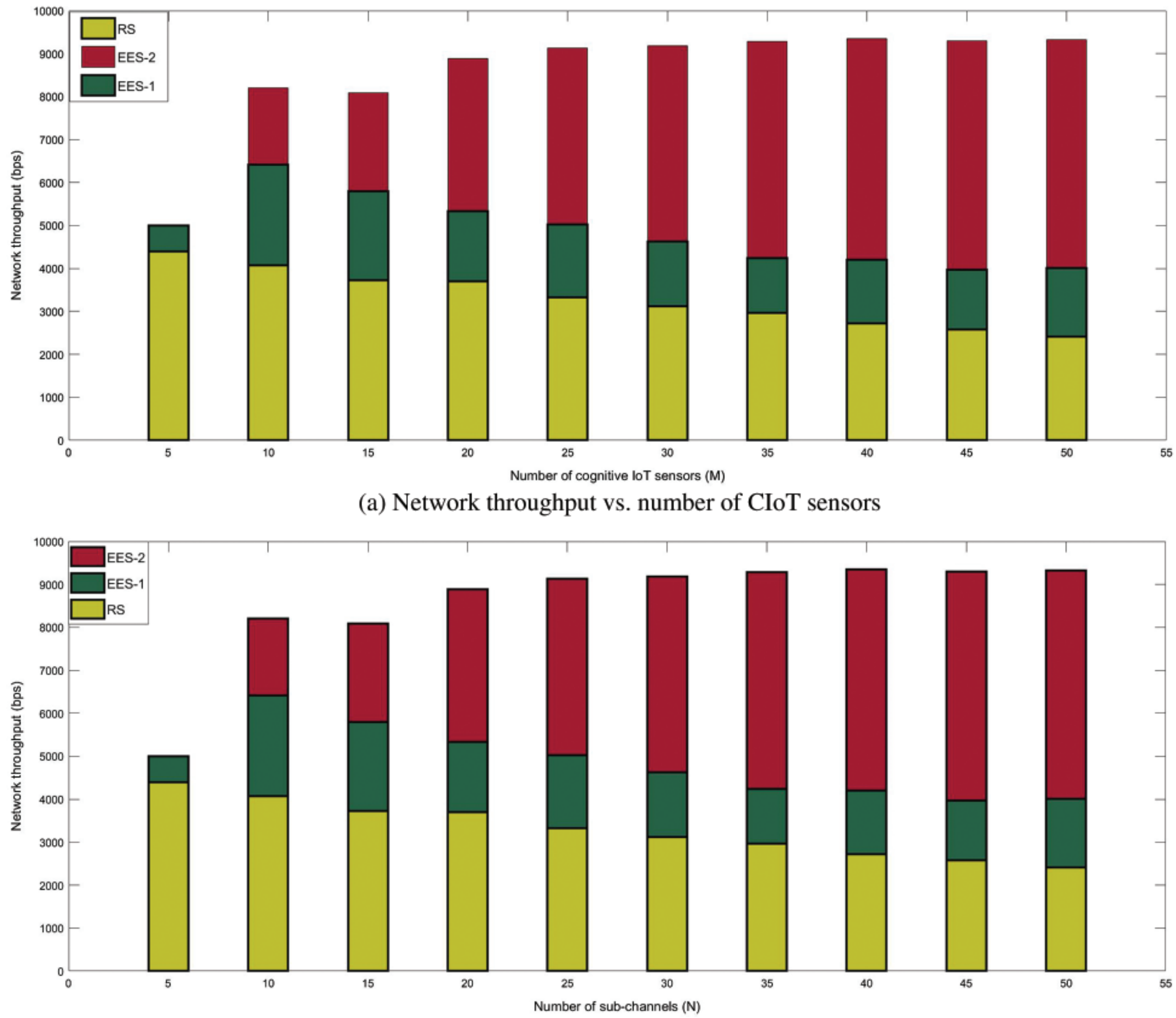


(a) Normalized energy efficiency vs. number of CIoT sensors



(b) Normalized energy efficiency vs. number of sub-channels

Figure 8: Normalized energy efficiency: (a) Effect of the number of CIoT sensors and (b) Effect of the number of sub-channels



(a) Network throughput vs. number of CIoT sensors

(b) Network throughput vs. number of sub-channels

Figure 9: Network throughput: (a) Effect of the number of CIoT sensors and (b) Effect of the number of sub-channels

5 Conclusions

In this work, we investigated a cognitive Internet of things (CIoT) network to develop a monitoring and early warning system (MEWS) to reduce the fatalities of flash floods. Considering the limited battery energy of CIoT sensors, we formulate an energy efficiency maximization problem. To solve the problem, we first propose a polynomial-time heuristic energy-efficient scheduler (EES-1) scheme. However, its performance can be unsatisfactory, since it provides local optimum values for some cases without considering the overall network energy efficiency. To enhance the energy efficiency of the proposed EES-1 scheme, we reformulate the optimization problem using a maximum weight matching bipartite graph. Additionally, we propose a Hungarian algorithm-based energy-efficient scheduler (EES-2) scheme. The proposed EES-2 scheme provides a significant performance improvement in terms of energy efficiency, compared to the proposed EES-1 and the conventional random scheduler (RS) scheme. As a result, the proposed EES-2 scheme, which achieves less energy consumption, can be applied for a MEWS system with battery-limited CIoT sensors under flash floods situations. More specifically, for a sufficiently large number of idle sub-channels, all CIoT sensors can acquire opportunities to transmit their collected sensing data, while a few CIoT sensors may not be able to transmit the data when the number of available idle sub-channels is less than the number of CIoT sensors. In the future, we plan to investigate a fairness issue in scheduling for more practical scenarios. Moreover, for an autonomous CIoT-based MEWS, we plan to integrate the reliability and a spectrum sensing capability in the objective function.

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Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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