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Joint power and channel allocation scheme for IEEE 802.11af based smart grid communication network



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HIGHLIGHTS

- A SG communication scenario using IEEE 802.11af in clustered NANs.
- Open loop GDD regulatory model for TVWS communications.
- Joint power and channel allocation (JPCA) with multiple constraints.
- Optimized power allocation based on SNR threshold.
- Two practical cases: fairness-based allocation and priority-based allocation.
- Effectiveness of proposed algorithms shown through plots and numerical comparisons.

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ABSTRACT

To reap the full potentials of Smart grid (SG), a reliable, resourceful, efficient and cost-effective communication network is inevitable. The crucial need to transmit a significant amount of smart grid application data in an efficient spectral manner makes cognitive radio (CR) technology most suitable for SG environment. Identically, TV white space (TVWS) is the most expectant candidate for CR based smart grid communication network (CRSGCN). In this paper, we are investigating the problem of joint power and channel allocation (JPCA), which is among the most important and widely explored area in cognitive radio domain. We first model a typical scenario in a neighborhood area network (NAN) communication using IEEE 802.11af via open loop regulatory framework for TVWS. A mathematical model is formulated to jointly address power and channel allocation considering practical constraints for two real-world scenarios of fairness-based and priority-based allocation. Next, an efficient power allocation (PA) scheme is presented, meeting quality-of-service (QoS) requirements, followed by channel allocation (CA) scheme based on cuckoo search algorithm (CSA). The performance of the proposed solutions is analyzed using exhaustive simulations to optimize power consumption, fairness and user rewards. The presented results in the form of graph and numerical comparisons indicate the effectiveness of our allocation algorithm to achieve the desired objectives.

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1. Introduction

Smart grid (SG) concepts have revolutionized the future of conventional electric grid by making it more efficient, resilient and reliable. The use of state of the art technologies, modern equipment, and automation control systems have provided benefits such as reduced power outages, increased power quality, cheap electricity,

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https://doi.org/10.1016/j.future.2019.01.027 0167-739X/© 2019 Elsevier B.V. All rights reserved. low operational costs and integration of renewable & sustainable energy sources. The two-way communication paradigm has enabled the consumers to take control of their energy consumption and electricity bills. However, the full realization of all the abovementioned benefits is not possible without the implementation of a fast, reliable and economical communication network that must exhibit spectral and energy efficiency. The data generated by various SG applications is not only in enormous proportion but also diverse in nature in terms of its delay tolerance [1]. Cognitive radio (CR) based cost-effective network solutions are widely adopted to carry a fair share of delay-tolerant data in the literature [2–15]. A typical CR based smart grid network is shown in Fig. 1, where

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CR technology is used for communication in neighborhood area network (NAN) and wide area network (WAN).

TV white space (TVWS) has been envisioned as the most promising spectrum contender for CR based smart grid communication network (CRSGCN), owing to its desirable propagation behavior, Spectrum under-utilization, better non-line of sight (LOS) coverage due to less harmful material obstruction and simplified secondary access paradigm using geo-location database (GDB) for incumbent service protection [16]. Currently, two IEEE communication standards: IEEE 802.11af (Wi-fi) and IEEE 802.22 (Wireless Regional Area Network — WRAN) designed for TVWS with CR paradigm are most commonly used by researchers for different SGCN scenarios. Both standards are very well-suited for SG environment and fulfill all the communication requirements [17]. However, we have used IEEE 802.11af in this research paper to model our communication scenario.

Unlike other variants of IEEE 802.11 Wireless Local Area Network (WLAN) standard, the modification in physical and medium access layer (MAC) in IEEE 802.11af have increased the range up to \sim 1 KM by incorporating TVWS. One fundamental difference is the entity geo-location database (GDB) that contains all the necessary information regarding operational parameters. The whole working of this standard revolves around GDB which itself is authorized and regulated by various countries. Regulatory implementation of GDB is governed by two approaches: open loop model and closed-loop model. We restrict our discussion to the open-loop model since it is more suitable for our scenario. Both fundamental concepts of IEEE 802.11af and open loop model are discussed in detail in Section 3.

In this research article, we focus on IEEE 802.11af with open loop geo-location based database-dependent (GDD) system to model a communication scenario in clustered Neighborhood Area Network (NAN) of an SGCN. Considering two practical cases of fairness-based allocation and priority-based allocation (detailed later in Section 5.2), we propose a joint power and channel allocation scheme using a heuristic approach to facilitate delaytolerant data produced by applications such as Demand Response Management (DRM), Advanced Metering Infrastructure (AMI) and Home Energy Management Systems (HEMS), etc. We then evaluate the performance of our algorithm for improving overall fairness and network utilization with the help of numerical results and graphs.

A significant amount of research is available on joint power and channel allocation (JPCA) as far as cognitive radio is concerned. However, we feel that a lot of effort is required to extend this work in SG environment. Therefore, we have tried to formulate a problem of JPCA for a very practical scenario in CRSGCN. Our contributions in this research work are as follows:

- ✓ We have present a network model for a communication scenario taking account of practical considerations such as coverage area, channel bandwidth, operating frequency band, number of sub-channels and transmitted power constraints for an open loop GDD regulatory model of IEEE 802.11af standard in clustered NANs for SG communications.
- ✓ We have investigated and formulated a JPCA problem with multiple constraints considering two practical cases of fairness-based allocation and priority-based allocation in an SG environment in an innovative way, which perhaps is among pioneer and premiere works in its technical domain.
- ✓ We propose a simple yet effective QoS based power allocation algorithm that serves the purpose of increasing power efficiency.
- ✓ We have proposed a cuckoo search algorithm (CSA) based solution for the channel allocation problem, which itself is rarely applied in such complex scenario before. Our proposed algorithm works well for both cases having conflicting requirements of fairness and priority, which is shown through plots and numerical comparisons in the form of tables.

Rest of the paper is organized in the following manner. A quick review of related work is described in Section 2. Section 3 is detailed with primitives and basics of IEEE 802.11af standard that are essential to comprehend the working of our modeled scenario fully. System model comes next in Section 4, which starts with an explanation of our scenario in the network model and the problem is formulated in the mathematical model. Our proposed joint power and channel allocation algorithms using a heuristic approach are described in Section 5. Simulations, results and discussions are carried out in Section 6. The research work is finally concluded in Section 7.

2. Related work

In this section, we present a brief review of related research work from the field of CRSGCN, TVWS in SG communication, JPCA and fairness in CR networks.

Authors in [1], presented a comprehensive review of smart grid communication network design requirements and viable communication technologies for HAN, NAN, and WAN. After depicting communication requirements for HAN, NAN, and WAN, a CR based SGCN architecture is proposed for carrying delay-tolerant data and potential challenges. [2] is another recent survey highlighting research gaps in design, modeling, and utilization of CR based sensor networks in smart grids, where authors have proposed a smart and unified solution for SG communication to answer different challenges. In [3], authors have done an extensive review of CRS-GCN paradigms including network architectures mainly drawing attention to potential applications, spectrum sensing classification, routing and MAC protocols. It also includes a detailed discussion of open issues and challenges along with future direction. [18] is among some pioneer systematic reviews to be conducted for communication and networking addressing issues like QoS, control management and optimizing network utilization. Authors in [19], presented a detailed review of some essential components of SG, enabling six SG applications. Issues like achieving interoperability of legacy and evolving protocols are also discussed. A detailed study on SG communication network architectures and applications along with standardization efforts is provided in [20]. In addition, some of the significant challenges in cross-functional domains of power and communication are also identified. In [21], authors have used software defined networking (SDN) paradigm to present a framework for communication in NAN using wireless sensor networks (WSN). An analytical model for NAN is developed to determine the no. of switches and controllers, and its performance is evaluated using Castalia based simulations. Comprehensive research is presented in [22], providing a full analysis and comparison of AMI related routing protocols and technologies in NAN.

A dynamic spectrum sharing (DSS) scheme comprising of designing network topology and channel allocation for CR networks is proposed in [23]. The authors have analyzed network performance for smart utility network (SUN) services using Markov chain models. In [24], authors have proposed power difference coding (PDC) scheme to model the behavior of SG power scheduling over CRNs using an On-demand approach that suggestively avoids power waste. Opportunistic transmission protocol combined with optimal power allocation and transmit beamforming for non-orthogonal random access in multiple-input-multipleoutput (MIMO) CRNs is used by authors in [25], to reduce interference temperature and transmission power, thereby increasing cognitive transmission capacity. In [26], a CDMA based resource allocation technique is proposed for a secondary network in CRSGCN. Authors have suggested with the help of numerical results that the proposed technique significantly improves the number of SUs. Authors in [27], have jointly studied heterogeneous networks (Het-Nets), CRNs and SGs to maximize energy efficiency and adopted



Fig. 1. CR based smart grid network architecture.

the game theoretic approach to not only reduce operational expenditure but reduce CO2 emissions. A novel routing protocol for increasing the energy efficiency in a CR based AMI networks for SGs is proposed in [28], that also provides a mechanism to protect PUs. In [29], authors have investigated interference management in CRS. Optimal precoders and decoders are then identified to reduce mean square error calculations at DCU and primary receivers. Authors in [30], have studied the suitability of Long Term Evolution (LTE) for SG applications. The proposed novel technique for estimation and allocation of bandwidth improves packet loss, delay, and throughput.

TVWS based on CR technology is widely used in a smart grid, owing to their better propagation characteristics. Authors in [31], proposed an online algorithm using a Lyapunov drift and penalty function, that can provide a trade-off between total cost and QoS in the internet of things (IoT) and SG applications. A case study to solve the service coverage for internet and SGs in Ecuador using TVWS is presented in [32]. Another research work utilizing TVWS for smart metering applications in an SG is shown in [33], in which authors have presented novel idea of high priority channel (HPC) leasing by CR operators. They developed a real-time support model that can help in the trade-off between HPC cost and QoS. In [16], authors have addressed the interference among multiple NANs in urban SG scenario, aiming at maximizing the achievable capacity. The problem of optimal power allocation and channel selection for TVWS for smart metering data between SMs and DCU is discussed in [34]. The authors have used spectrum engineering advanced Monte Carlo simulation tool (SEAMCAT) for interference analysis and optimized the SM configurations to achieve optimal channel and power efficiency using a genetic algorithm. Authors in [35], have provided a review of smart utility network (SUN) and TVWS. Then in an effort to combine these two separate and independent technologies, a hybrid solution is proposed, merging their individual strengths. In addition to identifying the opportunities and challenges, several regulatory and technical recommendations are listed, to help in the realization of a practical solution.

Both optimal channel and power allocation are essential objectives for CRNs since they contribute to goals such as spectral efficiency, interference mitigation, and maximizing throughputs. A JPCA problem is formulated for heterogeneous cognitive networks

in [36], using a game theoretic approach. Then an algorithm using Nash bargaining solution is proposed, whose computational complexity is further reduced heuristically, thereby increasing spectral efficiency but also guaranteeing fairness among SUs. In [37], a JPCA algorithm is proposed on presented that not only optimizes fairness among SUs but also considers the signal to interference ratio (SIR) to protect PUs. Authors in [38], investigated JPCA under fading channels in a CRNs to optimize the ergodic sum-rate of SUs under multiple power and interference constraints. A Joint opportunistic power and rate allocation algorithm based on the adaptive evolutionary algorithm is proposed in [39] to minimize the power and maximize the sum of source utilities with minimum power for wireless Ad hoc networks. An auction scheme for cooperation between PUs and SUs in CRNs is investigated in an exciting way in [40], where PUs relay data for SUs to earn revenue. SUs are given the option to select either purchase only PUs spectrum or both spectrum and power. Walrasian equilibrium is used to prove the convergence of the proposed algorithm and performance is verified using simulations. Considering constraints like SUs-PU interference and QoS for SUs, the problem is formulated as a maximization problem for CRNs in [41]. First, the available channels are dynamically allocated in a distributed manner meeting interference constraint, and then an iterative power allocation algorithm is applied considering both constraints. Another heuristic power control scheme joint with dynamic spectrum access (DSA) is presented in [42], that aims at maximizing spectral efficiency, throughput, and fairness among SUs. The optimization problem is formulated by cooperative game perspective and solved using the differential algorithm.

Fairness is a desirable trait in most of the CRNs applications where all SUs demands an equal share of resources. A cooperative CRN scenario where a hybrid access point (HAP) powers multiple SUs wirelessly is modeled in [43], where the SUs transmits in their respective timeslots to HAP. The objective is to prioritize SU transmission to enhance fairness among SUs by proposing three resource allocation schemes: equal time-allocation, min throughput maximization, and proportional time-allocation. It is shown that min throughput maximization outperforms the other two schemes in terms of fairness. A different resource allocation based on heuristic algorithms for controlling power and allocating spectrum in a dynamic way is proposed in [44], aiming at maximizing the overall fairness among SUs. The idea is to give priority to the nodes with less available holes thus increasing the throughput of the bottleneck user. The proposed algorithm is shown to achieve better fairness compared to traditional resource allocation schemes. A new scenario for fairness among SUs in CRSGCN is modeled in [45]. A cat swarm optimization (CSO) CA algorithm is proposed to solve the optimization problem for max-sum reward and fairness among SUs. The proposed algorithm is then compared with traditional heuristic approaches like GA and PSO to show that performs better for the problem under consideration. Authors in [46], have presented a ground-breaking work in the field of opportunistic spectrum access, latterly become CR. The problem is formulated using color graph theory as to maximize utilization fairness among users. A detailed analysis of different configurations is presented, and it is shown that proposed algorithms efficiently reduces interference and increases throughput. A novel and efficient decentralized spectrum access strategy for CRNs is presented in [47]. The proposed channel assignment scheme is based on spectrum usage history that provides stable network operation in addition to minimal interference, optimized throughput and improved fairness since SUs do not require to change their frequency regularly. A worthy contribution in the form of a comprehensive and detailed survey on resource allocation in underlay cognitive radio is presented in [48]. Authors have summed up state-of-the-art algorithms for resource allocation based on network architecture, objectives, management strategies and solving techniques. In addition to a review of some current problems, prospective future directions are also outlined. In our previous research work [49], we have modeled the same SG communication scenario in NAN as in this paper, for solving the problem of CA only, using Cat swarm optimization for the cases of fairness-based and priority-based allocation. Unlike this research, only channel allocation problem is addressed using cat swarm optimization by considering user rewards on the basis of channel bandwidth rather than channel capacity, as in this paper.

3. IEEE 802.11af: fundamentals

In this section, we will only focus on network architecture and some key functionalities in open loop regulatory model of IEEE 802.11af.

3.1. Network architecture

The network architecture of IEEE 802.11af, also known as whitefi, comprises three primary entities: Geo-location database, Registered location secure server, and Geo-location database dependent entities. The brief functionality of these elements is described below.

- Geo-location Database (GDB) is the primary element that stores list of vacant channels and operating parameters for white space devices (WSDs) administered and authorized by the regulatory authority.
- ii. **Registered Location Secure Server (RLSS)** is a local database (DB) that stores operational parameters and geographic location for a small number of basic service sets (BSSs). The RLSS controls access points (APs), and stations (STAs) connected to it by providing them with operating parameters.
- iii. Geo-location Database Dependent (GDD) Entities are rest of the two elements in the white-fi network that are controlled by authorized GDB to satisfy regulatory requirements. These entities are GDD-Enabling Station (ES) and GDD-Dependent Station (DS). The GDD-ESs are actually APs governed by GDB or RLSS controlling GDD-DS in its serving BSS. They ensure the updating and distribution of operational parameters received from GDB, represented as white



Fig. 2. Example of IEEE 802.11af network entities communicating with each other [50].



Fig. 3. TVHT different bandwidth combinations [51].

space map (WSM). The *GDD-DSs* get their operational parameters from GDD-ES or RLSS in the form of WSM. The GDD-ES confirms the validity of WSM by transmitting a contact verification signal (CVS). This channel utilization and WSM sharing between two GDD entities are performed using Registered location query protocol (RLQP) [50]. An example of a TVWS network is shown in Fig. 2.

3.2. Physical layer specifications

The PHY layer specifications in IEEE 802.11af, defined as TV high throughput (TVHT), that supports channel bandwidth of basic channel units (BCU) of 6, 7, and 8 MHz according to regulations of the operating regions. Single channel bandwidth (TVHT_W), single spatial stream and binary convolutional coding are mandatory. Additionally, the different bandwidth combinations of BCUs (both contiguous or non-contiguous) are also possible as shown in Fig. 3 [51]. Other supported features include multiple input multiple output (MIMO) transmissions with 4 times space-time block coding (STBC) and 4 times multi-user (MU) diversity. A summary of PHY specifications is presented in Table 1.

3.3. Regulatory framework

As mentioned previously, IEEE 802.11af or white-fi is driven by regulatory domain thus in order to implement TVWS regulations of different operating regions; it has to be flexible. The incumbent user service acting as primary user (PU) in TVWS band consists of digital terrestrial television (DTT) and program making & special event (PMSE) users such as wireless microphones etc. A wireless space device (WSD), also known as TV band device (TVBD), acts as a secondary user (SU). Working on the principle of interference avoidance, a WSD must have exact knowledge about operating parameters of licensed service, which it gets from centralized, secured and verified yet regulated GDB. Hence most of the regulatory authorities prefer this approach. Therefore, the regulatory implementation of GDB is indispensable to the proper working of IEEE 802.11af. Two main approaches that govern the regulatory implementation of GDB are open-loop GDD and closedloop GDD [52].

- i. **Open-loop GDD:** This implementation is regulated by Federal communications commission (FCC) in the US, within 54–698 MHz band using 6 MHz channels. The WSDs are operated in the flexible operating region since they have to follow a 48 h channel schedule by GDB requiring conservative and fixed transmitted power. This kind of implementation is more suitable for rural areas.
- ii. **Closed-loop GDD:** European telecommunication standards institute (ETSI) and United Kingdom regulator (OFCOM) follow this implementation model, within 470–790 MHz using 8 MHz channel. Unlike the open-loop model, WSDs are required to update parameters through GDB, every two hours. These operational parameters are only valid for a specific time period and only applicable to a specific location. Therefore, the transmitted power of WSDs in closed-loop is flexible.

4. System model

In this section, the network model is explained for the better understanding of the SG scenario and communication between entities, followed by formulation of a mathematical model of the JCPA problem in CRSGCN.

4.1. Network model

We consider a rural environment with moderate user density having fixed SUs in a slow-varying radio environment. Thus, the open loop model, described in the previous section, is applicable. The detailed network model is shown in Figs. 4 and 5. The service area is divided into different clusters, termed as NAN cluster, having several smart meters (same as WSDs) with a data concentrator unit (DCU) at the center, as shown in Fig. 4. DCU is connected to RLSS using 802.22 WRAN and LTE. Each SM gets its operating parameters such as transmitted power and channel availability from DCU which is controlled by cognitive NAN gateway (CNGW) having RLSS. RLSS server CNGW is merely a base-station with RLSS server, having the name gateway since it is the central entity of NAN side that communicates with control center (CC) through base-station of WAN, called cognitive WAN gateway (CWGW). RLSS is connected to GDB via the internet, which is the primary regulatory storage for all operating parameters for WSDs (SMs in our case). A single SM can only communicate with a single DCU or in other words; SM can only be registered in one cluster.

Communication inside the NAN cluster is shown in Fig. 5. A single DCU can communicate with all the smart meters (SMs) within 1 Km radius using hybrid spectrum management (HSM) using IEEE 802.11af and LTE (Long Term Evolution - 4G). The LTE technology is used for time-critical data and IEEE 802.11af for delay-tolerant data. A DCU plays a similar role as an access point (AP) or GDDenabling station (ES) and SMs as GDD-dependent station (DS), as described in Section 3. Both GDD-ES and GDD-DS are fixed in a slow varying radio environment where both location and duration of vacant channels remain same during channel assignment.

The number of WSDs (SMs) is higher than a number of holes since not every channel is available for all the SMs and there can be cognitive users (CUs) other than SMs. On the other hand, according to open loop regulatory model, the maximum effective isotropic radiated power (EIRP) for a fixed WSD/SM is 4 W (36 dBm) and 100 mW (20 dBm) for portables WSDs. It is desirable to keep transmitted power to a lower level and still able to reach the receiver for energy efficiency. Transmitted power of each SM affects SNR at DCU, directly related to user reward (explained in a later section) thus joint power and channel allocation (JPCA) is mandatory to avoid serious quality of service (QoS) constraints. Both PA and CA are implemented through DCU as it manages all SMs within a NAN cluster.

There are two interference constraints that are needed to be addressed for smooth operation within a NAN cluster. First one is interference between SUs (SMs) and PUs (DTT or PMSE) and the other is Inter-SU interference. To cater the first constraint, we adopt the interference avoidance approach where the channels occupied by PUs are never used by SUs, but only unused channels are available within a NAN cluster. Moreover, the channel adjacent to the one assigned to PUs, cannot be assigned to SUs. Similarly, each SM is assigned a unique channel, or in other words, none of the holes is reused within a NAN cluster thus evading any inter-SU interference. However, more than one channel can be allocated to an SM provided channel is available and not assigned to any other SM. We assume that each SM is equipped with a directional antenna and the transmit power is kept to the minimum allowable level so as to reach the DCU at required threshold SNR level to not only increase the overall energy efficiency but also to reduce co-channel interference. Further, it can be assumed that DCUs of neighboring NAN clusters have an inter-cluster link to facilitate the smooth channel assignment, specifically for the SMs at boundary edges since a single SM can only be a registered in only one NAN cluster.

4.2. Mathematical model

Consider total *S* number of SMs in a service area, divided into total *C* disjunct clusters, each having a single DCU/AP at center as shown in Fig. 5. Table 2 lists all the notations used in this Section 4.2, to formulate the mathematical model. Let *S* denote set of SMs in a service area, $S = \{1, 2...S\}$, *C* denotes set of disjunct clusters, $C = \{1, 2...C\}$. The clustering constraints C1 & C2 can be written as C1: $\bigcup_{i=1}^{C} C_i = S$ and C2: $\bigcap_{i=1}^{C} C_i = \emptyset$. Let *N* represents a number of available holes, $N = \{1, 2, 3, ..., N\}$, and there are *K* number of SMs (users) in a single cluster connected to a single DCU. Let d^k be the distance of *k*th SM from DCU, transmitting with a power p^k , then the respective signal to noise ratio (SNR) Γ^k , at AP is given by:

$$\Gamma^k = \frac{p^k \|g^k\|^2}{p_{noise}} \tag{1}$$

In (1), p_{noise} is the noise power, $||g^k||^2 = ||g_1||^2 \cdot \frac{1}{L(d^k)}$ is the channel gain [53] between *k*th user and DCU including large scale path loss $L(d^k)$ shown in (2) and g_1 is account for Rician fading [54].

$$L(d^{k}) = \begin{cases} 20 \log\left(\frac{4\pi\lambda}{d^{k}}\right) = L(d_{0}) & \text{for } d^{k} \le d_{0} \\ L(d_{0}) + 10 * \varepsilon * \log\left(\frac{d^{k}}{d_{0}}\right) + X_{g} & \text{for } d^{k} > d_{0} \end{cases}$$
(2)

Table 1

Summary of PHY specifications for IE	EEE 802.11af.	
Parameter	PHY specifications	
Bandwidth (MHz)	Mandatory: TVHT_W (Single BCU) 6, 7, and 8 depending upon the regulatory domain	Optional: i. TVHT_2W: Two contiguous BCUs (12, 14, or 16) ii. TVHT_W+ W: Two non-contiguous BCUs (6 + 6, 7 + 7, or 8 + 8) iii. TVHT_4W: Four contiguous BCUs (24, 28, or 32) iv. TVHT_2W + 2W: Two non-contiguous frequency segments, each composed of two BCUs (12 + 12, 14 + 14, or 16 + 16)
Coding	Mandatory: Convolutional	Optional: Space-Time block codes (STBC)
Modulation		OFDM
Payload modulations		BPSK, QPSK, 16-QAM, 64-QAM, and 256-QAM
Coverage	Indoor: up to 100 m	More than 1 KM
Coding Rate		1/2, 2/3, 3/4, 5/6
Guard interval (µs)		6 and 3 (6, 7 MHz) 4.5 and 2.25 (8 MHz)
Max. data rate (Mbps)	26.7 (6	,7 MHz) and 35.6 (8 MHz) using single spatial stream



Fig. 4. Network model for overall NAN communication.

Where, λ is the wavelength of transmission frequency, d_0 is reference distance, ε is path loss exponent and X_g is account for shadowing.

Next, we describe the following key components essential to our mathematical model:

Distance Matrix, \mathcal{D} : The distance matrix is defined as $\mathcal{D} = \{d^k\}_{K \times 1}$, where $d_{min} \leq d^k \leq d_{max}$ is the distance of the *k*th user from DCU and d_{min} , d_{max} define the upper and lower limit. Each SM must be located within these boundary values.

Availability Matrix, *L*: It is a binary matrix that defines the availability of a channel for each SM, in a single cluster. Mathematically,

 $\{l_n^k | l_n^k \in \{0, 1\}\}_{K \times N}$, where l_n^k means that *n*th channel is available for *k*th SM or not. $l_n^k = 1$ means the channel is available, $l_n^k = 0$ means otherwise.

Reward Matrix, β : The reward matrix $\beta = \{\beta_n^k\}_{K \times N}$ is the reward or weight associated with each channel available to the user at a particular location, where β_n^k is the weight of the *n*th channel available to *k*th SM. A channel is given a weight only if it is available for a particular user in other words $\beta_n^k = 0$ if $l_n^k = 0$.

Channel reward β is very important and crucial parameter for calculating overall user rewards or utilization of resources. In literature, β is often taken in terms of coverage area or bandwidth



Fig. 5. Network model showing communication inside the NAN cluster.

Table 2
List of notations/symbols used to formulate mathematical model.

Sr #	Symbol/notation	Explanation
i.	d ^k	Distance of <i>k</i> th SM from DCU
ii.	p^k	Transmitted power of <i>k</i> th SM
iii.	Δp	Fractional power increment/decrement
iv.	Γ^k	Signal-to-noise (SNR) ratio of kth SM at DCU
v.	g^k	Channel gain between kth user and DCU
vi.	$L(d^k)$	Large scale path loss
vii.	p_{noise}	Noise power
viii.	l ^k n	Shows the availability of <i>n</i> th channel for <i>k</i> th SM
ix.	β_n^k	Weight of the <i>n</i> th channel available to <i>k</i> th SM
х.	w_n^k	bandwidth of <i>n</i> th channel assigned to <i>k</i> th SM
xi.	$f_n^{k,m}$	Indicates whether or not an <i>n</i> th channel is assigned to <i>k</i> th and <i>m</i> th SM at same time
xii.	α_n^k	Indicates whether or not <i>n</i> th channel is assigned to <i>k</i> th SM
xiii.	α_{max}	Maximum number of channels that can be assigned to a single SM
xiv.	ρ^k	Total number of channels assigned to the <i>k</i> th user
xv.	γ^{k}	User reward of kth SM
xvi.	h_t^k	Represents the reward history of the <i>k</i> th SM after <i>t</i> th round
xvii.	Ū _{sum}	Overall sum reward of all the SMs in a cluster.

or throughput [21–24]. Channel reward for our problem is given by:

$$\beta_n^k = w_n^k \log 2(1 + \Gamma^k) \tag{3}$$

Where, w_n^k is the bandwidth of *n*th channel assigned to *k*th user and Γ^k is the respective signal to noise ratio (SNR).

Channel Interference Matrix, \mathcal{F} : In order to avoid inter-SU interference, the necessary condition is that a single channel cannot be re-used with in a NAN cluster. To ensure this, we define a matrix $\mathcal{F} = \{f_n^{k,m} | f_n^{k,m} \in \{1,0\}\}_{K \times K \times N}$, where $f_n^{k,m} = 1$ means that *n*th channel is assigned to *k*th and *m*th SM in a same cluster at the same time and $f_n^{k,m} = 0$ must be true for any channel assignment.

Channel assignment Matrix, A: It is binary matrix $A = \{\alpha_n^k | \alpha_n^k \in \{0, 1\}\}$ showing channel assignment for all the SMs in a cluster, subject to availability matrix, where $a_n^k = 1$ means that *n*th channel is assigned to *k*th SM, otherwise $\alpha_n^k = 0$. A conflict free allocation requires that $\alpha_n^k \times \alpha_m^k = 0$, where $m, k \in C$ and $n \in \mathbf{N}$. It means that

a channel may be available for more than one SM at a particular time but it can only be allocated to just one SM.

Max channel assignment, α_{max} : A single channel can only be assigned to single SM, but theoretically a SM can be assigned more than one channel, subject to interference and availability condition, thus better utilization of resources. The channel assigned to the *k*th user is given by: $\rho^k = \sum \alpha^k$

This α_{max} defines the upper limit to how much channels can be assigned to a single user.

User reward Matrix, R: Reward of a kth SM in a cluster is given by:

$$\gamma^{k} = \sum_{n=1}^{N} \alpha_{n}^{k} \beta_{n}^{k} \tag{4}$$

Where $a_n^k \in \{0, 1\}$ and b_n^k a reward of *k*th SM having allocated an *n*th channel. Thus, matrix \mathcal{R} represents user rewards of every SM in the cluster i.e., $\mathcal{R} = \{\gamma^k\}_{K \times 1}$, where γ^k is the reward of *k*th SM. It is clear from (4) that more assignments per user leads to greater reward, however, it may degrade fairness.



Fig. 6. Power allocation on the basis of the distance from central DCU.



Fig. 7. Flowchart for power allocation algorithm.

User History Matrix, \mathcal{H} : History matrix $\mathcal{H} = \{h_t^k\}_{K \times 1}$ is essential in implementing overall fairness. The term h_t^k represents the reward history of the *k*th SM after *t*th round. Following equation is used to update user rewards and channel allocations per user:

$$h_t^k = \gamma_{t-1}^k + \gamma_t^k \tag{5}$$

Where, γ_t^k is the reward of *k*th SM in *t*th round and γ_{t-1}^k is the reward of *k*th SM in the previous round.

Fairness: To measure fairness among users, one may calculate Jain's fairness index (J.F.I) or counting no. of allocations per user, given by:

$$J.F.I = \frac{(\sum_{k=1}^{K} \sum_{n=1}^{N} \alpha_n^k \beta_n^k)^2}{K \sum_{k=1}^{K} (\sum_{n=1}^{N} \alpha_n^k \beta_n^k)^2}$$
(6)

$$\rho^k = \sum_{n=1}^N \alpha_n^k \tag{7}$$

Max-Sum Reward (MSR) is a measure of how the overall sum reward is increasing, given by:

$$U_{sum} = \sum_{k=1}^{K} \sum_{n=1}^{N} \alpha_n^k \beta_n^k$$
(8)

The primary objective of our problem under consideration is to optimize the power and channel allocation to maximize utilization factor.

Utilization Factor $U(\mathcal{R})$: The utilization factor is the same as objective function, depending on the problem under consideration. We have two different objectives for two different allocation requirements, therefore we use different $U(\mathcal{R})$ to tackle each case (described in later a section). To maximize the utilization factor $U(\mathcal{R})$, we have to optimize the channel assignment \mathcal{A} meeting multiple constraints, which can be written as:

$$\mathcal{A}^* = \max_{C,f,l,p,\Gamma,\beta,\rho} U(\mathcal{R}) \tag{9}$$

s.t C1:
$$\cup_{i=1}^{C} C_i = \mathbf{S}$$
, where $C_i \subseteq \mathbf{S}$

C2:
$$i = 1^{\mathsf{C}}\mathsf{C}_i = \emptyset$$
, where $\mathsf{C}_i \subseteq \mathsf{S}$

$$C3: \qquad p_{min} \leq p^k \leq p_{min}$$

$$4: \qquad \eta_{th}^{\min} \ge \eta^k \ge \eta_{th}^{\max}$$

C5:
$$l_n^k \times l_n^p = 0$$
, where $p, k \in C$ and $n \in \mathbf{N}$

C6 :
$$f_{k,m}^n = 0, \forall k \neq m$$
 where $k, m \in \mathbf{K}$ and $n \in \mathbf{N}$

C7:
$$\rho^k \leq \alpha_{max}$$

C

C8:
$$\beta_n^k \in [0, 1]$$
 and $\beta_n^k = 0$ if $\alpha_n^k = 0$

C1 and C2 require that all clusters are disjunct and disjoint. C3 ensures that transmit power of each SM remains within allowable limits and C4 guarantees sufficient QoS by keeping SNR of each SMs signal in between allowable thresholds. C5 is the PU constraint that SUs can only be assigned channels left vacant by PUs and channels adjacent to the one used by PUs cannot be used by SMs. C6 dictates that no channel is re-used in a single round. C7 puts an upper limit of maximum allocations to any SM and C8 is intuitive.

5. Proposed solution

In this section, we present two proposed algorithms, first for optimized power allocation in terms of energy efficiency and then channel allocation scheme based on the cuckoo search algorithm.

Power Allocation Algorithm
1 Step I: Initialization
$- \text{Set } n_{min} n_{min} n_{min}^{max} d_{min} d_{min} \Lambda n \lambda w_{k}^{k} n_{min} \varepsilon \text{ meeting C1 C2}$
Sot pmax, pmin 11, 11, 11, 11, 11, 11, 11, 11, 11, 11
2. Step II:
— Randomly distribute K users in the area
— Generate distance matrix \mathcal{D} , containing distance $d_{min} \leq d^k \leq d_{max}$
3. Step III:
for all K
— Calculate path loss using (2) and compute channel gains
end
4. Step IV:
for all K
— Allocate Tx power to each user according to the distance from
DCU, meeting constraint C3
— Compute SNRs using (1)
end .
5. Step V:
for all K
- Compare SNRs with threshold values meeting constraint C4 th = k = th
$\eta_{min}^{n} \geq \eta^{n} \geq \eta_{max}^{m}$
IJ C4 is satisfied. Terminete
Go to the next sten
and
3. Step VI:
- C4 is not satisfied. Add or subtract fractional power to allocated power for each user
$p^k + \Delta p$
— Compute SNRs
— Repeat Step V

Fig. 8. Proposed power allocation algorithm based on SNR threshold.

5.1. Power Allocation Algorithm (PAA)

Our objective in this proposed algorithm is to increase energy efficiency by allocating less transmit power but still fulfilling the QoS criteria of threshold SNR. All clusters are disjoint and disjunct and independent of each other; thus, our power allocation scheme is applicable in each cluster at the same time. We assume that the approx. distances of each SM from the central DCU are known. Then power is allocated in such a way that SM closest to the DCU transmits with the least power and the SM at the farthest location has the max transmitting power. This distance-wise power is shown in Fig. 6.

SNR for each SMs transmission is calculated through (1) using this allocated power. Each SNR is then compared with upper and lower SNR thresholds. If the SNR is within the threshold range, then this power is approved otherwise a fractional power (Δp) is added/subtracted to allocated power until the desired SNR is achieved. The flow chart of the proposed algorithm is shown in Fig. 7, while algorithm is detailed step by step in Fig. 8. The transmitted power allocated to each SM is used to calculate respective SNR at the central DCU which is used in (3) for channel reward and finally contributes towards user reward in (4). 5.2. Channel Allocation Algorithm (CAA) based on Cuckoo Search Optimization

First, we brief the cuckoo search algorithm in this section, and then we discuss our proposed CA algorithm for a scenario under consideration.

Cuckoo Search Algorithm (CSA), inspired by the aggressive breeding behavior of Cuckoos, was first introduced by Xin-She and Suash Deb in 2009. It was first proposed as a numerical function optimization tool for continuous problems and performed better on some well-known benchmarks compared to GA and PSO [55]. Since then it has been applied in many domains such as engineering optimization, image processing, classification, scheduling and other real-world applications for both continuous and discrete problems.

Cuckoos dump their own eggs in the nest of host cuckoos. Each egg in a nest represents a candidate solution whereas cuckoo's egg denotes a new solution. Each cuckoo can lay only one egg at one time, which is then dumped in a host nest chosen randomly. The best solution is identified by comparing the fitness/quality of each nest. In this way, CSA obtains an optimum solution by putting an average solution in a host nest. CSA is based on two

	Cuckoo Search Algorithm (CSA)
1.	Step I: Initialization — Set number of nest, eggs, pr_a , ζ , δ , μ , ν — Generate initial population
2.	Step II: Check Fitness — Check fitness of each egg — Identify global best
3. 4. 5.	 Step III: Levy flights for all eggs Update eggs using levy flight function in (10) Check fitness of each updated egg end Step IV: Survival of the fittest for all eggs Compare fitness of each updated egg with eggs of the initial population Keep the best eggs and discard the remaining end Step V: Alien egg discovery for all eggs Update all eggs using (12) Calculate the fitness of each egg in the new generation
4.	Step VI: Termination Criteria If Required fitness is achieved, or number of iteration reached then terminate else Go to step III

Fig. 9. Cuckoo search algorithm.

operations: Levy flights and alien egg discovery, both are used to evolve better generations in terms of fitness/quality. Levy flights can be implemented (10) and alien egg discovery having discovery probability pr_a using (12) [56].

$$x_i^{t+1} = x_i^t + \delta \frac{\vartheta \mu}{|\nu|^{\frac{1}{\zeta}}} (x_i^t - x_{best}^t)$$
(10)

Where, x_i^{t+1} is the next solution, x_i^t is the previous solution, x_{best}^t is the fittest solution, δ is a constant, μ and ν are normally distributed pseudorandom numbers, ζ is also a constant between (1, 2) and

$$\vartheta = \frac{\Gamma\left(1+\zeta\right) * \sin\left(\frac{\pi\zeta}{2}\right)}{\Gamma\left(\left(\frac{1+\zeta}{2}\right) * \zeta * 2^{\frac{\zeta-1}{2}}\right)} \tag{11}$$

$$\mathbf{x}_i^{t+1} = \mathbf{x}_i^t + \psi \,\Omega \tag{12}$$

Where Γ is gamma function, ψ is updated coefficient and

$$\Omega = \begin{cases}
1 & \text{if } rand() < pr_a \\
0 & \text{otherwise}
\end{cases}$$
(13)

CSA can be implemented following the steps, described in Fig. 9.

For our channel allocation scheme which is based on CSA (described above), we have to deal with two practical cases having conflicting requirements that lead to two different allocation modes.

Case I: Fairness-based Allocation

First one is a daily routine scenario where all the SMs have scheduled transmission regarding DRM and AMI data towards central AP in a cluster. It necessitates that all the SMs should have an equal share of resources, e.g., same bandwidth or equal user rewards or equal channel allocations per user. Vacant channels are assigned to every SM in a cluster, meeting the constraints (C5–C8). Since the objective here is to maximize the fairness among SUs, only one channel is allocated per user. In other words, for case 1, we set $\alpha_{max} = 1$. User rewards are computed according to the power allocated by our proposed algorithm (described previously in this section). The objective function in (9) for implementing fairness in user rewards (4) is given by:

$$\gamma_e = \|\gamma^{max} - \gamma^{min}\|^2 \tag{14}$$

Where, γ_e is mean square error (MSE) between max. user reward, γ^{max} min user reward γ^{min} . Jain's fairness index (J.F.I) in (6) is another indicator that shows fairness among users. The values of user rewards, channel allocations to each user are stored in history matrix \mathcal{H} . Next, the holes are assigned in a way as to maximize the fairness among SMs, again meeting constraints (C5–C8). Values of γ^k , ρ^k are updated in history matrix \mathcal{H} using (5) at the end of each round. After completing the total number of rounds T, all SMs should have almost the same user rewards and equal allocations per user.

Case II: Priority-based allocation

The second case is to implement a typical practical scenario when some user asks to remotely access the power/load profile of his/her home. Therefore, priority is required for such users, although for a comparatively shorter period of time. To deal with such a task, we allocate a significant share of resources to priority users K_{pr} and remaining resources are distributed evenly among standard users K_{sd} . The channel assignments, in each round, are performed meeting the constraints (C5–C8), same as case I. Instead of fairness, here the requirement is to maximize the user reward of priority users and the standard users should have an equal share of remaining resources. Therefore, a priority user can be assigned more than one channel subject to availability condition, provided that the channel is not reused. The objective function in (9), however, is given by:

$$Avg \ \gamma_{pr} = \frac{1}{K_{pr}} \sum_{i=1}^{K_{pr}} \gamma_{pr}^{i}$$
(15)

Where, γ_{pr} denotes a priority user reward. The average reward for standard users is given by:

$$Avg \ \gamma_{sd} = \frac{1}{K_{sd}} \sum_{i=1}^{K_{sd}} \gamma_{sd}^i$$
(16)

Flowchart of the proposed CA algorithm is shown in Fig. 10 and algorithm is detailed in Fig. 11.

6. Performance evaluation

In this section, we evaluate the performance of our proposed joint power and channel allocation (JPCA) scheme via intensive computer simulations using MATLAB R2015a. First, we describe the simulation parameters and scenario, followed by analysis and discussion on results for both cases.

6.1. Simulation configuration

The NAN communication scenario is already explained in Section 4.1. All clusters are independent of each other. Therefore our JPCA scheme can be implemented in each cluster at the same time. We have only considered cognitive communications between SMs and single DCU for delay-tolerant data (such as AMI and DRM). PUs and SMs are randomly distributed in the 1×1 Km2 area around a single DCU at the center. The distance of each SM from central DCU is calculated, as shown in Fig. 12. We have adopted the open-loop regulatory paradigm thus all the parameter values regarding TVWS are in accordance with IEEE 802.11af PHY specifications [50], as described in Table 1. We assume that all WSDs (SMs) operate in fixed MODE. Therefore, the max effective isotropic radiated power (EIRP) cannot exceed 4 W.

It must be noted that for 22 TV channels (14-35) with 4 subchannels per TV channel gives a maximum of 88 sub-channels. To avoid the confusion, we use channels instead of the word subchannels. According to the open-loop regulatory paradigm, a TV channel adjacent to incumbent service cannot be utilized. Therefore, a single PU means that 12 channels (4×3) at max are occupied. Therefore, for our simulations, we have considered 75, 60 and 50 channels for 1, 2 and 3 PUs respectively.

For power allocation (PA) algorithm and channel allocation (CA), described in Section 5, we use parameters in agreement with IEEE 802.11af standard [51], as shown in Tables 3 and 4. A number of vacant channels (holes) available to the SMs have same bandwidth of 1.25 MHz. Transmit powers, allocated to each SMs through PAA, is used to compute user rewards for channel allocation (CA) algorithm. As described in previous Section 5.2, our proposed CSA based CA scheme has to tackle two cases. The parameter values used for CSA are described in Table 5.

Table 3	
---------	--

i v vvs parameters.	
Parameter	Value
TV channels	14–35
No. of sub-channels per TV channel	4
Total no. of sub-channels (max)	88
Frequency range	470–602 MHz
TV channel bandwidth	6 MHz
Sub-channel bandwidth	1.25 MHz
Max Tx Power (EIRP)	4 W
Coverage area	$1 \times 1 \text{ Km}^2$

Table 4

Parameter values for Power and channel allocation algorithm.

Parameter	Value
Max Tx power = p_{max}	4 W
Min Tx. Power = p_{min}	0.2 W
Fractional power increment = Δp	0.1 W
Noise power = p_{noise}	10 ⁻¹³
Number of SMs, K	100, 200, 300
No. of PUs	3, 2, 1
No. of channels, N	50, 60, 75
No. of Priority users, <i>K</i> _{pr}	0.02* K
Max channel assignment, α_{max}	$(0.5 * N/K_{pr})$
Reference distance $= d_0 = d_{min}$	50 m
Max range = d_{max}	1000 m
Min. SNR threshold = η_{th}^{min}	20 dB
Max. SNR threshold = η_{th}^{max}	40 dB
Tx antenna gain = G_{tx}	0 dB
Rx antenna gain = G_{rx}	12 dB
Channel bandwidth $= w_n^k$	1.25 MHz
Wavelength = λ	0.6 m
Pathloss exponent = ε	3.5
Shadowing constant $= X_g$	10 dB

Table 5

Parameters for CSA.	
Parameter	Value
Number of nests	10
Number of eggs	10
Discovery probability $= pr_a$	0.3
$Constant = \zeta$	[1,2]
$Constant = \delta$	Random distribution
Pseudorandom number = μ	Random distribution
Pseudorandom number = v	Random distribution
No. of Rounds	50

Table 6

Case I: Comparison of power allocation Schemes.

No. of	PA	P _{cluster}	P _{avg}	Power
SMs	scheme	watts	watts	consumption
100	FPA	400	4	100%
	DPA	263.2	2.63	65.8%
	SPA	225.27	2.25	56.32%
200	FPA	800	4	100%
	DPA	537.8	2.69	67.22%
	SPA	458.57	2.29	57.32%
300	FPA	1200	4	100%
	DPA	824.75	2.75	68.73%
	SPA	713.4	2.38	59.45%

6.2. Results and analysis

In this sub-section, we analyze the performance of our proposed algorithms for each of the cases explained in the previous section.

6.2.1. Case I: Fairness-based allocation

The primary objective of power allocation among SMs is to have better power efficiency, but decreasing the transmit power



Fig. 10. Flowchart for CSA based Channel allocation scheme.

of SMs, decreases the SNRs which reduces the user reward. Therefore, we compare three power allocation schemes to analyze the performance of our PAA in this trade-off situation. First one is fixed power allocation (FPA), which is mainly for the reference to tell how much power is saved. In FPA, all the SMs operate at max transmit power, i.e., 4 W. The second scheme is distancebased power allocation (DPA), with only considering min SNR threshold. The last scheme is SNR-based power allocation scheme (SPA), described in Section 5.1, having both upper and lower SNR thresholds.

In case I, all SMs have same priority thus the idea is to allocate power to increase power efficiency and user reward. The comparative analysis of the three schemes is shown in Table 6, in terms of total power consumed in a NAN-cluster $P_{cluster}$, Average



Fig. 11. CSA based channel allocation scheme.

transmitted power allocated to a single SM P_{avg} and over all power consumption with in a NAN-cluster taking FPA as reference.

Table 6 summarizes the performance of three PA schemes in terms of power efficiency. FPA just provides a reference point to measure how much power is saved with DPA and SPA. It is observed that increasing the SMs in a cluster, the avg allocated power P_{avg} is also slightly increased thus increasing power consumption

a touch. Although there is a significant reduction in overall power consumption in a cluster using DPA and SPA but in comparison, SPA saves \sim 9.5% more power than DPA.

Next, we evaluate our proposed channel allocation scheme based on CSA for the case I, where the idea is to assign vacant channels in a way as to maximize the fairness in terms of user reward.



Fig. 12. Random distribution of SMs around DCU along with their distances.



Fig. 13. Case I: Plot of Jain's Fairness Index (JFI) for 50 rounds.



Fig. 14. Case I: Plot of MSE Vs. Rounds.

Considering the SPA scheme for 200 SMs, we measure fairness on the basis of user rewards at the end of 50 rounds. As described earlier in Section 5.2, the two fairness indicators J.F.I (using Eq. (6)) and MSE, γ_e , of max and min user rewards (using Eq. (14)) are plotted against 50 number of rounds in Figs. 13 and 14 respectively, with proposed CSA optimized CA and without optimization. The optimized number of allocations to each SM for 50 rounds is also shown in Fig. 15.

Plots in Figs. 13 and 14, clearly manifests the effectiveness of proposed CSA based CA scheme compared to baseline plot of fairness indicators without optimization. The fairness indicators are at a very low value at the start. The reason being that the user rewards differs a lot, mainly due to indifferent user SNRs that varies because of diverse locations of users (range: 50 m to 1000 m). However, as soon as channels are allocated using our proposed algorithm, there is a drastic improvement in both fairness indicators J.F.I and MSE γ_e . The difference in user rewards starts at almost 22 which is considerably reduced with a number of rounds, even though the user rewards are quite different. This is achieved by controlling assignments per users in a way as to optimize the fairness as seen in Fig. 15. For the case I, we allowed only one channel to be allocated to a single user per assignment, thus in this case, channels assignments and allocations are same. However, lots of variation is observed in channel assignment per user, as users with poor rewards are allocated comparatively more channels to match the users with better rewards, thus in turn optimizing fairness.

Impact of varying number of channels and number of users. Table 7 is presented to evaluate the impact of varying the different number of users and channel combinations on avg user rewards γ_{avg} and avg Max-Sum reward U_{sum} . It is observed that increasing users from 100 to 300, keeping the channels constant results in decreasing the γ_{avg} , whereas U_{sum} increases but not considerably, comparing to a three-fold increase in users since the available channels are very limited. Similarly, increasing the number of channels from 50 to 75, which has the same impact as reducing the number of PUs, shows a significant increase in both γ_{avg} and U_{sum} , since more resources are available for allocation in each round.

Table 8 (CA without optimization i.e., just on the basis of channel availability), is presented for just baseline comparison. The avg. user rewards and Max-Sum rewards are slightly better in Table 8 because the objective here is to maximize fairness thus our proposed algorithm achieved better fairness at the cost of lower γ_{avg} and U_{sum} .



Fig. 15. Case I: No. of assignments per user using proposed CSA optimization algorithm for 50 rounds for 200 SMs and 75 channels with optimization.

Table 7

Case I: Avg. user rewards and Max-Sum rewards for different combinations of channels and users with CSA optimization.

	Number of SMS					
No. of Channels	100		200		300	
channels	Yavg	U _{sum}	γ_{avg}	U _{sum}	γ_{avg}	U _{sum}
50	5.49	550.87	2.68	536.92	1.81	543.39
60	6.60	660.27	3.21	642.69	2.17	651.45
75	8.29	829.42	4.01	802.34	2.72	816.22
	No. of Channels 50 60 75	No. of Channels 100 γ_{avg} γ_{avg} 50 5.49 60 6.60 75 8.29	No. of Channels 100 γ_{avg} U_{sum} 50 5.49 550.87 60 6.60 660.27 75 8.29 829.42	No. of Channels 100 200 γ_{avg} U_{sum} γ_{avg} 50 5.49 550.87 2.68 60 6.60 660.27 3.21 75 8.29 829.42 4.01	No. of Channels100 γ_{avg} 200 γ_{avg} 505.49550.872.68536.92606.60660.273.21642.69758.29829.424.01802.34	No. of Channels100200300 γ_{avg} U_{sum} γ_{avg} U_{sum} γ_{avg} 505.49550.872.68536.921.81606.60660.273.21642.692.17758.29829.424.01802.342.72

Table 8

Case I: Avg. user rewards and Max-Sum rewards for different combinations of channels and users without optimization.

	No. of Channels	Number of SMs					
No. of PUs		100		200		300	
		γ_{avg}	U _{sum}	γ_{avg}	U _{sum}	γ_{avg}	U _{sum}
3	50	5.63	563.91	2.76	552.23	1.91	573.31
2	60	6.74	674.69	3.26	652.23	2.26	679.26
1	75	8.48	849.25	4.11	821.93	2.79	836.23

6.2.2. Case II: Priority-based allocation

For the same area $1 \times 1 \text{ Km}^2$, the number of priority users K_{pr} are taken as 2% of total SMs K and remaining $(K - K_{pr})$ user are normal or standard users K_{sd} . Resources are shared such that 50% of total channels are equally divided among K_{pr} .i.e., the max channel assignment α_{max} is taken as $(0.5*\text{N}/K_{pr})$ and rest of the channels are fairly distributed among K_{sd} using the same strategy as in case I.

In case II, the idea is to allocate the power in such a way as to maximize the reward of priority users. Therefore, the priority users transmit with max power, i.e., $P_{pr} = 4$ W while normal users are allocated power using the same DPA or SPA. The comparative analysis of the three schemes is shown in Table 9. Similar observations, as in the case I, indicates the comparatively better behavior of SPA in terms of power saving at almost ~9.5% power on average. The slightly increase in overall power consumption compared to the case I, is due to the priority users $K_{pr}(2\% \text{ of total users})$ are allocated maximum power of 4 W.

Fig. 16 shows the number of assignments for every user for a total of 50 rounds considering 200 users and 75 channels. It must be noted that a number of assignment means how many times a user has a channel assignment in 50 rounds. Typically, as standard users can have one channel per assignment, where priority users have more than one channel per assignment depending upon availability. It can be seen that all the four priority users have been assigned in all 50 rounds compared to standard users with less than 20 assignments at max.

Considering the same combination of 200 SMs ($K_{pr} = 4$, $K_{sd} = 196$, $\alpha_{max} = 0.5*N/K_{pr}$) and 75 channels, the user rewards, with

 Table 9

 Case II: Comparison of power allocation sche

case in companison of power anocation schemes.									
No. of	PA	P _{cluster}	AvgP _{sd}	Avg P _{pr}	Power				
SMs	scheme	watts	watts	watts	consumption				
100	FPA DPA	400 265 1	4 2.65	4	100%				
100	SPA	203.1	2.05	4	56.96%				
200	FPA	800	4	4	100%				
	DPA	545.4	2.73	4	68.17%				
	SPA	466.37	2.33	4	58.30%				
300	FPA	1200	4	4	100%				
	DPA	837.10	2.79	4	69.76%				
	SPA	726.2	2.42	4	60.52%				

CSA based CA scheme, are plotted against the number of rounds in Fig. 17. It can be seen that the user rewards of all the priority users are very high as compared to avg. user reward of standard users (shown by the black line). The variation in rewards of priority users is because of different SNRs of each priority user, mainly due to their indifferent location. Plots for same configuration and parameters without optimization are shown in Fig. 18. Comparing both Figs. 17 and 18, clearly highlights the supremacy of proposed solution by observing considerable increase in avg. user rewards of priority users ($Avg \gamma_{pr}$) and Max-sum reward (U_{sum}).

The objective in case II is that priority users should have maximum share of resources. The increased number of allocations for priority users in Fig. 16 and the greater priority user rewards than standard users as shown in Fig. 17, are clear indicators of the



Fig. 16. Case II: Number of Assignments per user for 200 SMs and 75 channels using CSA optimization.



Fig. 17. Case II: User Rewards vs. No. of Rounds with CSA optimization.



Fig. 18. Figure 18. Case II: User Rewards vs. No. of Rounds without optimization.

validity of our proposed CA algorithm in achieving the desired objective.

Impact of varying number of channels and number of users. To analyze the impact of varying different combination of users and

channels, Table 10 compares avg. user reward for both priority users ($avg \gamma_{pr}$) and standard users ($avg \gamma_{sd}$) as well as avg Max-Sum reward (U_{sum}). For all combinations, the $avg \gamma_{pr} \gg avg \gamma_{sd}$, which was the main objective for case II. By increasing the number

Case II: Avg. User and Max-Sum rewards comparison for priority users and standard users for different combinations of users and channels with CSA optimization.

No. of PUs		Number of users									
	No. of Channels	$K_{sd} = 98, K_{pr} = 2$			$K_{sd} = 196, K_{pr} = 4$			$K_{sd} = 196, K_{pr} = 6$			
	of channels	$\overline{\text{Avg}_{\gamma_{pr}}}$	Avg γ_{sd}	U _{sum}	Avg γ_{pr}	Avg γ_{sd}	U _{sum}	Avg γ_{pr}	Avg γ_{sd}	U _{sum}	
3	50	111.25	3.08	528.6	58.03	1.58	541.23	44.57	1.08	584.82	
2	60	139.75	3.63	635.82	68.38	1.91	648.74	57.13	1.24	706.56	
1	75	169.35	4.62	793.6	90.01	2.43	833.55	67.04	1.61	875.7	

Table 11

Case II: Avg. User and Max-Sum rewards comparison for priority users and standard users for different combinations of users and channels without optimization.

No. of PUs	No. of Channels	Number of users									
		$K_{sd} = 98, K_{pr} = 2$			$K_{sd} = 196, K_{pr} = 4$			$K_{sd}=196, K_{pr}=6$			
		Avg γ_{pr}	Avg γ_{sd}	U _{sum}	Avg γ_{pr}	Avg γ_{sd}	U _{sum}	Avg γ_{pr}	Avg γ_{sd}	U _{sum}	
3	50	70.28	3.76	508.8	48.64	1.62	511.81	25.5	1.41	568.01	
2	60	87.58	4.30	596.79	60.21	2	631.46	36.31	1.60	687.04	
1	75	107.81	5.06	711.71	80.31	2.51	812.03	36.75	2.11	841.47	

Table 12

Case II: Avg. User and Max-Sum rewards comparison for fixed priority and standard users with different combinations of α_{max} and channels with CSA optimization.

No. of PUs		Number of users $K_{sd} = 200$, $K_{pr} = 4$,									
	No. of Channels	$\alpha_{\rm max} = 0.2 * N/K_{pr}$			$\alpha_{\rm max} = 0.4 * N/K_{pr}$			$\alpha_{\rm max} = 0.6 * N/K_{pr}$			
	of channels	Avg γ_{pr}	Avg γ_{sd}	U _{sum}	Avg γ_{pr}	Avg γ_{sd}	Usum	Avg γ_{pr}	Avg γ_{sd}	U _{sum}	
3	50	22.22	2.22	523.48	51.01	1.70	537.83	67.59	1.41	546.87	
2	60	33.01	2.55	631.05	61.33	2.04	645.77	86.03	1.60	658.40	
1	75	42.76	3.31	818.9	73.52	2.61	805.46	104.20	2.06	820.74	

Table 13

Case II: Avg. User and Max-Sum rewards comparison for fixed priority and standard users with different combinations of α_{max} and channels without optimization.

No. of PUs		Number of users $K_{sd} = 200, K_{pr} = 4$,									
	No. of Channels	$\alpha_{\rm max} = 0.2 * N/K_{pr}$			$\alpha_{\rm max} = 0.4 * N/K_{pr}$			$\alpha_{\rm max} = 0.6 * N/K_{pr}$			
	of channels	Avg γ_{pr}	Avg γ_{sd}	U _{sum}	Avg γ_{pr}	Avg γ_{sd}	U _{sum}	Avg γ_{pr}	Avg γ_{sd}	U _{sum}	
3	50	18.75	2.27	518.49	45.12	1.77	527.9	60.58	1.49	534.1	
2	60	27.6	2.58	615.7	54.47	2.13	636.02	74.82	1.77	645.8	
1	75	34.3	3.43	808.87	69.81	2.78	823.67	93.88	2.24	813.7	

of users from 100 to 300, keeping the channels fixed, both $avg \gamma_{pr}$ and $avg \gamma_{sd}$ decreases since the same number of channels are to be shared among more users, whereas U_{sum} increases since more priority users having a larger share of resources contribute better in overall reward. On the other hand, keeping the users fixed and increasing the number of channels, results in increasing all three rewards $Avg \gamma_{pr}$, $Avg \gamma_{sd}$ and U_{sum} since more channels contributes towards more reward.

Table 11 is presented for the comparison of proposed CA schemes with baseline CA scheme (without optimization). Comparing Tables 10 and 11, one can easily see the significant increase in *avg* γ_{pr} and U_{sum} in using proposed optimization allocation, that validates the achievement of desired objective. *avg* γ_{sd} , on the other hand, is slightly decreased which is understandably due to the fact that among standard users the fairness is maintained.

Impact of varying α_{max} . As described earlier, α_{max} is maximum number of channels that can be allocated to a single SM. For case II, we reserved 50% of total channels for priority users and for each priority user, $\alpha_{max} = 0.5*N/K_{pr}$. For standard users (SMs), the α_{max} is same as in case I.

To analyze the impact of varying the value of α_{max} , we compare $avg \gamma_{pr}$, $avg \gamma_{sd}$ and U_{sum} by taking α_{max} as 20%, 40% and 60% of the total channels in Table 12 (for proposed optimized CA scheme) and Table 13 (without optimization). For both Tables, increasing α_{max} from 20% to 60% for different set of channels, shows a considerable increase in $avg \gamma_{pr}$ and decrease in $avg \gamma_{sd}$. Also, there is a slight improvement in U_{sum} keeping channels fixed but increasing the channel has

a more pronounced Impact on user rewards compared to increase in α_{max} .

Comparing Tables 12 and 13, increasing α_{max} from 20% to 60%, there is a significant rise in *avg* γ_{pr} and U_{sum} , for optimized CA scheme which is the main objective of assignment exercise in case II. On the other hand, *avg* γ_{sd} is slightly reduced showing the maintained fairness among standard users.

Comment of scalability. We have considered maximum up to 300 SMs/SUs for our SG scenario considering a rural environment, but this solution is scalable and practical to have SMs in the range of thousands. Since we are only considering delay-tolerant data, so time-scheduling can be used to provide service to these SUs, other than priority users. The priority users, on the other hand, can be serviced in the same fashion as in case II.

7. Conclusion

This research work explored the problem of JPCA in CRN applied to neighborhood area network (NAN) in SGCN. First, the detailed network model is presented to depict NAN communication in SG using open loop regulatory framework for TVWS with IEEE 802.11af standard. Then a mathematical model is formulated for the JPCA problem with practical limitations and constraints of SGCN, followed by proposed schemes of QoS based power allocation and channel allocation using cuckoo search optimization. The comparative results in the form of plots and numerical tables manifest that both power and channel allocation algorithms achieve the conflicting objectives of fairness-based and prioritybased channel allocation using a heuristic approach, together with reducing power consumption for desired QoS. Moreover, the detailed analysis of the impact of varying number of standard users, priority users, channels and PUs shows the effectiveness of the proposed solution.

The work presented here for multi-constraint JPCA problem formulation to proposed solution, considering TVWS with IEEE 802.11af standard using open loop regulatory framework is among the premier works of its kind in SG communication. We hope this research work will act as a cornerstone and pave way for further research studies for the problem under consideration. For future work, the implementation of the closed-loop regulatory framework for the same scenario is a challenging and intriguing task. The other optimization techniques like game theory and machine learning techniques in addition to heuristic approach can be explored. Sum-rate maximization using non-orthogonal multiple access (NOMA) is currently gaining a lot of attention for some practical scenarios. The trade-off situation for fairness and Maxsum reward, for our modeled scenario, can be improved subject to meet QoS constraints using NOMA [57]. We performed clustering on the basis of the distance from the central node DCU where an SM in a cluster can only connect to a single DCU. It will be interesting to investigate if the SM can connect to other neighboring DCU within its range but better channel gain, thus better SNR. Coordination between DCUs of neighboring clusters to better facilitate the SMs at the cluster edge in another exciting direction.

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