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Adaptive Spectrum Sharing in TV White Spaces

Muhammad Asif Raza

School of Electrical Engineering and Computer Science

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박사 학위논문

TV 화이트 스페이스를 위한 적응형 주파수 자원 공유방법 연구

무하마드 아시프 라자

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Advisor: Heung-No Lee

by

Muhammad Asif Raza

School of Electrical Engineering and Computer Science

Gwangju Institute of Science and Technology

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Approved by

Professor Heung-No Lee

Thesis Advisor

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Muhammad Asif Raza

Accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy

October 24, 2017

Thesis Advisor ______________________
Prof. Heung-No Lee (GIST)

Committee Member ______________________
Prof. Jalel Ben Othman (Uni. Paris 13)

Committee Member ______________________
Prof. Hyuk Lim (GIST)

Committee Member ______________________
Prof. Hyo-Sung Ahn (GIST)

Committee Member ______________________
Prof. Sang-Seon Byun (Catholic Uni. Pusan)

To my LORD, HIS MESSENGER, my parents, and my family

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Abstract

With the proliferation of mobile devices, services and different wireless technologies, the traffic demand has been increasing at much faster pace than the networks can handle on existing wireless spectrum. The licensed wireless spectrum and industrial, medical and scientific (ISM) bands are already congested. Fortunately, the digitization of TV transmissions has relinquished much of the TV spectrum in VHF/UHF band. Considering its under utilization and scarcity in wireless spectrum, the regulatory bodies worldwide have permitted unlicensed use of TV spectrum unless the licensed operators are protected from interference. Note that the TV spectrum not in use by licensed operator in a spatio-temporal region is referred to as, TV white space (TVWS). The regulatory bodies have provided several regulations to protect incumbents from harmful interference from unlicensed transmissions in TV spectrum. However, the problem of coexistence of secondary devices operating in the same TV band was not dealt by the regulatory bodies.

The coexistence among secondary devices operating in TV spectrum is considered a challenging task due to signal propagation characteristics in TV spectrum, spatiotemporal variation of TV spectrum and disparity in network technologies of devices operating in the TV spectrum. These diversities may cause coexistence issues, such as an unresolvable interference, spectrum congestion, diversity in network size. To address coexistence issues and regulate access to TV spectrum, IEEE 802 LAN/MAN committee has approved a standard 802.19.1 for enabling peaceful coexistence among unlicensed networks operating in heterogeneous network technologies in TVWS. The standard provides a set of procedures to enable coexistence among secondary networks

operating in heterogeneous network technologies in TVWS, namely WSOs (white space objects).

In this context, our research is on the IEEE 802.19.1 protocol where focus is on resource sharing among WSOs operating in different network technologies in TVWS. In this research, we highlight two distinct issues in TVWS sharing domain and provide solution to each of them as follows.

Firstly, quality of service (QoS) provisioning in the channel allocation in TVWS. With the rapid increase in the use of content delivery multimedia applications, the QoS provisioning is becoming an important factor to be taken care in the channel allocation process. Any lag in the throughput may cause severe damage in the service provisioning of such applications. To this end, we define the channel allocation problem as an optimization problem that adapts the QoS (throughput) demand of the WSOs during the allocation process. A channel allocation algorithm is then defined that solve the TVWS sharing optimization problem to allocate the TV channels among an optimal set of coexisting WSOs.

Secondly, accommodating as many as WSOs in the available TVWS.
Considering the free to use status of the TVWS, each coexisting WSO has an equal right to access the TV spectrum for its data transmission. While, in highly congested urban areas, the TV spectrum available for an unlicensed use is quite limited. The available whitespace could be possibly insufficient to allocate channel to each coexisting WSO, satisfying its channel demand. Consequently, the channel demand of each coexisting WSO needs to be adjusted to accommodate as many as WSOs in the available TVWS. A straightforward solution is equally distributing the available bandwidth (TV spectrum) among the coexisting WSOs. However, such allocation is not optimal. A WSO with bad channel conditions gets the same bandwidth (spectrum width) as that of the WSO with good channel conditions. Such allocation shall underutilize the scarce TV spectrum. The effective utilization of the scarce spectrum is also equally important. In this situation, we define a mechanism to relax the channel demands of the coexisting WSOs based on multiple coexisting requirements like WSO channel conditions, channel demands, bandwidth utility, inter-WSO interference and disparity in network technologies, fairness in allocation and system throughput optimization. Consequently, the TVWS sharing problem in this context is defined as a multiobjective

optimization problem (MOP) where each objective function tackles above mentioned coexisting requirements.

The simulation results show that the proposed channel sharing schemes achieve a higher fairness in allocation and a better satisfaction in WSOs' fraction of channel occupancy requirements as compared to the state-of-the-art related works.

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Chapter 1

Introduction

In recent years, an unprecedented increase in the deployment of content delivery networks (CDNs) has resulted in the rapid growth of IP traffic. It is expected that by 2019, global IP traffic will exceed 2 zettabytes (10^9 terabytes) per year, of which 62% will be attributable to CDNs [1]. It is also anticipated that by 2019, nearly two-thirds of global IP traffic will originate from non-PC devices, mainly portable and mobile devices [1]. The currently available wireless spectrum, including ISM (industrial, scientific and medical) band and cellular spectrum, is deemed insufficient for accommodating such large volumes of data. On other hand, the digitization of TV transmission has partially relinquished VHF and UHF spectrum [2]. The TV spectrum not in use by licensed operators in a spatio-temporal region is referred to as TV whitespace (TVWS). Considering the scarcity of the available spectrum for increasingly deployed wireless networks, the regulatory bodies worldwide [3], [4], [5], [6], have permitted the unlicensed wireless devices to make an unlicensed use of the TV spectrum unless they do not cause overwhelming interference to the primary users. However, the problem of coexistence of secondary devices operating in the same TV band was not dealt by the regulatory bodies.

The coexistence among secondary devices operating in TV spectrum is considered a challenging task due to signal propagation characteristics of TV channels, spatiotemporal variation of TV spectrum and disparity in network technologies of devices operating in the TV spectrum [7]. These diversities may cause coexistence issues, such as an unresolvable interference, spectrum congestion, diversity in network size, etc., as explained in [7], [8], [9], [10]. To address coexistence issues and regulate access to TV spectrum, IEEE 802 LAN/MAN committee has approved a standard 802.19.1 for enabling peaceful coexistence among unlicensed networks operating in heterogeneous network technologies and operating in TVWS [11]. The standard provides a set of procedures to enable coexistence among secondary networks operating in heterogeneous network technologies in TVWS, namely WSOs (white space objects). The coexistence system in 802.19.1 standard is discussed in the Section 1.1.

Any channel allocation mechanism defined for TVWS, it needs to take care of the variability in the TVWS. It is because, the TVWS varies spatiotemporally both, in the number of available channels and in the quality of the available TV channels. The variability in the number of channels in a geographic region results from the active presence of the licensed operators in the region. On the other hand, the quality of the TV channel to the WSO (in terms of signal to interference and noise ratio) is characterized by the interference resulted from the licensed operators and collocated unlicensed operators, operating in the channel.

In this dissertation, we discuss resource allocation in TVWS focusing the two underlooked TV spectrum allocation requirements.

- The first requirement relates to satisfying the QoS (quality of service) demands of the allocated WSOs, under the scarcity of the TVWS. On an intuitive level, the QoS represents a certain type of requirements to be guaranteed to the WSOs (e.g., jitter, delay, throughput, etc.) [12]. For example, the content delivery multimedia applications have stringent bandwidth requirements to meet the QoS demands of the users. Any lag in the throughput may cause severe damage in the service provisioning of such applications. While, an increasing smartphone usage is resulting in an exponential growth in mobile video (multimedia) traffic [13]. In fact, since 2012 video traffic is more than half of the global mobile traffic [1]. Therefore, WSO QoS provisioning is becoming an important factor to be taken care in the channel allocation process. Moreover, it is anticipated that in future many independently operated WSOs may utilize the TVWS for data offloading[7]. While, on the other hand, in highly congested urban areas the TV spectrum available for an unlicensed use is quite limited [14]. This is possibly due to the active presence of the licensed operators in such areas [14]. The available whitespace could be possibly insufficient to meet the QoS demands of all the collocated WSOs deployed in such areas. Considering the scarcity of the TVWS, its optimal use also becomes equally important. Thus, any TVWS sharing mechanism must take care of the WSO QoS provisioning objective as well as the TVWS utility maximizing objective in conjunction.

- The second TVWS sharing requirement relates to the equity of access to the whitespace. It can be defined as follows. Considering the free to use status of the TVWS, each WSO may have an opportunity to access the TV channel for unlicensed use. However, in highly congested spectrum environments the whitespace available in the geographic region of the collocated WSOs could be insufficient to satisfactorily accommodate all the coexisting WSOs in the TVWS available in their geographic region. Here, satisfactorily refers to the state of satisfying the channel demands of the WSOs while scheduling them in the TVWS. Consequently, to respect the equity of access right of the WSOs, a channel allocation mechanism is required to relax the channel demands of WSOs to accommodate as many as WSOs in the available TVWS.

Considering the above coexistence requirements in TVWS sharing, we explore the problem of resource allocation in TVWS by developing a unique channel allocation model for each of the TVWS sharing requirement defined above. We define two formulations: *a)* adapting the QoS requirements of the coexisting WSOs, and *b)* accommodating as many as coexisting WSOs in the available whitespace. The TVWS sharing formulations are discussed in detail in chapter two and three in the dissertation. For each of the TVWS sharing formulation, we define a unique channel allocation system based on the 802.19.1 coexistence system architecture. A short description of an 802.19.1 coexistence system architecture is discussed in the following section.

1.1 802.19.1 System Architecture

IEEE 802.19.1 [11] is a standard-independent coexistence framework for the coexistence of TVBDs operating in the TVWS. Here "standard-independent" means the coexistence mechanism is not affected by the standards that the TVBDs follow (e.g., PHY/MAC techniques)[15]. Rather, the 802.19.1 standard [11] provides a set of proce-

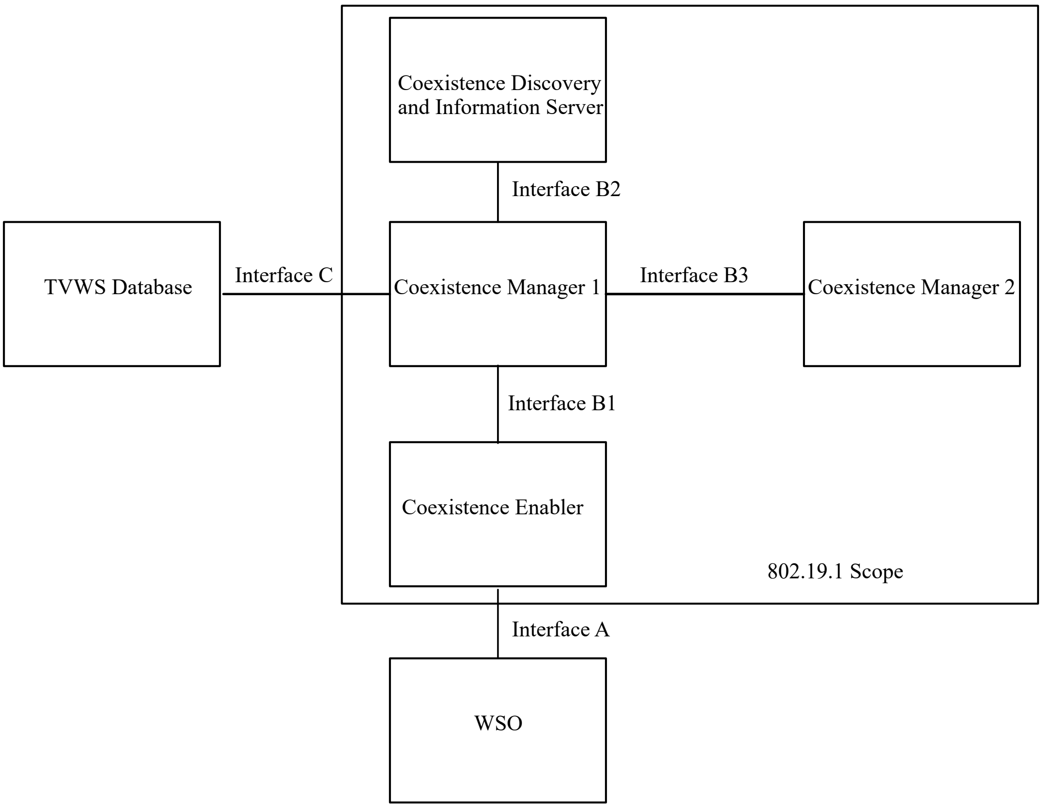

Figure 1.1: The IEEE 802.19.1 coexistence system architecture.

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dures to enable coexistence among TVBDs operating in heterogeneous network technologies and operating in the TVWS. In order to provide coexistence, the standard defines a coexistence system, its architectural and functional components, and their interrelations [11]. Fig. 1.1 shows the framework of 802.19 coexistence system architecture. The framework consists of three logical entities; coexistence manager (CM), coexistence discovery and information server (CDIS), and coexistence enabler (CE) and five interfaces to have interaction among entities in the system.

Briefly, these system components are defined as follows.

- The CE registers a WSO (white space object) to the CM and acts as a communication bridge by translating messages between the WSO and the CM serving the WSO.

- The CM makes coexistence decisions for WSOs registered in it. Moreover, it is required to interact with other CMs, called as neighboring CMs in [11] to resolve coexistence issues among WSOs served by neighboring CMs. In general, it sends configuration commands and control information to the CE.
- The CDIS provides coexistence discovery services like coexistence set information to CMs for registered WSOs.
- The TVWS database (TVDB) is not part of the coexistence system architecture. It contains information about channels available in the geographic region of each WSO registered with the 802.19.1 system. The TVWS database provides information about the set of TV channels free for whitespace activity to the CMs.
- A WSO is an entity in 802.19.1 that represents a TVBD device or network of devices that interact with the system externally.

A WSO is not part of the 802.19.1 coexistence system architecture. Rather, it registers with the CM in the 802.19.1 coexistence system through the logical entity, CE, before operating in the TV spectrum. The main objective of registering the WSO to the system is to acquire a TV channel to operate. In the registration process, a general principle for a WSO to acquire a TV channel is defined in IEEE 802.19.1, summarized as follows. A WSO may perform spectrum sensing to identify and select an available free TV channel and update the CM about its selected TV channel. However, if no free channel is available in the geographic region of the WSO, the CM may perform channel sharing among the requesting WSO and the WSOs already operating on a TV channel. If such WSOs are registered with other CMs, the CM interacts with the other CMs to perform channel sharing. These other CMs are called as neighboring CMs to the requesting CM. In this channel sharing procedure, two types of topology are defined in the 802.19.1 [11]. A distributed CDM topology where neighboring CMs mutually interact to perform channel sharing among WSOs registered within them. A centralized CDM topology where multiple CMs agree to select one of them a master CM and rest of the CMs become slave CM [11]. The master CM performs channel sharing among WSOs registered in it and registered with SCMs, as shall be discussed in Section (2.3.1). Some other terms used in the thesis are defined as follows.

- The *channel occupancy* is the duty cycle in a percentage that a network (WSO) occupies a channel [11].

- The *window time* is a slot duration of a scheduling repetition period that satisfies the essential system QoS performance [11].

- The *Coexistence Set* (CS) of a WSO w is a set of WSOs that are registered in the neighboring CMs that may affect the performance of the WSO. In other words, it is a set of WSOs which create interference to the WSO w.

- The *heterogeneous*-WSOs refers to the set of WSOs operating in heterogeneous network technologies in the TVWS.

1.2 Contributions of this Thesis

We summarize the contributions of this thesis in the following categories:

- Given the scarcity of the availability of the TVWS, a CDM system for unlicensed spectrum access in the TVWS is defined. The system implements the channel allocation process to augment system performance metrics under the constraint of fulfilling the QoS requirements (throughput) of the allocated WSOs. The channel allocation problem is thus defined as an optimization problem that jointly focuses three distinct TVWS sharing requirements;

  1. optimizing system performance metrics like maximizing system throughput and fairness in allocation during the TVWS sharing among *heterogeneous*-WSOs
  2. improving the TVWS utility by implementing the frequency reuse in a joint time-frequency domain
  3. adapting the QoS requirement of the WSOs in the channel allocation process.

  A subgradient algorithm is then designed to solve the optimization problem and allocate the TV channels among coexisting WSOs.

- Considering the spatial variability and channel quality issues in the TVWS, a CDM system is defined that focus on accommodating as many as WSOs on the available TVWS by relaxing their channel requirements. Such strategy shall improve the fairness in allocation among WSOs. Besides fairness in allocation, the

CDM system also maximize the system throughput and improves utilization of the scarce TVWS. The channel sharing problem is thus implemented as a multi-objective nonlinear optimization problem where each objective function defines a distinct performance metric of the channel allocation system. An evolutionary algorithm is then defined to solve the nonlinear optimization problem and perform channel sharing among coexisting WSOs.

The achievements of this research have been published as follows:

[16]. M. Asif Raza, Zafar Iqbal, Sang-Seon Byun, Hyunduk Kang, and Heung-No Lee, "A Versatile Coexistence Decision-Making System for Efficient TV Whitespace Sharing among Whitespace Objects," *Accepted for Publication in Wireless Communications and Mobile Computing, Hindawi*, Aug. 2017.

[17]. M. Asif Raza, S. PArk, and H.-N. Lee, "Evolutionary Channel Sharing Algorithm for Heterogeneous Unlicensed Networks," *IEEE Transactions on Wireless Communications*, vol. 16, issue 7, pp. 4378-4389, Jul. 2017.

[18]. M. Asif Raza, Zafar Iqbal, Seungchan Lee, Haeung Choi, and H.-N. Lee, "Issues and Resolution Efforts Pertaining to TV Whitespace Usage," *Korea Info. and Commun. Society Global Conference 2014*, pp. 77-79, Korea, Jan. 22-24, 2014.

Chapter 2

Coexistence Decision Making in TVWS

In this chapter, we discuss coexistence among WSOs during an unlicensed access to the TV spectrum under the constraint of fulfilling the QoS requirements of the allocated WSOs. The, ”coexistence” refers to a situation where multiple TVBDs or WSOs in a certain geographic region share the same TVWS band and are allowed to access the same band simultaneously [15]. Similarly, a coexistence decision making (CDM) procedure refers to the set of tasks to achieve peaceful coexistence among WSOs sharing the common spectrum. A system implementing the CDM procedure is referred to as a CDM system [10].

To achieve coexistence among *heterogeneous*-WSOs, we design a novel CDM system in Eq. (2.1) based on the centralized decision making topology, shown in Fig. 2.1. The defined system is versatile in nature as it jointly takes care of three TVWS sharing requirements, as discussed in Section 1.2. The proposed system is unique to the knowledge of the authors as, there is no channel allocation mechanism in TVWS literature that jointly optimize the three TVWS sharing requirements discussed in Section 1.2. In the following section, we present some prominent related work in the TVWS sharing domain.

2.1 Related Work

After the regulatory bodies worldwide [3], [4], [5], [6], have permitted unlicensed use of the TV spectrum, numerous efforts for spectrum sharing among collocated WSOs have been proposed. These schemes are classified based on the standards developed for coexistence in TVWS and algorithms designed for achieving coexistence among secondary users in TVWS.

On standadization side, for example, IEEE 802.15.2 [19] and 802.15.4 [20], [21] have partially addressed the coexistence issue among devices operating on wireless local area networks and low power wireless personal area networks, respectively. However, these networks operate on industrial, scientific, and medical bands. Similarly, IEEE 802.22 has recently defined PHY and MAC layer extensions for TVWS [22]. IEEE 802.11af [23] has adopted new cognitive radio features to protect incumbents and achieve efficient spectrum utilization among unlicensed devices. IEEE 802.22.1 has also defined methods for peaceful coexistence when a low-power licensed device such as a microphone broadcaster and an unlicensed device both coexist and share the same channel [24]. The European Computer Manufacturers Association (ECMA) has also defined a specification (ECMA 392) for personal/portable cognitive wireless networks operating in TVWS [25]. However, all these standards define self-coexistence in TVWS operations [25]. Non-availability of cross-platform coexistence mechanisms shall cause issues such as an inability to diagnose interference among networks with dissimilar network technologies and may lead to inefficient utilization of the scarce wireless spectrum [24]. Perceiving the need for cross-platform coexistence mechanisms, IEEE has defined an

802.19.1 standard. This standard provides coexistence protocols and policies for efficient utilization of TVWS across platforms [11].

On the other hand, some CDM algorithms are also provided in the TVWS sharing literature. For example, a CDM algorithm that results in fair TVWS sharing among neighboring CMs is presented in [11]. However, it focuses fairness in allocation only, neglecting improving utilization of the scarce TV spectrum. Bansal et. al., [26] present an algorithm for opportunistic whitespace sharing among secondary networks. The problem is defined as a graph coloring problem. This scheme, however, has performance issue when interference among neighboring access points is relatively high. This situation is quite possible in highly congested areas where multiple of collocated WSOs are deployed. Similarly, the TVWS sharing algorithm in [27] maximizes fairness in allocation. However, it has polynomial runtime complexity $\mathcal{O}(N^3)$, for the number of networks (N). This complexity shows that in areas with a high number of deployed networks, the algorithm shall require substantial channel allocation time.

On spectral reuse of TVWS, some of the TVWS sharing algorithms also define frequency reuse method. For example, in [28], Bian et al., have implemented the concept of FR in sharing a single TV channel among Cognitive Radios (CR). The CR networks operating in orthogonal frequency division multiple access apply the uplink soft FR concept [29]. Again, the proposed method is defined for CR systems deployed in cellular infrastructure. Similarly, Hessar and Roy [30] have presented an FR method in cellular networks operating in TVWS. Moreover, the algorithm proposed in [30] orthogonalizes WSOs in frequency domain only. None of the existing TVWS sharing algorithms reuses

TVWS in a joint, time-frequency domain for WSOs operating in an ad-hoc coexisting environment. Spectrum reuse in both time and frequency domains shall result in even a better utilization of the available TVWS, as discussed in Section (2.6.

Similarly, some genetic algorithms (GA), defined for implementing the channel sharing problem, also exist in the literature. For example, The authors in [31] proposed solutions for the problem of efficient resource allocation (radio spectrum and power) in the OFDMA-based multicast wireless system that balances the tradeoff between maximizing the total throughput and ensuring a flexible and controllable spectrum sharing among multicast groups. It proposes two separate optimization methods for subcarriers and power and a GA-based joint optimization scheme is used. Results show that the proposed schemes can attain a high total sum-rate and more flexible and fair distribution of the available bandwidth among multicast groups. The GA in these and such literature work [32], [33] are well suited for multi-objective optimization problems that require searching over a large space under several constraints. However, GA-based methods are computationally expensive and therefore not suitable for the optimization problem with single objective function and a small search space, like the one defined in this paper. Therefore, GA suffers from the drawbacks of slow convergence speed, and low stability. The channel allocation in highly dynamic spectrum environments requires an algorithm that can do allocation process in a quick runtime. Therefore, rather than applying the GA method, the nonlinear, binary constrained optimization problem, defined in Section 2.3.2 is transformed into linear optimization problem. Such formulation helps us to apply linear programming solvers to solve the optimization problem and complete the allocation process in a quick, linear runtime, as discussed in Section 2.6.5.

2.2 Research Focus

The focus of this chapter is to define a CDM system to perform channel allocation in TVWS. Considering the channel allocation requirements defined in Section 1.2, the TVWS sharing problem is defined as,

Definition 1. *Given a set of available TV channels, a set of CMs with each CM having at least one WSO registered in it and WSOs channel demands, share the TV channels among WSOs such that the following objectives are achieved.*

1) Maximize the system throughput,

2) Minimize unfairness in allocation among WSOs registered in neighboring CMs,

3) Fulfill the QoS (throughput) demand of the allocated WSOs.

These objectives contradict each other. For example, maximizing the system throughput shall decrease fairness in allocation. Note that from a spectrum allocation perspective, fairness is regarded as equity in access to the resource, the TV spectrum. In other words, being free to use, each network should have an equal opportunity to an access to the given TV spectrum. Similarly, fulfilling the second and third objectives in conjunction, under the scarcity of the available TVWS, restricts the system accommodating as many as WSOs in the TVWS. Thus, maximizing the fairness while satisfying the channel demands of each allocated WSO is quite complicated in highly congested spectrum environments [30]. Therefore, the fairness in allocation is measured at CM level. The fairness among CMs is deemed at minimum if at least a single WSO in each CM gets the channel. Considering the above conditions, we design a CDM system, as defined in the following section.

2.3 Coexistence Decision Making System

In this section, we explain the system design process. We also formulate the TVWS sharing problem as an optimization problem for achieving coexistence in TVWS sharing among *heterogeneous*-WSOs.

2.3.1 The CDM System Design

The CDM system in (2.1) is modeled as shown in Fig. 2.1. The system is designed based on the 802.19.1 centralized decision making topology. Briefly, in a centralized decision making topology, the IEEE 802.19.1 provides different a protocol for selecting master CM. In this protocol multiple CMs exchange message flows to agree to select one of them a master CM (MCM) and rest of the CMs become slave CM (SCM). Each SCM provides essential information about operating parameters, including the channel characteristics of each WSO registered within it and its channel demands to the MCM. The MCM implements some CDM procedure to performs coexistence services like radio resource allocation to WSOs registered in the SCMs. In the followings we define our unique CDM system based on the model in Fig. 2.1 that implements the TVWS sharing problem define in Section 2.2.

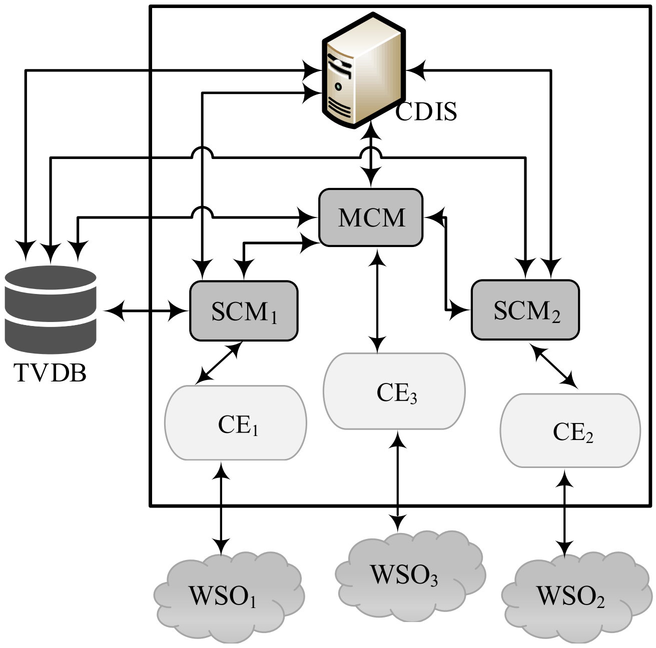

Figure 2.1: The CDM system designed on centralized decision making topology in IEEE 802.19.1.

The TVWS sharing CDM system is defined as,

$$\mathbf{X} = TVWS(\mathcal{C}, \mathcal{J}, \mathcal{Z}, \mathcal{T}, \mathcal{D}) \tag{2.1}$$

The system parameters are defined based on the information clauses defined in 802.19.1, as follows. Let c be an index to a set of C neighboring CMs in the system, denoted as $\mathcal{C}$ in Table (2.1). Let $\mathcal{W}^c$, $\forall c \in \mathcal{C}$ be a set of network IDs of WSOs registered in the CM c, as shown in Table (2.1). Let the network ID, $NID_w \in \mathcal{W}^c$ represents an identifier of the network the WSO w, registered in CM c, represents. For example, in the case of IEEE 802.11 type WSO, the *NID* contains the basic service set identifier used by the WSO.

Let j be an index to the set of all permissible TV whitespace channels, $\mathcal{J}$ =

Table 2.1: CDM System Parameters

Parameter	**Value**
CM set: $\mathcal{C}$	$\mathcal{C} = \{1, 2, \cdots, C\}$
A set of *NID* of WSOs registered in CM c	$\mathcal{W}^c = \{NID_1, NID_2, \cdots, NID_W\}$
Set of available TV channels: $\mathcal{J}$	$\mathcal{J} = \{1, 2, \cdots J\}$
COT of WSO w on channel j	$\mathbf{O}^c_w = \left[O^c_{w,j}\right]_{1\times J}$, $O^c_{w,j} \in \mathbb{R}_{[0,T_j]}$
Coexistence set of WSO w on channel j	$\mathcal{S}_{w,j} = \{m \in \mathcal{W} : m \text{ interfers } w\}$

$\{1, 2, \cdots, J\}$, where each set element corresponds to a TV channel number, defined on the basis of the regulatory authority rulings. For example, in USA where FCC defines each TV channel to be 6 MHz bandwidth in V/UHF band, therefore, $\mathcal{J} = \{2, 3, \cdots, 36, 38, \cdots, 51\}$ in the USA. Since, the availability of a TV channel to a WSO w is a function of geographic location of the WSO and the primary user activity in the region. Therefore, the availability of a TV channel for the secondary use varies spatiotemporally and needs to be determined. We assume that a channel sensing mechanism, as defined in [11] is implemented such that the TVDB contains the set of TV whitespace channels available in the geographic region of each WSO registered in the CMs in the system. Let j be an index to the set $\mathcal{J}$, then, channel j availability status to the WSO w, registered in CM c, is represented by an indicator function defined as,

$$z^c_{w,j} := \begin{cases} 1, & \text{if channel } j \in \mathcal{J} \text{ is available to WSO } w \\ 0, & \text{otherwise} \end{cases} \tag{2.2}$$

The availability of J channels to the WSO w, registered in CM c, are thus represented by a vector of indicator functions defined as,

$$\mathbf{z}_w^c = \left(z_{w,1}^c, \cdots, z_{w,J}^c\right) \tag{2.3}$$

The set of channels available to W WSOs registered in CM c is defined as,

$$\mathbf{Z}^c = \left(\mathbf{z}_1^c, \mathbf{z}_2^c, \cdots, \mathbf{z}_W^c\right)^{\mathrm{T}}, \ \forall c \in \mathcal{C} \tag{2.4}$$

The system parameter $\mathcal{Z}$ is then defined as follows,

$$\mathcal{Z} = \left\{\mathbf{Z}^1, \ \mathbf{Z}^2, \cdots, \mathbf{Z}^C\right\}. \tag{2.5}$$

The parameter $\mathcal{T}$ in the system in (2.1) represents the set of window times for the channels in the set $\mathcal{J}$. In 802.19.1, an algorithm is provided that enables CMs to define the slot duration of the window time. We assume the CMs implement such an algorithm to define the window time, $T_j, \ \forall j \in \mathcal{J}$, which we then use to define system parameter $\mathcal{T}$ as,

$$\mathcal{T} = \{T_1, \cdots, T_J\} \tag{2.6}$$

The system parameter $\mathcal{D}$ in (2.1 encodes channel demands of CMs, defined as follows. In 802.19.1, a Discovery Information abstraction is provided that allows WSOs to send channel statistics and channel demands like SINR, desired channel occupancy, desired bandwidth etc., to their serving CM [11]. Such information of *heterogeneous*-WSOs is used to define a set of channel demands of WSO w as follows.

Let $\mathrm{SINR}_{w,j}^c$ represents the quality of channel j to WSO w registered in CM c. The channel quality is measured in terms of signal to interference and noise ratio (SINR) which depends on interference from primary-to-secondary users and noise floor due to environmental factors. We assume that an interference discovery mechanism is in place that enables each WSO to measure SINR value on each of the channels in $\mathcal{J}$, as will be further discuss in Section 2.5.1. The quality of all J channels to WSO w is then defined as,

$$\mathbf{s}'^c_w = \left(\mathrm{SINR}^c_{w,1}, \mathrm{SINR}^c_{w,2}, \cdots, \mathrm{SINR}^c_{w,J}\right), \forall w \in \mathcal{W}^c \tag{2.7}$$

Let $p^c_{w,j}$ be the allowed transmission power to WSO w in the channel j. Note that the transmission power allowed for unlicensed operations in the TV spectrum is defined by the regulatory body. For example, in USA, FCC defines maximum transmission power for different type of TVWS device. We assume that a system is in place that has already allocated the transmission power to the WSOs in the system. The allowed transmission power to WSO w on J channels is then defined as,

$$\mathbf{p}'^c_w = \left(p^c_{w,1}, \cdots, p^c_{w,J}\right), \forall w \in \mathcal{W}^c \tag{2.8}$$

The QoS (throughput) demand of the WSO w registered in CM c is then defined on a channel j as follows. Let b_j be the bandwidth of TV channel j in the system. For example, in USA, each TV channel is of 6MHz. Let $O'_{w,j}j$ be the desired duty cycle of WSO w on channel j. Then, the throughput required is defined in terms of Shannon capacity formula as follows,

$$T^c_{w,j} = O^c_{w,j} b_j \log\left(1 + SINR^c_{w,j}\right) \tag{2.9}$$

where $O^c_{w,j}$ translates to a timeslot, here called as channel occupancy time (COT) in a window time, such that the WSO w registered in CM c can achieve its desired channel occupancy in the allocated channel j. The relation of COT to a channel window time

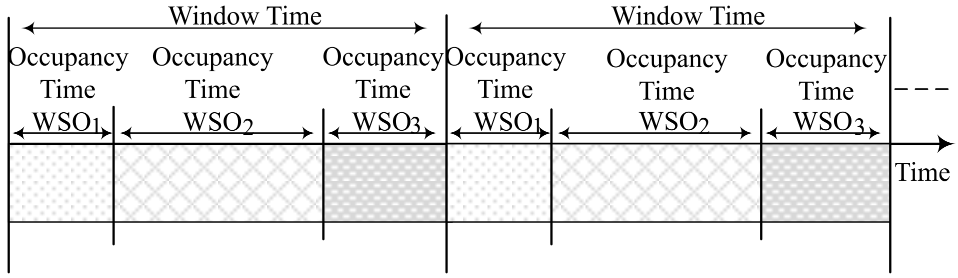

Figure 2.2: Scheduling transmission periods for three WSOs on a TV channel.

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is shown in Fig. 2.2 where three WSOs are scheduled in the window time in a single TV channel. Note that the channel occupancy is defined as duty cycle that a network occupies a channel. The COTs of WSO w in J TV channels are then represented as,

$$\mathbf{o}'^{c}_{w} = \left(O^{c}_{w,1}, \cdots, O^{c}_{w,J}\right) \tag{2.10}$$

Let B^{c}_{w} be the bandwidth demand of WSO w. The number of channels required by WSO w is then calculated as,

$$n^{c}_{w} = \tfrac{B^{c}_{w}}{b}, \forall w \in \mathcal{W}^{c},\, \forall c \in \mathcal{C} \tag{2.11}$$

Finally, the channel demand set of WSO w is defined as follows,

$$\left\{\mathbf{s}'^{c}_{w},\, \mathbf{p}'^{c}_{w},\, n^{c}_{w},\, \mathbf{o}'^{c}_{w}\right\},\, \forall c \in \mathcal{C},\;\, \forall w \in \mathcal{W}^{c} \tag{2.12}$$

The channel demand set of CM c is then defined using the channel demands of its registered WSOs as follows,

$$\mathcal{D}'^{c} = \left\{\mathbf{s}^{c}, \mathbf{p}^{c}, N^{c}, \mathbf{o}^{c}\right\}\,,\;\, \forall c \in \mathcal{C} \tag{2.13}$$

where $\mathbf{s}^{c} = (\mathbf{s}'^{c}_{1}, \cdots, \mathbf{s}'^{c}_{W})$, $\mathbf{p}^{c} = (\mathbf{p}'^{c}_{1}, \cdots, \mathbf{p}'^{c}_{W})$, $N^{c} = (n^{c}_{1}, \cdots, n^{c}_{W})$, and $\mathbf{o}^{c} = (\mathbf{o}'^{c}_{1}, \cdots, \mathbf{o}'^{c}_{W})$. Let for all CM in the system we define, $\mathbf{S} = \left(\mathbf{s}^{1}, \mathbf{s}^{2} \cdots, \mathbf{s}^{C}\right)^{T}$, $\mathbf{P} = \left(\mathbf{p}^{1}, \mathbf{p}^{2} \cdots, \mathbf{p}^{C}\right)^{T}$,

$\mathbf{N} = \left(N^1, N^2 \cdots, N^C\right)^T$, and $\mathbf{O} = \left(\mathbf{o}^1, \mathbf{o}^2 \cdots, \mathbf{o}^C\right)^T$. The system parameter $\mathcal{D}$ is then defined using the channel demands of all neighboring CMs as follows,

$$\mathcal{D} = \{\mathbf{S},\ \mathbf{P}, \mathbf{N}, \mathbf{O}\} \tag{2.14}$$

The system in (2.1 then executes the channel allocation algorithm, as will be discussed in Section (2.4.3), to allocate TV channels to the WSOs registered in the neighboring CMs such that the allocation satisfies the required system QoS performance. The system QoS performance is preserved if the following allocation condition is satisfied,

$$\sum_{c \in \mathcal{C}} \sum_{w \in \mathcal{W}^c} O^c_{w,j} \leq T_j,\ \forall j \in \mathcal{J} \tag{2.15}$$

where T_j refers to the window time in a channel j. The algorithm proposed in Section (2.4.3) solves the TVWS sharing optimization problem, as will be defined in (2.23) and outputs a channel allocation matrix $\mathbf{X}$, defined as follows. Let $x^c_{w,j} \in \{0, 1\}$, be a binary decision variable such that if $x^c_{w,j} = 1$, the channel j is allocated to the WSO w registered in CM c; otherwise $x^c_{w,j} = 0$. The allocation status of WSOs registered in the neighboring CMs is then represented by a matrix $\mathbf{X}$ as,

$$\mathbf{X} := \begin{bmatrix} x^1_{1,1} & x^1_{1,2} & \cdots & x^1_{1,J} \\ & & \vdots & \\ x^1_{W^1,1} & x^1_{W^1,2} & \cdots & x^1_{W^1,J} \\ x^2_{1,1} & x^2_{1,2} & \cdots & x^2_{1,J} \\ & & \vdots & \\ x^c_{W^c,1} & x^c_{W^c,2} & \cdots & x^c_{W^c,J} \\ & & \vdots & \\ x^C_{W^C,1} & x^C_{W^C,2} & \cdots & x^C_{W^C,J} \end{bmatrix} \tag{2.16}$$

where $W^c = |\mathcal{W}^c|$, $\forall c \in \mathcal{C}$ be the number of WSOs registered in the CM c. The wth row in the $\mathbf{X}$ represents the channels allocation status, in the set $\mathcal{J}$, to the WSO w registered in CM c. The channel j in the $\mathbf{X}$ represents the channels allocation status of all the WSOs, from all the CMs in the set $\mathcal{C}$. The allocation matrix thus orthogonalizes WSOs, registered in the neighboring CMs, in a joint frequency-time domain. The WSOs scheduled on different channels can transmit at the same time using their respective allotted channel (frequency slot) while WSOs scheduled on the same channel can transmit in their respective time slot (here COT). The system in (2.1) thus, implements the TVWS sharing problem, defined in Section (2.2), as an optimization problem, as discussed in the following section.

2.3.2 Problem Formulation

In this section, the proposed TVWS sharing problem is formulated as an optimization problem using well-established proportional fairness method. We make use of the proportional fairness technique as it is considered as one of the most suitable methods to achieve a trade-off between two competing interests [34], [35], [36]. Originally, Kelly defined the proportional fairness as an adjustment process which adjusts the rates of users according to the charges they pay. The proportional fairness method thus was defined for elastic traffic in computer network services [37]. Similarly, in the channel sharing literature, a proportionally fair allocation mostly has been achieved by adjusting the rates of the users based upon some performance criteria like maximizing the resource utilization, etc. [38], [39]. However, applying the proportional fairness in its original to model the TVWS sharing problem is not suitable. It is because, the third objective in the problem defined in Section (2.2) makes the resource allocation as binary decision allocation, i.e., a channel is either allocated to a WSO, $x^c_{w,j} = 1$ or not $x^c_{w,j} = 0$. Therefore, WSO allocation (here COT) adjustment is not possible. Consequently, we rewrite the proportional fairness in a binary decision allocation perspective as follows. Let the maximum data rate the WSO w can achieve on channel j be defined by using Shannon channel capacity formula,

$$r^c_{w,j} = b_j \log\left(1 + SINR^c_{w,j}\right) \tag{2.17}$$

The maximum rate, $r^c_{w,j}$, $\forall w \in \mathcal{W}^c$ is then used to defined a utility function as a normalized rate achieved by CM c in channel j as follows,

$$\mathcal{U}_{c,j} = \sum_{w \in \mathcal{W}^c} \frac{x^c_{w,j} r^c_{w,j}}{O^c_{w,j} + \delta_{O^c_{w,j}0}} \tag{2.18}$$

where $\delta_{O^c_{w,j}0}$ defines Kronecker delta function as:

$$\delta_{O^c_{w,j}0} := \begin{cases} 1, & \text{if } O^c_{w,j} = 0, \\ 0, & \text{otherwise.} \end{cases} \tag{2.19}$$

This function prevents denominator term in (2.18) from becoming zero. The utility function in (2.18) measures the worth of the resource (channel) to CM c, i.e., given a channel is allocated to the WSOs in the CM c for the duration of $\sum_{w\in\mathcal{W}^c} O^c_{w,j}$, how does it translate for the CM in terms of the achieved throughput. In other words, maximizing the function in (2.18) shall prefer a CM with WSOs achieving high data rate and lower channel occupancy demand over a CM with WSOs achieving low data rate and high channel occupancy demand. Such preference based allocation shall lead to an efficient use of the resources (TVWS). The distribution $\mathbf{U} = [\mathcal{U}_{c,j}]_{C\times J}$ is then said to be proportionally fair if it is feasible and for all other feasible solutions $\mathbf{V} = [v_{c,j}]_{C\times J}$, the following holds [37],

$$\sum_{c\in\mathcal{C}}\sum_{j\in\mathcal{J}} \frac{v_{c,j} - \mathcal{U}_{c,j}}{\mathcal{U}_{c,j}} \ \leq \ 0 \tag{2.20}$$

It has been shown in [37], [40] that the rates achieved by users become proportionally fair if the sum of logarithmic rates obtained is optimized. Moreover, it is shown in [41] that if all rates are proportionally fair, they maximize the throughput over all other feasible throughput. Therefore, if the logarithmic sum of the utility function in (2.18) is maximized, the normalized rate achieved by neighboring CMs shall become proportionally fair. Let a channel j is said to be allocated to the CM c if at least one of its registered WSO is scheduled on the channel. The allocation status of the channels in the $\mathcal{J}$, to the CM c, is then defined as follows,

$$\mathbf{x}^c := \begin{bmatrix} x^c_{1,1} & x^c_{1,2} & \cdots & x^c_{1,J} \\ & \vdots & & \\ x^c_{W^c,1} & x^c_{W^c,2} & \cdots & x^c_{W^c,J} \end{bmatrix} \tag{2.21}$$

Let $\mathbf{1} = (1, 1, \cdots, 1)_{1\times J}$. Let $\mathbf{O}_j \in \mathbf{O}$ be the j^{th} column vector in COT demand matrix in the system parameter $\mathcal{D}$, defined as,

$$\mathbf{O}_j = \left(O^1_{1,j}, O^1_{2,j}, \cdots, O^1_{W^1,j}, O^2_{1,j}, \cdots\cdots, O^C_{W^C,j}\right)^T \tag{2.22}$$

where $W^c = |\mathcal{W}^c|, \forall c \in \mathcal{C}$. Let $\mathbf{X}_j \in \mathbf{X}$ represents the j^{th} column vector of the allocation matrix $\mathbf{X}$. The TVWS sharing problem is then defined as follows,

$$\text{maximize} \quad \sum_{c\in\mathcal{C}} \sum_{j\in\mathcal{J}} \log\left(\mathcal{U}_{c,j} + 1\right) \tag{2.23a}$$

$$\text{subject to} \quad \mathbf{x}^c \leq \mathbf{Z^c}, \forall c \in \mathcal{C}, \tag{2.23b}$$

$$\mathbf{X}_j^{\mathrm{T}} \mathbf{O}_j \leq T_j, \, \forall j \in \mathcal{J}, \, \forall c \in \mathcal{C}, \tag{2.23c}$$

$$\mathbf{x}^c \mathbf{1}^{\mathrm{T}} \leq (N^c)^{\mathrm{T}}, \forall c \in \mathcal{C}, \tag{2.23d}$$

$$\mathbf{x}^c \in \{0, 1\}, \, \forall c \in \mathcal{C}. \tag{2.23e}$$

The constraint in (2.23b) ensures that a channel can be allocated to the WSOs registered in CM c only if the channel is available in their respective region, i.e., $\left(x^c_{w,j} = 1\right) \in \mathbf{x}^c$ iff $\left(z^c_{w,j} = 1\right) \in \mathbf{z}^c_w$. The constraint in (2.23c) ensures that the WSOs scheduled in a channel j preserve the system QoS performance, as defined in (2.15), i.e., the total allocated channel occupancy time of coexisting WSOs must preserve the channel window time. The constraint in (2.23d) ensures that the number of channels allocated to the CM c is restricted by the number of channels desired by its WSOs. Finally, (2.23e) forces the decision variable to be binary valued. The constraints in (2.23e) and (2.23c) helps the system in (2.1) to satisfy the third objective of TVWS sharing problem in Section (2.2). The optimization problem in (2.23) seeks to optimize a concave objective function over a convex set. The problem in (2.23) has a unique solution, as from the optimization theory [42], maximizing a concave function over a convex set has a unique solution. A solution approach to the problem in (2.23) is presented in the following section.

2.4 Solution to Channel Allocation Problem

The nonlinear objective function (2.23a) and binary-valued constraint (2.23b) makes the problem in (2.23) a nonlinear combinatorial optimization problem. Determining the optimal solution of such a problem is a challenging task as the problem becomes intractable as the number of discrete variables increases [43]. Therefore, to ease the solution approach, the problem in (2.23) is transformed into a linear programming problem as discussed in the following section.

2.4.1 Linearization

The objective function (2.23a) is linearized using a piecewise linear approximation. In this process, tangent line approximation is used to approximate the objective function in (2.23a), denoted as, F. The detailed description of linear approximation is provided in Appendix A. Using this function, the problem in (2.23) is linearized as,

$$\begin{aligned}
&\text{maximize} && \sum_{c\in\mathcal{C}}\sum_{j\in\mathcal{J}} F\left(\mathcal{U}_{c,j}\right) && \text{(2.24a)}\\
&\text{subject to} && \mathbf{x}^c \leq \mathbf{Z}^{\mathbf{c}}, \forall c \in \mathcal{C}, && \text{(2.24b)}\\
& && \mathbf{X}_j^{\mathrm{T}}\mathbf{O}_j \leq T_j,\ \forall j \in \mathcal{J},\ \forall c \in \mathcal{C}, && \text{(2.24c)}\\
& && \mathbf{x}^c\mathbf{1}^{\mathrm{T}} \leq \left(N^c\right)^{\mathrm{T}}, \forall c \in \mathcal{C}, && \text{(2.24d)}\\
& && \mathbf{x}^c \in \{0,1\},\ \forall c \in \mathcal{C}. && \text{(2.24e)}
\end{aligned}$$

The binary-valued constraint in $(2.24b)$ makes the problem in (2.24) hard to solve. It is therefore tackled using Lagrangian relaxation technique, as discussed in the following section.

2.4.2 Relaxation Hard Constraint

Lagrangian relaxation [44] relaxes a subset of constraints by adding them to the objective function with a penalty term called the Lagrangian multiplier. Let $\lambda := [\lambda_{w,j}]_{W\times J}$ be the Lagrangian multipliers matrix. Then, the relaxed problem can be defined as,

$$\begin{aligned}
&\underset{\mathbf{X}}{\text{maximize}} && P(\mathbf{X},\boldsymbol{\lambda}) = \sum_{c\in\mathcal{C}}\sum_{j\in\mathcal{J}} F\left(\mathcal{U}_{c,j}\right) + \boldsymbol{\lambda}^{\mathrm{T}}\left(\mathbf{Z}^c - \mathbf{x}^c\right) && \text{(2.25a)}\\
&\text{subject to} && \mathbf{X}_j^{\mathrm{T}}\mathbf{O}_j \leq T_j,\ \forall j \in \mathcal{J},\ \forall c \in \mathcal{C}, && \text{(2.25b)}\\
& && \mathbf{x}^c\mathbf{1}^{\mathrm{T}} \leq \left(N^c\right)^{\mathrm{T}}, \forall c \in \mathcal{C}, && \text{(2.25c)}\\
& && \mathbf{x}^c \in \{0,1\},\ \forall c \in \mathcal{C}. && \text{(2.25d)}
\end{aligned}$$

For a given $\boldsymbol{\lambda}$, the Lagrangian relaxation can be defined as,

$$h(\boldsymbol{\lambda}) = \max_{\mathbf{X}} \ \{P(\mathbf{X}, \boldsymbol{\lambda}) : \text{constraints}\,(2.24b),\ (2.24c),\ (2.24d)\} \tag{2.26}$$

Then the generalized dual problem of the relaxed problem is defined as followings,

$$L^* = \min_{\boldsymbol{\lambda}} \ \{h(\boldsymbol{\lambda}) : \boldsymbol{\lambda} \geq 0\} \tag{2.27}$$

The solution to (2.26) is the upper bound of the solution to the original problem (2.25). Note that (2.26) is a concave function. For a concave function, a gradient-based approach is generally used to compute a value as close as desired to the optimal value. Thus, if h would have been differentiable, we can use a gradient descent method to have a convergence toward the optimal value. The proposed problem, however, cannot be solved using a gradient descent method. It is because the objective function is piecewise linear which is non-differentiable at the intersection point of adjacent linear pieces, but sub-differentiable at this point. The subdifferential of $h(\lambda)$ at such a point is the set of all subgradients at that point. Thus, we need to compute a sequence of $\left\{\boldsymbol{\lambda}^k\right\}_{k\in\{1,2,\cdots,K\}}$ such that either $h\left(\lambda^k\right)$ converges to the optimal solution using the subgradient method, which is given in the following dual algorithm. The convergence property of the subgradient algorithm is presented in Appendix B.

2.4.3 Subgradient Algorithm for Relaxed TVWS Sharing Problem

The algorithm is defined in 2.1. In Step 0, the input parameters to the algorithm are initialized as follows. The initial values of $\boldsymbol{\lambda}^0$ are defined randomly. The parameter ρ is used in defining step size t^k, defined in the range $\rho^{\min} < \rho \leq 2$ [44]. The ρ_{iter} with upper limit of ρ^{maxiter} counts the number of iterations after which the parameter ρ is updated. The $k^{\max}$ is defined as stopping criteria for the algorithm.

The algorithm uses variables initialized in Step 0 to apply a linear programming (LP) solver to solve the dual problem and obtain the k^{th} iteration allocation matrix $\mathbf{X}_k$. LP solvers are available on both the commercial and freeware basis. The entries in $\mathbf{X}_k$ are then adjusted based upon the corresponding entries in $\mathbf{Z}^c$ such that $x^c_{w,j} \in \mathbf{x}^c_k, \ \forall \mathbf{x}^c_k \in \mathbf{X}_k$ are set equal to zero if the corresponding element, $z^c_{w,j} \in \mathbf{z}^c_w, \ \forall \mathbf{z}^c_w \in \mathbf{Z}^c$ is zero. This validation ensures the constraint in (2.23b).

The algorithm then applies the FR process in Step 3 in Algorithm (2.1). In this process, the algorithm makes use of the current allocation vector, $\mathbf{X}_k$ and the interference matrix, $\mathbf{Y}$ as shall be discussed in Section (2.5.1), to identify a set of WSOs which do not get the channel. The algorithm then repeatedly applies LP solver to performs channel allocation to the unallocated WSOs such that they do not cause interference to the allocated WSOs of neighboring CMs. The FR process is detailed in Section (2.5.2). The outcome of FR process is an updated allocation matrix $\mathbf{X}'_k$ which is then used to compute the function values in (2.25a) and the fairness in allocation among neighboring CMs.

Several fairness measures or metrics are used in the literature to determine whether networks are receiving a fair share of spectrum or not. For example, max-min fairness, Jain's fairness index, fairly shared spectrum efficiency, worst-case fairness. We adopt Jain's fairness index [45] to measure fairness in allocation among neighboring CMs. The reason is that it satisfies the desired properties of fairness measure like population size

Algorithm 2.1: Subgradient Algorithm for Relaxed TVWS Sharing Problem

Input: $\boldsymbol{\lambda}^k$, $\mathbf{X}_k^{'} = \mathbf{X}_k$, $\mathcal{Z}$, CS;

Output: $\mathbf{X}_k^{'}$;

Algorithm Steps

0: a) Choose initial values of $\boldsymbol{\lambda}^0$;

b) Set initial parameters as: $\rho = 2.0$, $\rho^{\min} = 0.001, \rho_{iter} = 0, \rho^{\max iter} = 5, k = 0 k^{\max} = 10, F^{\text{best}} = 0, h^{\text{best}} = -\infty, h^{\text{upper}} = 0, \mathbf{X'}_k = [0]_{W \times J}$.

1: a) Increment counter as: $k = k + 1$, $\rho_{iter} = \rho_{iter} + 1$

b) Given $\boldsymbol{\lambda}^k$, solve the relaxed problem using any linear programming technique and obtain $\mathbf{X}_k$.

2: Validate $\mathbf{X}_k$ as: set $x_{w,j}^c := 0$ if $z_{w,j}^c = 0$.

3: Perform frequency reuse as in Algorithm (2.2) and get $\mathbf{X}_k^{'}$.

4: a) Use $\mathbf{X}_k^{'}$ to compute the value of the function in (2.25a), called as F, and fairness index value H in (2.31).

b) **If** $F > F^{best}$: set $F > F^{best}, h^{upper} = F^{best}, \mathbf{X} = \mathbf{X'}_k$

5: a) Use $\mathbf{X}_k^{'}$ to compute:

- Subgradient vector as, $\nabla h\left(\lambda^k\right) = \left[\frac{\partial h}{\partial \lambda_{w,j}^k}, \forall w\right]$,
- Dual objective in (2.27),
- Step size as, $t_k = \frac{\rho\left(h^{upper} - h\left(\lambda^k\right)\right)}{\left\|\nabla h\left(\lambda^k\right)\right\|^2}$.

b) Update the dual variable as, $\lambda^{k+1} = \max\left\{\lambda^k + t_k \nabla h\left(\lambda^k\right),\ 0\right\}$.

Algorithm 2.1: Subgradient Algorithm (continued)

6: **If** $h^{best} < h\left(\lambda^k\right)$ **then** $h^{best} = h\left(\lambda^k\right)$

elseif $\rho_{iter} > \rho^{\max iter}$ **then** $\rho = \max\left\{\frac{\rho}{2}, \rho^{\min}\right\}$ and $\rho_{iter} = 0$.

7: **If** $t_k < 0.001$ or $k >k^{\max}$ stop; otherwise go to Step 1.

independence, continuity etc., as listed in [46]. These properties are important to be considered in measuring the fairness in allocation. For example, the continuity property shows any slight change in the allocation of individual WSO. Thus, an inefficient use of the TVWS is identified by the fairness index as a WSO with bad channel characteristics gets a high proportion of the spectrum. It is ensured through the use of the continuous allocation metric like fraction of throughput demand, as defined in (2.28). Such an allocation metric is suitable to measure the fairness in allocation for the case where WSOs demand unequal channel bandwidth [46]. Therefore, based on the fraction of throughput demand of CMs, an allocation metric is defined as follows,

$$T^c = \frac{d^c}{d'^c}, \ \forall c \in \mathcal{C} \tag{2.28}$$

where d^c and d'^c represents the maximum data the CM c desire to transmit and it can transmit using its allocated channels, respectively. These terms are defined as follows. Let the maximum data the CM c can transmit using its allocated channels is defined in terms of the data the WSOs registered in it can transmit, defined as follows.

$$d^c = \sum_{j \in \mathcal{J}} \sum_{w \in \mathcal{W}^c} x^c_{w,j} O^c_{w,j} r^c_{w,j}, \ \forall c \in \mathcal{C} \tag{2.29}$$

Note that channels are considered as additive white Gaussian noise (AWGN). The data the CM desires to transmit is defined as,

$$d'^c = \sum_{j \in \mathcal{J}} \sum_{w \in \mathcal{W}} O^c_{w,j} r^c_{w,j}, \ \forall c \in \mathcal{C} \tag{2.30}$$

The normalized throughput vector $\left(T^1, \cdots, T^C\right)$ is then adopted to measure fairness in allocation using Jain's fairness index [45] as,

$$H\left(T^1, T^2, \cdots, T^C\right) = \frac{\left(\sum\limits_{c \in \mathcal{C}} T^c\right)^2}{C \sum\limits_{c \in \mathcal{C}} \left(T^c\right)^2} \tag{2.31}$$

Function H in (2.31) outputs a value in the range of [0, 1]; when the value is closer to 1, the allocation is deemed fairer.

If the current iteration value of the objective function, F, is optimal, then F^{best} is updated with F and $\mathbf{X}$ with $\mathbf{X}_k'$. As the iteration progresses, the feasible primal F^{best} and lower bound h^{best} approach gradually to the integer optimal by adjusting $\boldsymbol{\lambda}^k$ using the subgradient method as defined in Step 5. In Step 5, the sub-gradient vector of the objective function and the Lagrangian multiplier vector $\boldsymbol{\lambda}^k$ for the k^{th} iteration are calculated. The step size t_k is used to calculate the multiplier vector for the next iteration. The Lagrange multipliers are thus adjusted iteratively. The convergence property of the subgradient algorithm is discussed under Appendix B. The algorithm terminates as one of the termination conditions satisfied:

- Dual step size becomes less than a set threshold or,
- the number of iterations exceeds the maximum number of iterations.

After the overall iteration ends, we regard the final value of F^{best} as the optimal solution and the corresponding allocation matrix $\mathbf{X}$ is the algorithm output. The spatial reuse of the TVWS that is used to implement the FR step in Algorithm (2.2) is discussed in the following section.

2.5 Spatial Spectrum Reuse in Heterogeneous TVWS Sharing Environment

TVWS varies spatiotemporally. The active presence of licensed operators, especially in a highly congested urban environment, results in a limited number of TV channels available for unlicensed use [14]. On the other hand, the number of deployed networks (WSOs) in such areas is possible quite large. Consequently, the whitespace available in the geographic region of collocated WSOs may be insufficient to accomodate all of the WSOs. Moreover, WSOs operating in different network technology may coexist in a geographic region. These networks may greatly vary is size, shape, coverage area. Thus, creating a heterogeneous coexistence environment. Considering spectrum congestion issues in such environment, we propose a novel frequency reuse method to have spatial resue of the TVWS in harsh, heterogeneous coexisting environment. The proposed method makes use of the WSOs interference information to defines an interference matrix which is afterwards used to define a set of WSOs where spatial spectral reuse is possible. The interference matrix and frequency reuse techniques are discussed in detail in the following sections.

2.5.1 Interference Matrix Definition

The WSOs registered in the neighboring CMs and interfering on the available TV channels is represented using an interfering matrix called as Y-matrix in this thesis. Note that the Y-matrix does not model the interference among coexisting WSOs. Rather, it represents the set of WSOs which cannot transmit simultaneously on the available TVWS due to interfering transmission regions. In fact, in IEEE 802.19.1 [11], a coexistence discovery algorithm is presented that the CDIS and CM run to perform the statistical analysis of the expected interference among coexisting WSOs. Briefly, the algorithm in [11] takes the WSOs' geographic location, transmitter and receiver characteristics, antenna height and directivity, height above average terrain and other related parameters to execute interference discovery process. In this process, a cumulative distribution function of the potential interference from WSO m to WSO w is estimated. Both of these WSOs, m and w, may register to the same CM or different CMs in the system. The minimum interference level, experienced by 90% devices of the WSO w, is then taken as the potential interference value from a WSO m to WSO w. The measured interference value is then compared to a threshold. If the value is greater than the threshold, the WSO m is considered a potential interferer to the WSO w and is included in its CS. A similar rule is applied for interference discovery of the WSO w into the WSO m. Thus, the outcome of the interference analysis process is a CS of each WSO registered in the CMs in the system. The system in (2.1) then makes use of the CS of each WSO to generate a Y-matrix as follows.

Let an encoded CS of WSO w on channel j is defined as, $\mathcal{S}_{w,j} = \{I_{w,m}(j)\}, \forall m \in$

$\mathcal{W}$, where the indicator variable $I_{w,m}(j) = 1$ if WSO m interferes WSO w transmission on the channel j, i.e., $m \in \mathcal{S}_{w,j}$; otherwise $I_{w,m}(j) = 0$. The encoded CS of all the WSOs coexisting on channel j are then used to define a channel j interference matrix $\mathbf{y}(j)$ as follows,

$$\mathbf{y}(j) := \begin{bmatrix} \times & I_{1,2}(j) & \cdots & I_{1,w}(j) & \cdots & I_{1,W}(j) \\ & & \vdots & & \vdots & \\ I_{w,1}(j) & I_{w,2}(j) & \cdots & \times & \cdots & I_{w,W}(j) \\ & & \vdots & & \vdots & \\ I_{W,1}(j) & I_{W,2}(j) & \cdots & I_{W,w}(j) & \cdots & \times \end{bmatrix} \tag{2.32}$$

where $\times$ in diagonal vector in $\mathbf{y}(j)$ represents don't care condition. This condition translate a self-interference indicator variable, $I_{w,w}(j)$, having no meaning. The wth row in $\mathbf{y}(j)$ matrix represents encoded CS of WSO w. The interference matrices for all channels in the system are then used to define an interference matrix $\mathbf{Y}$ as follows,

$$\mathbf{Y} = [\mathbf{y}(1) \;\; \mathbf{y}(2) \;\; \cdots \;\; \mathbf{y}(J)] \tag{2.33}$$

The TVWS sharing algorithm in (2.1) makes use of the interference matrix $\mathbf{Y}$ to implement FR in sharing TVWS among heterogeneous WSOs, as discussed in the following subsection.

2.5.2 Frequency Reuse Mechanism

The frequency reuse (FR) subroutine in Algprithm (2.2) performs spatial reuse of the TV spectrum to enhance its effective utilization. The FR process is implemented to the WSOs do not getting channel in the initial allocation phase in Step 1 in Algorithm (2.1). This requires to identify a set of unallocated WSOs eligible for the FR. In this process, an encoded CS $\mathcal{S}_{w,j}$, $\forall m \in \mathcal{W}$ and an interference matrix $\mathbf{Y}$ are used to define the set of unallocated WSOs, $\mathcal{W}'$. To generate encoded CS and Y-matrix, we make use of the CS of each WSO available at MCM. Note that the 802.19.1 defines different message clauses that enable CMs to exchange their WSO related information [11].

Let us assume the CS of WSOs are available to CDM at MCM. Given such information available, an encoded CS of WSOs, $\mathcal{S}_{w,j}$, $\forall m \in \mathcal{W}$ and an interference matrix $\mathbf{Y}$, are generated, as defined in Section (2.5.1) Initially the Y-matrix is filled with all ones. Let $\mathbf{X}_k$ be an initial allocation matrix available from Step 2 in Algorithm (2.1). The Y-matrix is then updated based on the $\mathbf{X}_k$ and $\mathcal{S}_{w,j}$, $\forall m \in \mathcal{W}$ in Step 1 in Algorithm (2.2), as follows. For each channel j in the system, update interference matrix $\mathbf{y}(j) \in \mathbf{Y}$ as,

1) If channel j is allocated to WSO w, set all wth row elements in $\mathbf{y}$, $\forall \mathbf{y} \in \mathbf{Y}$ equal to zero, or

2) If channel j is allocated to WSO m and WSO w is in the CS of WSO m, set all wth row elements in the matrix $\mathbf{Y}$ equal to zero.

The above two steps identify the eligibility of the WSOs for implementing the FR process. For example, if the WSO w is already allocated a channel, we aim to restrict it in taking part the FR process. Therefore, the wth row entries in the entire Y-matrix are flipped zero in the first step above. Similarly, if a channel j is already allocated to WSO m and if WSO w transmission in the channel j shall create harmful interference

Algorithm 2.2: Frequency Reuse Subroutine

Input: $\boldsymbol{\lambda}^k$, $\mathbf{X}_k^{'} = \mathbf{X}_k$, $\mathcal{Z}$, CS;

Output: $\mathbf{X}_k^{'}$;

Algorithm Steps

0: Given CS, generate $\mathcal{S}$ and interference matrix, $\mathbf{Y}$, as defined in Section (2.5.1).

1: Given $\mathbf{X}_k^{'}$, update $\mathbf{Y}$, as: for each WSO w do:

if $x_{w,j} = 1$ and $\sum x_{w,j} = n_w^c$ **then** update $\mathbf{y}(j) \in \mathbf{Y},\ \forall j \in \mathcal{J}$, as: $I_{w,m}(j) = 0,\ \forall m \in \mathcal{W}$;

elseif $x_{w,j} = 1$ and $\sum x_{w,j} < n_w^c$ **then** update $\mathbf{y}(j) \in \mathbf{Y}$ as: $I_{w,m}(j) = 0,\ \forall m \in \mathcal{W}$;

elseif $(x_{m,j} = 1$ and $w \in \mathcal{S}_{m,j})$ **then** update $\mathbf{y}(j) \in \mathbf{Y}$ as: $I_{w,m}(j) = 0,\ \forall m \in \mathcal{W}$;

2: Define unallocated WSO set in the system as,

$$\mathcal{W}' = \left\{ \forall w \in \mathcal{W}\ :\ \exists j \in \mathcal{J} \mid \sum_{m \in \mathcal{W}} I_{w,m}(j)\ > 0 \right\}.$$

3: **While** $\sum\limits_{w \in \mathcal{W}} \sum\limits_{m \in \mathcal{W}} I_{w,m}(j) > 0,\ \forall j \in \mathcal{J}$ and $\mathcal{W}' \neq \{\}$, **do**:

a) Given $\boldsymbol{\lambda}^k$ and $\mathcal{W}^{'}$; solve the relaxed problem using any linear programming solver and obtain $\mathbf{X}_k$.

b) Perform the following updates:

– $\mathbf{X}_k$ as: set $x_{w,j}^c := 0$ if $z_{w,j}^c = 0$,

Algorithm 2.2: Frequency Reuse Subroutine (continued)

- $\mathbf{X}_k'$ as: set $\mathbf{X'}_k = \mathbf{X'}_k + \mathbf{X}_k$,

- $\mathcal{W}'$ as: $\mathcal{W}' \leftarrow \mathcal{W}' \backslash \left\{ \forall w \in \mathcal{W}' \mid \exists j \in \mathcal{J} : x^c_{w,j} = 1 \right\}$.

- $\mathbf{Y}$ as in Step 1.

to the WSO m transmission, the channel j cannot be spatially reused at unallocated WSO w. Therefore, Y-matrix entries corresponding to wth row are also flipped zero. The updated Y-matrix thus defines a set of unallocated WSOs. These are the WSOs for which at least one nonzero entry exists in the corresponding row in the Y-matrix, as defined, in Step 2 in Algorithm (2.2).

The subroutine in Step 3 in Algorithm (2.2) then repeatedly allocates the available TV channels to the WSOs in the set $\mathcal{W}'$ as follows. The relaxed problem in (2.26) is solved using any LP solver for the WSOs in the set $\mathcal{W}'$ and an allocation matrix bfX_k is obtained. The bfX_k is then used to update bfX_k', $\mathcal{W}'$, and Y-matrix, as defined in Step 3-b)2), 3-b)3), and 3-b)4), respectively. This repetitive update and allocation process continues until all WSOs in the set $\mathcal{W}'$ get the channel or no more FR is possible.

Let us apply the FR implementation in the coexisting scenario shown in Fig 2.3. In this figure, four WSOs operating in three network technologies, an IEEE 802.22 regional area network, IEEE 802.11 local area networks and IEEE 802.15.4 personal area network are deployed in some geographic region. The shaded area around each transmitter denotes its transmission radius. The circular links between a transmitter and receivers show wireless connectivity between them. The receiver nodes in some

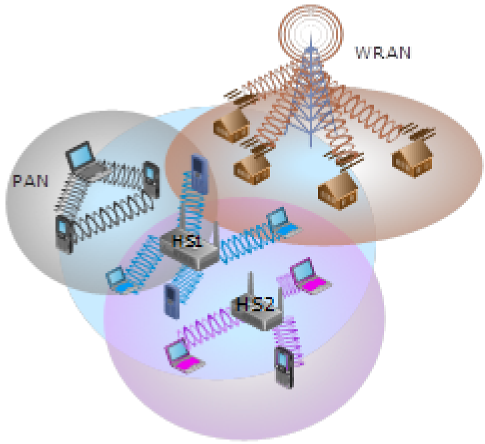

Figure 2.3: IEEE 802.22 wireless regional area network (WRAN), IEEE 802.11 hotspots (HS1, HS2), and IEEE 802.15.4 personal area network (PAN) coexisting in some geographic region.

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networks receive interfering signals from other collocated transmitters as shown in the figure. Let WRAN, HS1, HS2, and PAN are labeled as, WSO 1, 2, 3 and 4, respectively. Let us assume each of the WSO is registered in a dedicated CM, i.e., four neighboring CMs are available in the CDM system. Let us suppose that a single TV channel is available in the region for secondary use. Then, based on coexisting scenario shown in the figure, the encoded CS of each WSO can be defined as follows.

$$\mathcal{S}_{1,1} = \{0,\, 1,\, 0,\, 0\}\,,\ \mathcal{S}_{2,1} = \{1,\, 0,\, 1, 1\}\,,\ \mathcal{S}_{3,1} = \{0,\, 1,\, 0,\, 0\}\,,\ \mathcal{S}_{4,1} = \{0,\, 1,\, 0,\, 0\}\,.$$

The Y-matrix is then populated from the bitwise OR operation on the CS of the WSOs. The generated Y-matrix is $\mathbf{Y} = [1\ \ 1\ \ 1\ \ 1]$. Let for some given input parameters, as listed in Table (2.1), the algorithm in (2.1) finds an initial allocation vector, $\mathbf{Y} = [1\ \ 0\ \ 1\ \ 0]$. The allocation vector shows WSO 1 and WSO 3 are allocated the channel. The FR process is then invoked. The Y-matrix is updated to identify WSOs eligible for spatially reusing the channel, as follows. The XOR operation is performed as, ($\mathbf{Y} = \mathbf{X} \oplus \mathbf{Y}$). This operation turns the entries in Y-matrix equal to zero where the corresponding entries in X-matrix are ones. The Y-matrix at this stage looks like, $\mathbf{Y} = [0\ \ 1\ \ 0\ \ 1]$. It is then updated using the CS of allotted WSOs as previously defined in the second rule of Y-matrix update. The second entry in Y-matrix is thus flipped zero as WSO 2 is in the CS of allotted WSO 1. The updated Y-matrix then looks like, $\mathbf{Y} = [0\ \ 0\ \ 0\ \ 1]$. The algorithm then solves the dual problem again and allocates the channel to WSO 4. The final allocation matrix then looks like $\mathbf{Y} = [1\ \ 0\ \ 1\ \ 1]$. The final allocation shows that the available TV channel is reused at WSO 4 without causing harmful interference to allotted WSO 1 and WSO 3.

Scheduling Map Generation

Once the allocation process in Algorithm (2.1) and frequency reuse in Algorithm (2.2) terminates, the CDM system generates a scheduling map to send it to the CMs in the system. The scheduling map (SM) is a map showing the WSOs' scheduling periods arranged in window time in the allocated channels. In this thesis the scheduling period of a WSO w refers to its channel timeslot, i.e., COT. For example, SM of three WSOs scheduled in an allocated TV channel is shown in terms of their COT defined in the window time in Fig. 2.2. Thus, given the COT of WSOs and the allocation matrix X, from the algorithm in (2.1), the SM is a simple procedure of defining two timing parameters; transmission start time and transmission end time. The CDM system defines the timing parameters for WSOs registered in the CMs in the system as follows.

Let a pair of transmission variables, $\left(t_{w,j}^{start}, t_{w,j}^{stop}\right)$, precisely define the time instance the WSO w, registered in CM c, may start and stop its transmission on an allotted channel j, respectively. The $t_{w,j}^{start}$ and $t_{w,j}^{stop}$ are calculated as follows. Let a variable $C_{w,m(w)}$ be defined as the cost of sharing a channel between two WSOs, $w, m \in \mathcal{W}$, where $m(w)$ represents a WSO m sharing a channel with WSO. Let τ_w represents the control overhead associated with MAC technology of the WSO w. The control overhead is defined as the amount of time required to perform control signaling while operating in the TVWS. This value is fixed and predetermined based upon the underlying network technology of the WSO. For example, if an 802.22 WSO employs OFDMA, one OFDM symbol is used for both the frame preamble and the frame header; except for the first frame in the superframe which consumes two additional symbols (1/4 cyclic prefix mode). If we consider two OFDM symbols per frame as a control region then using a symbol duration, $\mathrm{T}_{Sym} = 0.3733$ ms [24], the control overhead per frame is computed as, 0.7466 ms. Other settings may generate different overhead. Similarly, if a WSO m operates in a different network technology than that of the WSO w, its control overhead will be different from that of WSO w. The total overhead in a channel varies as the channel is shared among heterogeneous WSOs. The value of the parameter $C_{w,m(w)}$ is then defined simply by adding the control overhead of all WSOs sharing a channel as follows:

$$C_{w,m(w)} := \begin{cases} \tau_w + \tau_m & \text{if } MAC_w \neq MAC_m,\ \forall\,(w,m) \in \mathcal{W}'^c \\ 0 & \text{otherwise} \end{cases} \tag{2.34}$$

where $\mathcal{W}'^c \subset \mathcal{W}^c$ refers to the set of WSOs with *NID* listed before *NID* of WSO w in $\mathcal{W}^\rfloor$. The timing parameters are computed as,

$$t_w^{start} = \sum_{m \in \mathcal{W}'^c} O^c_{m,j} x^c_{m,j} + C_{m,m(w)} \quad \text{and} \quad t_w^{stop} = t_w^{start} + O^c_{w,j} \tag{2.35}$$

Thus, the $t_{w,j}^{start}$ refers to the time instance in the scheduling window that all the WSOs m have utilized the channel for the duration of their respective COT. Note that in defining the scheduling map we make a simplifying assumption that the timers of WSOs in the system are pre-synchronized and WSOs sharing a channel j have agreed on the reference time (the time instance the window time starts) as defined in [11]. Timer synchronization may be done by having agreements between service providers managing the WSOs which is outside the scope of this research work.

The CDM defines SM and send it to the SCMs. The SCMs send the SM to the registered WSOs. Such implementation shall reduce the control signaling between the WSOs and the pertinent CM. The control signaling is otherwise inevitable while performing context switching among WSOs scheduled in the TV channel. Once the spectrum has been allocated, the SM remains unchanged unless i) an incumbent appears in one of the assigned channels ii) a change in a WSO's channel occupancy demand or some other coexisting WSO's demand requires readjusting the WSO's allocation.

2.6 Numerical Results

In this section, we aim to analyze the performance of the designed channel allcoation algorithm in terms of system throughput gain, fairness in allocation among CMs and WSO satisfaction from the allocation. The performance of the proposed algorithm is also compared with two other channel allocation algorithms, proposed in [26] and [14]. These algorithms are briefly summarized in the following section.

2.6.1 Comparative Channel Allocation Schemes

In this section, we summarize the allocation mechanism of the comparative TVWS allocation schemes. In [14], two TVWS sharing problems are defined; one for maximizing the number of channels allocated to the networks and the second for maximizing the total throughput under the minimum fairness constraint of allocating at least a single channel to each network. In this simulation setup, we implement the second problem as it closely matches with the channel sharing scheme proposed in Section (2.3.2). The TVWS sharing algorithm in [14] selects a node (WSO) having a minimum of the assigned channels and the minimum number of the available channels to it. The algorithm assigns a TV channel to the selected WSO and calculates the total throughput. It keeps assigning the channel to other WSOs as long as the total throughput is increasing. This procedure is repeated for every channel. The algorithm terminates as no more increase in the throughput is observed.

The TVWS sharing problem in [26] is modeled as a lexicographic ordering of throughput of access points of coexisting networks. The proposed problem is then transformed into a graph coloring problem. An algorithm called as, Share, is then proposed to solve the graph coloring problem. The Share algorithm operates in three phases. In the first phase of allocation, it orthogonalizes the WSOs in the available TV channels (frequency slots). In the second phase, a mutual channel sharing is performed among allotted WSOs of the first phase under the condition that their first phase throughput do not decrease. The fairness is improved in the third phase by sharing the channel with unallocated WSOs such that lexicographically ordered throughput do not decrease.

We select the algorithms in [26] and [14] due to the close resemblance of their TVWS sharing problems to the proposed channel sharing mechanism. For example, both considers optimizing throughput under minimum fairness in allocation. However, there exist some fundamental differences as well. For example, both the allocation schemes orthogonalize the WSOs in frequency domain by allocating a dedicated channel to each allocated WSO while the proposed scheme orthogonalize WSOs in a joint time-frequency domain by slicing the available TVWS in the frequency bands and further slicing each channel (frequency band) into a number of COTs in the channel window time. Moreover, the algorithm in [14] is intended for TVWS channel allocation to cellular networks while the proposed scheme is intended for TVWS sharing in an ad-hoc coexisting environment, as discussed in Chapter 1. Similarly, the TVWS sharing algorithm in [26] does not implement the FR concept. Therefore, we implement the proposed algorithm without FR process as well to have a fair comparison with the scheme in [26]. This is achieved by omitting Step 3 in Algorithm (2.1) during the implementation of the proposed algorithm.

2.6.2 Simulation Setup

Simulation setup consists of 32 WSOs deployed in some geographic region and connected to an 802.19.1 coexistence system. The system has 32 CMs, each serving a single WSO. We select a dedicated CM for each WSO as the schemes in [26] and [14] performs TVWS sharing at network (WSO) level. The number of available TV channels in the region varies from 2 to 16. The WSO types and transmission powers are modeled using FCC regulations [3]. For this purpose, the specifications for fixed, mode 1 and mode 2 WSO types are used. The fixed, mode 1 and mode 2 type WSOs are allowed to have maximum antenna gain of 4 watts (W) effective isotropic radiated power (EIRP), 100 mW EIRP, and 100 mWatt EIRP respectively. The WSO access technologies are IEEE 802.22 and IEEE 802.11af. In this simulation setup, we implement the compulsory channel requirement of each WSO where the standard definition of the above technologies mandates a single TV channel of regulatory defined bandwidth as a requirement of a device to operate in the TVWS. Note that the bandwidth of a TV channel is set equal to 6 MHz.

Two parameters; WSO channel occupancy demand, $O^c_{w,j}$ and WSO density in the region, $K^c_{w,j}$ are varied to observe their effect on allocation behavior of the three allocation schemes as follows. Let T_j represents the window time on the channel j. Note that the 802.19.1 [11] does not define MAC layer frame structure for operations in TVWS. Therefore, the channel window time is not defined in an absolute time domain in 802.19.1. In this simulation setup, we define the channel window time as a unit length, without loss of generality, i.e., $T_j = 1,\ \forall j \in \mathcal{J}$. Then, three allocation subdomains are defined on the T_j as follows; low subdomain consists of up to 33 percent of the channel window time, defined as, $O^L := (0,\ 0.33]\, T_j$, A medium subdomain consisting of 34 to 67 percent of the channel window time, defined as, $O^M := [0.34, 0.67]\, T_j$ and a high subdomain consists of 67 to 100 percent of the channel window time, defined as, $O^H := [0.67, 1]\, T_j$. The channel occupancy demand of each WSO is then randomly defined on these subdomains.

The WSO density in the region is reflected using the number of WSOs in the CS of each WSO as follows. Let W be the number of WSOs registered in all CMs in the system then, we define three WSO density subdomains as; low $K^L := (0, 0.33]\, W$, medium $K^M := [0.34, 0.67]\, W$, and high $K^H := [0.67, 1]\, W$. The CS of each WSO is randomly defined on these subdomains. Let $K^c_{w,j}$ represents the number of WSOs in the CS of WSO w on the channel j, registered in CM c. Then, the effect of the variability in the translated channel occupancy demand and WSO density is measured using a pair of parameters $\left(O^c_{w,j},\ K^c_{w,j}\right)$. Note that varying each of these parameters on three respective subdomains results in $2^{32} = 27$ possible allocation combinations. Out of 27, we select three cases to study the performance metrics defined in Section (2.6.3), as follows.

- Low: low COT, low WSO density, i.e., $O^c_{w,j} \in O^L$ and $K^c_{w,j} \in K^L$,
- Medium: medium COT, medium WSO density, i.e., $O^c_{w,j} \in O^M$and $K^c_{w,j} \in K^M$,

- High: high COT, high WSO density, i.e., $O^c_{w,j} \in O^H$ and $K^c_{w,j} \in K^H$.

Next, we apply the `intlinprog` routine of MATLAB®to solve the proposed TVWS sharing problem. The routine applies the mixed-integer linear programming technique. Since we need binary valued vector $\mathbf{X}$, therefore, we set all the decision variables, $x^c_{w,j} \in \mathbf{X}^c, \forall \mathbf{X}^c \in \mathbf{X}$, to be integer variables in the `intlinprog` routine. The binary decision may lead to the situation where the COT of allocated WSOs may not fit the channel window time. For example, let us assume the WSO 1, 2, 3 and 4 in Fig. 2.3 coexist in a TV channel. Let their COT demand is defined as, 0.25, 0.33, 0.37 and 0.15, respectively. Let us assume the `intlinprog` routine outcome as $\mathbf{X} = [1\ \ 0\ \ 1\ \ 1]$, i.e., the WSO 1, 3 and 4 gets the channel. This results in total COT of allocated WSOs equal to 0.77 which is less than the channel window time; 1. The second WSO cannot be accommodated in the channel considering the constraint (2.25b). In this simulation, the solution $\mathbf{X}$ is engineered such that the second WSO is partially allocated the desired COT so as to maximize the channel utilization while maintaining constraint (2.25b). The purpose of such engineering the solution is to reduce the channel waste. In order to have a fair comparison, the same engineering principle is applied to the allocation matrix generated by the comparative allocation schemes. The comparative analysis of the three allocation schemes is then performed as discussed in the following section.

2.6.3 Comparative Analysis

The relative performance of the three allocation schemes is evaluated using the following metrics: system throughput, fairness in allocation among CMs and WSO

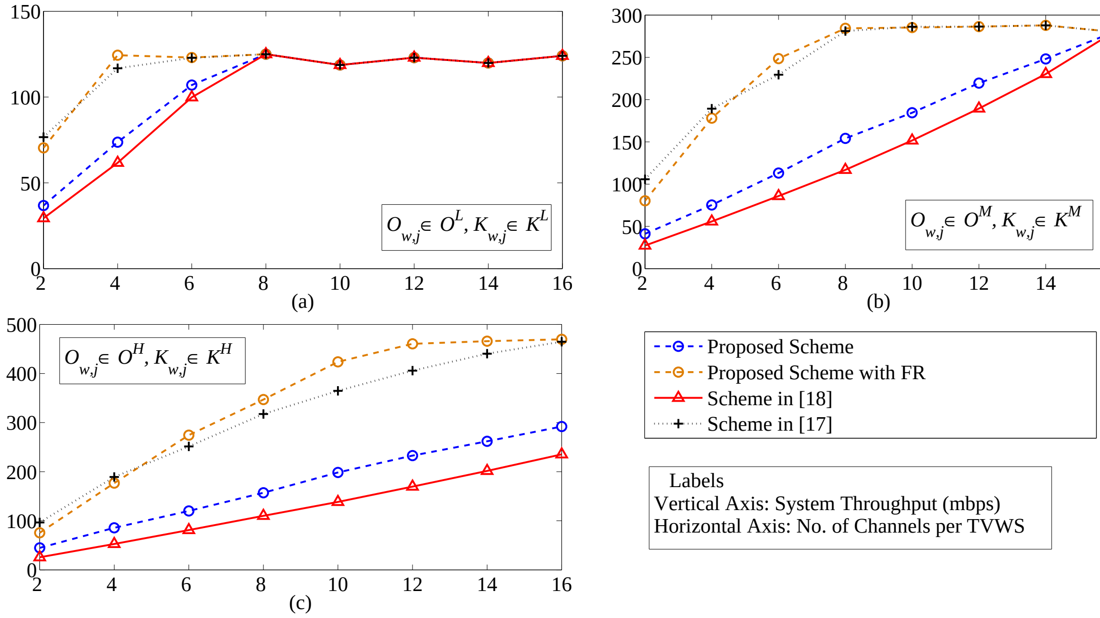

Figure 2.4: System throughput for 32 WSOs registered in all CMs for a varying number of TV channels in the system.

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satisfaction from the allocation. The simulation results of the performance metrics are presented in Fig. 2.4 to Fig. 2.6, respectively. Subplots (a), (b), and (c) in these figures show the effect of varying the $\left(O^c_{w,j},\ K^c_{w,j}\right)$ pair in low, medium and high subdomains, respectively. The study results are discussed as follows.

System Throughput

Fig. 2.4 shows the system throughput (ST) achieved by the three allocation schemes. Given the allocation matrix , and the SINR values, the ST is defined using Shannon capacity formula [47] as,

$$ST = \sum_{c\in\mathcal{C}} \sum_{j\in\mathcal{J}} \sum_{w\in\mathcal{W}^c} x^c_{w,j} O^c_{w,j} b_j \log_2 \left(1 + \mathrm{SINR}^c_{w,j}\right) \tag{2.36}$$

It is shown in Fig. 2.4 that, for most of the channels in the system, the proposed scheme achieves higher ST gain than the comparative TVWS sharing schemes. However, the proposed scheme with FR implementation achieves slightly lower ST than the Scheme in [14] for the case when the number of channels in the system is two. This is because the Scheme in [14] focuses on maximizing the throughput in the TVWS allocation process while the proposed scheme focuses on making a balance among the contradicting QoS metrics; ST and fairness in allocation. Consequently, the WSOs with lower channel quality (here lower SINR value) also get a proportion of the available TVWS which reduces the total ST gain in the proposed scheme. However, as the number of channels in the system reaches to four and above, the proposed scheme achieves higher ST gain and remains so until both the schemes converge to the maximum achievable ST. The reason for such improvement is that the proposed scheme applies a joint time-frequency FR concept which accommodates a higher number of WSOs in the available TV channels while the Scheme in [14] applies FR concept in frequency domain only. Note that the ST gain in this study is defined as maximum if all of the WSOs in all the CMs get their desired channel demands.

The effect of variability in the $\left(O^c_{w,j},\ K^c_{w,j}\right)$ pair values on the ST gain of the three allocation schemes is shown in Fig. 2.4(a), 2.4(b) and **??**(c), respectively. The three allocation schemes converge to the maximum ST, as the number of channels in the system reaches 8 and 16, as shown in Fig. 2.4(a) and 2.4(b), respectively. However, in high subdomain case (Fig. 2.4(c)), none of the allocation scheme achieves the maximum ST. The reason is that the high channel occupancy demand of WSOs results in a few

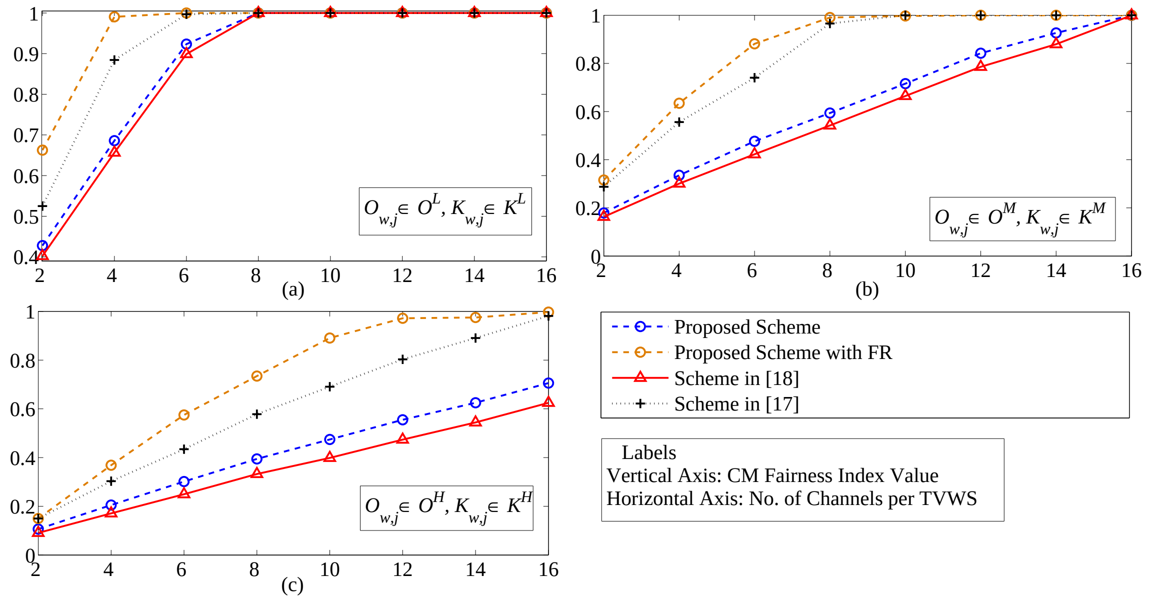

Figure 2.5: Fairness index value calculated using normalized throughput vector of CMs for a varying number of TV channels in the system.

WSOs to saturate the available TVWS while leaving no channel share for rest of the WSOs.

Another notable property of the ST study is that, as the $\left(O^c_{w,j},\ K^c_{w,j}\right)$ pair values increases from low to high subdomains, the ST gain of the proposed scheme improves over ST gains in the comparative scheme, as shown in Fig 2.4(a) through Fig. 2.4(c), respectively. This improvement is attributed to the combined effect of the use of the proportional fairness in the allocation and implementing FR in a joint time-frequency domain in the proposed scheme, as defined in the Section 2.3.2 and 2.5.2 respectively.

Fairness

The fairness in allocation among CMs in the system is measured using function in (2.31) where the variability in CMs' normalized throughput vector, $\mathbf{T} = \left(T^1, T^2, \cdots, T^C\right)'$ is used as a fairness metric to compute the fairness index (FI) value. The FI result, as shown in Fig. 2.5, confirms that the proposed scheme achieves the highest FI value due to the combined use of the proportional fairness method and the FR implementation in the joint time-frequency domain. On the other hand, though both, the Scheme in [14] and the Scheme in [26], optimize the fairness in allocation. However, both the schemes make an orthogonal TV channel allocation thus, resulting in lesser number of WSOs to get the channel which reduces FI value. Moreover, the constraint of maintaining the lexicographically ordered throughput of the WSOs in the Scheme in [26] further reduces the degree of the fairness in allocation.

The effect of varying the values of the $\left(O^c_{w,j},\ K^c_{w,j}\right)$ pair in low, medium and high subdomains is shown in Fig. 2.5(a), 2.5(b) and 2.5(c), respectively. It is shown in Fig. 2.5(a) and Fig. 2.5(b) that the FI values of all the comparative allocation schemes converge to the maximum FI value, i.e., 1, as the number of channels in the system reaches 8 and 16, respectively. However, in the high subdomain case (Fig. 2.5(c)), none of the comparative allocation schemes converge to the maximum FI value except for the proposed scheme with the FR implementation. It is because, in all other schemes, their orthogonal channel allocation policy result in a few WSOs to saturate the available TVWS while in the proposed scheme, the spatial reuse of the TVWS in a joint time-frequency domain accommodates as many as WSOs, registered in the CMs which improves fairness in allocation.

WSO Satisfaction

In this study, we analyze the performance of the three allocation schemes the third objective of the TVWS sharing problem defined in Section (2.2). In this study, a WSO is considered as satisfied from the allocation if it gets its desired channel demand for the duration of desired channel occupancy. The system-wide WSO satisfaction percentage (S) is then calculated using percentage of the mean satisfaction as,

$$S = 100 \sum_{c \in \mathcal{C}} \frac{\sum_{w \in \mathcal{W}^c} \frac{\left(\sum_{j \in \mathcal{J}} x^c_{w,j} \right)}{n_w}}{\mathcal{W}^c} \tag{2.37}$$

Fig. 2.6 shows the simulation result of the satisfaction study of the three allocation schemes. This figure shows that the proposed scheme and the Scheme in [26] achieves similar satisfaction result as their lines overlap each other. However, the proposed scheme with FR implementation achieves better satisfaction result than that of the Scheme in [14]. It is because, the TVWS allocation in a joint time-frequency domain enables the proposed scheme to accommodate as many as WSOs in the available TVWS while the third objective in the TVWS sharing problem, in Section (2.2), requires the proposed scheme to satisfy the channel demand of each allotted WSO. Such an allocation strategy improves the satisfaction result of the proposed scheme.

From the results in Fig. 2.4 to Fig. 2.6, it is clear that none of the comparative schemes results in better performance than the proposed scheme in any of the performance metric. The proposed scheme, however, gives fairer channel allocation among all

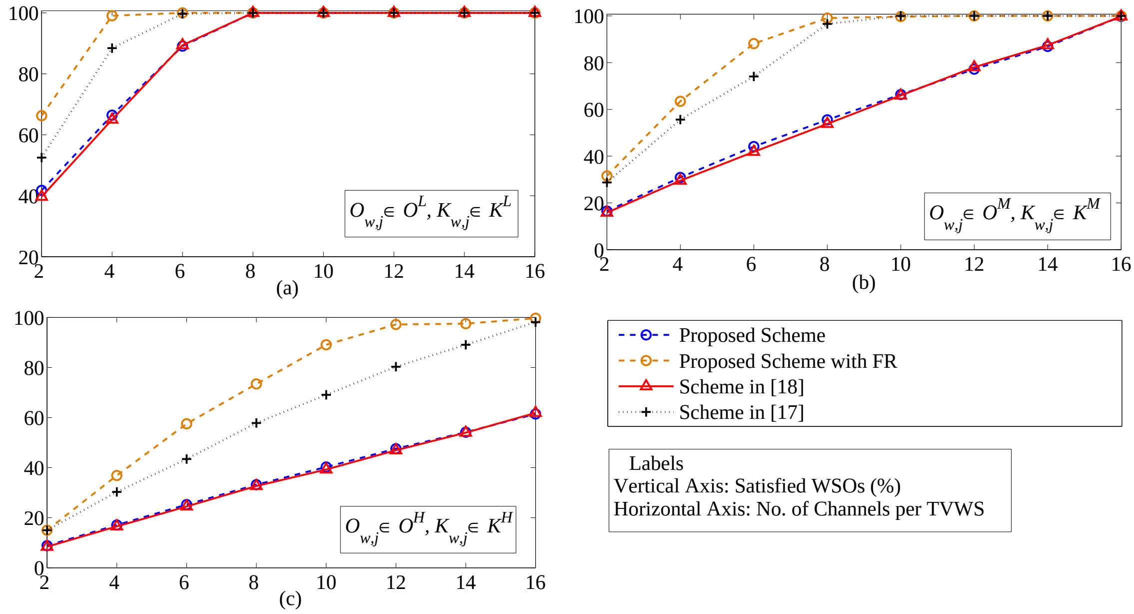

Figure 2.6: Percentage of total 32 WSOs satisfied from the allocation.

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comparative allocation schemes. The proposed scheme with the FR implementation, however, outperforms the comparative schemes, in most of the TV channels in the system, in all the three performance metrics as shown in Fig. 2.4 to Fig. 2.6.

2.6.4 Increasing WSO Density

In this section, the effect of increasing the number of coexisting WSOs in the performance of the proposed allocation scheme is evaluated. The performance is measured using the metric like system throughput and WSO satisfaction, for the three subdomain cases, i.e., low, medium and high. The number of WSOs registered in each CM in the system varies in a set,$W \in \{8, 16, 24, \cdots, 64\}$. The number of available TV channels remains constant at 4, and the other simulation parameters are same as defined in Section (2.6.2). The results of the performance study are shown in Fig. 2.7 and Fig.

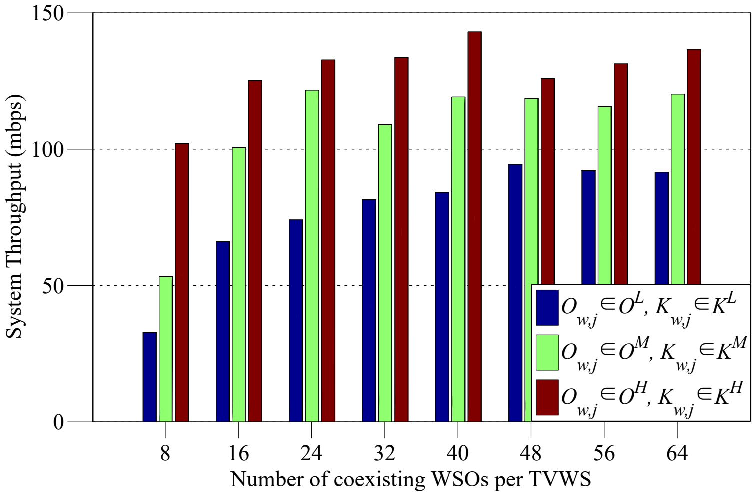

Figure 2.7: System throughput achieved by the proposed scheme for 4 TV channels and a varying number of WSOs.

2.8.

Fig. 2.7 shows that the highest throughput gain is achieved in the high subdomain case, i.e., when $\left(O^c_{w,j} \in O^M,\, K^c_{w,j} \in K^M\right)$. The reason is that the proportional fairness method in the proposed scheme selects the WSOs with high throughput gain to share the available TVWS. While spatially reusing the frequency further helps the proposed scheme to accommodate as many as WSOs in the available TVWS. Consequently, the ST increases in high subdomain case. On the other hand, the achieved throughput is the least in low subdomain case, i.e., when $\left(O^c_{w,j} \in O^L,\, K^c_{w,j} \in K^L\right)$. It is because; the low channel occupancy demand of the WSOs could not saturate the available whitespace.

Fig. 2.8 shows the percentage of the number of WSOs satisfied from the allocation, calculated using (2.37). This figure shows that the satisfaction is the highest in the low subdomain, followed by the medium subdomain, especially in the case when W=8, for

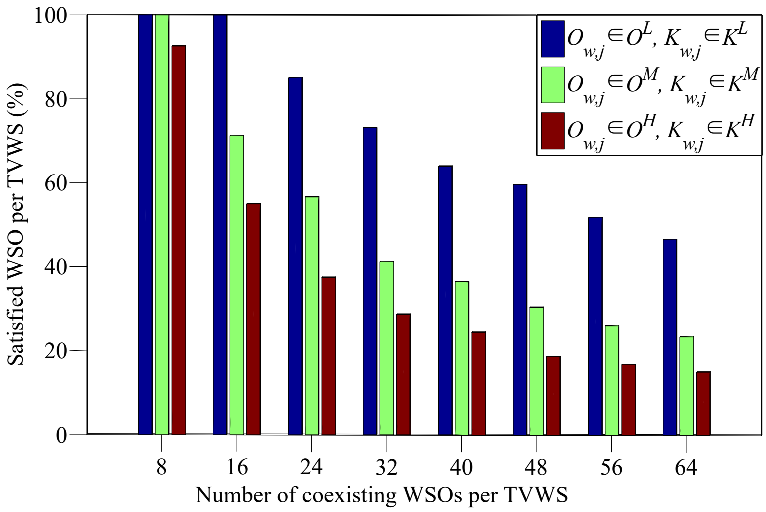

Figure 2.8: WSOs satisfied from allocation with varying WSO density in the region. The number of TV channels in the system is 4.

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each CM. The reason is that a relatively greater number of WSOs can be satisfied per TVWS when W = 8. The WSP value then sharply declines as the number of WSOs in the system increases, especially for the medium and high subdomain cases.

The results in Fig. 2.7 and Fig. 2.8 shall facilitate the modeling of a channel sharing system such that given the statistics of channel quality, the WSOs channel demands and the WSO density in the system, one can estimate an optimal number of WSOs that can be accommodated on the available TVWS such that the resource utilization is maximized.

2.6.5 Algorithm Scalability Test

The scalability of the proposed algorithm in terms of time taken to complete the allocation process is evaluated. In this experiment, the total number of coexisting

Table 2.2: System Configuration

Parameter	**Value**
Processor	Intel (i5-2500K)
On board memory	8555 MB
Memory used by MATLAB	1289MB

WSOs registered in all the CMs in the system varies geometrically as, 2^W where $W \in \{3,4,5,6,7\}$. The number of TV channels in the system increases at a constant interval of 4 as, $J \in \{4,8,12,\cdots,48\}$. The remaining simulation parameters are same as defined in Section (2.6.2). The specifications of the computer system used for the scalability test is listed in Table (2.2). Using the above parameters, the `intlinprog` routine solves the proposed TVWS sharing problem. The routine uses the branch and bound method to find an optimal solution point . The branch and bound split the problem into sub-problems, and each sub-problem is expanded until a solution is found as long as its cost does not exceed the set upper bound. The exact computational complexity of any branching algorithm is hard to find as time complexity of such a branching algorithm is usually analyzed by the method of branching vector. However, it has been mentioned in [48] that when the best-first search branch and bound technique is used, the upper bound to generate an expected solution is

$$\sum_{i=0}^{n} T\left(i\right) \leq \sum_{i=0}^{n} n - i + 1 \leq \left(n+1\right)^2$$

where n is the number of nodes visited. Thus, the complexity of such an algorithm is $\mathcal{O}\left(n^2\right)$.

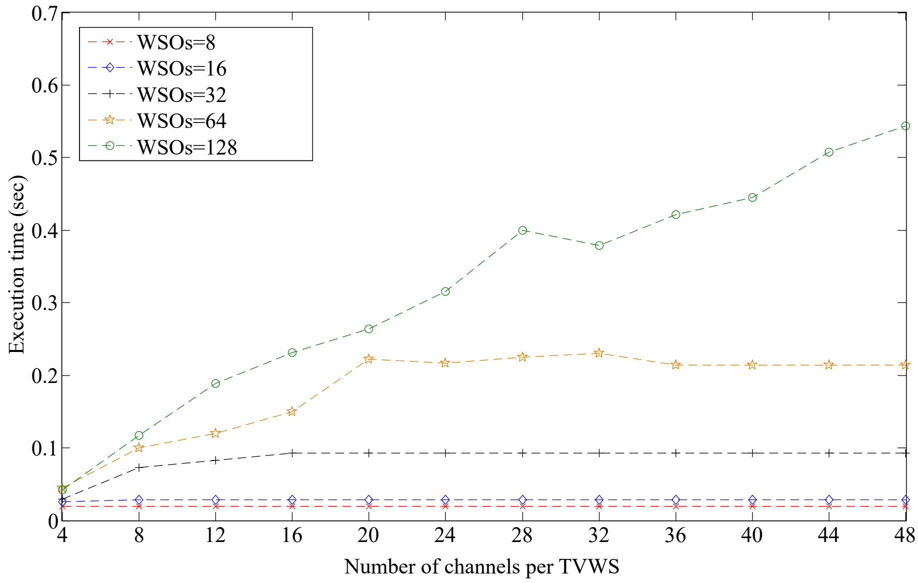

Figure 2.9: Algorithm execution time for varying number of WSOs and varying number of TV channels in the system.

In this experiment, we measure the simulation time taken using the MATLAB® tic-toc stopwatch timer. The time recorded for the high domain channel assignment is shown in Fig. 2.9. The result in this figure is generated using the average time required to complete allocation for the high subdomain case. The figure indicates that for defined simulation parameters, the channel sharing process took a few hundreds of milliseconds to complete the allocation process which is quite acceptable for real-time implementation of the algorithm. The Fig. 2.9 shows that the algorithm execution time does not grow geometrically as the number of WSOs in the system increases. Rather, the algorithm has linear time allocation behavior as shown in Fig. 2.9.

2.7 Conclusion

In this chapter, we design a novel CDM system for unlicensed TV spectrum sharing among WSOs operating in heterogeneous network technologies. The system implements three distinct channel allocation objectives: a) maximizing system performance metrics like maximizing system throughput and fairness in allocation, b) improving the TVWS utility by implementing the novel frequency reuse in a heterogeneous TVWS sharing environment, c) adapting the QoS requirement of the *heterogeneous*-WSOs. These objectives then define the TVWS sharing problem which is then defined as an optimization problem. The system then implements a subgradient algorithm for solving the optimization problem and identifying a set of WSOs to allocate the TV channels. We found that the frequency reuse property of the proposed system results in comparatively higher WSO satisfaction from the allocation and better fairness in allocation as compared to the state-of-the-art work in TVWS sharing domain. Satisfying the QoS requirements and entertaining WSOs on the available TVWS is improved approximately 22% as compared to the frequency reuse mechanism defined in [14]. The simulation results also show that the CDM system improves fairness in allocation maximum about 22.45% and 11.5% as compared to the allocation schemes in [14] and [26], respectively. Moreover, the fast allocation process of the proposed algorithm makes it a promising candidate for implementation in 802.19.1 based coexistence system. Another compelling advantage of the proposed algorithm is its integration into the IEEE 802.19.1 system without requiring any major change in the baseline architecture of 802.19.1 TVWS sharing system.

Chapter 3

WSO Accommodation in Spectrum Allocation in Heterogeneous Coexisting Environments

Several wireless standards, [19], [20], [23], [24], [25], have adapted MAC/PHY layer technologies for unlicensed transmission in TVWS. Since, network technologies in such standards are incompatible, therefore, the WSOs operating in such standard shall also be incompatible, in terms of network infrastructure, transmission pattern, coverage area, asymmetry in interference. A collocated deployment of such *heterogeneous*-WSOs shall create heterogeneous coexistence environment. It is anticepated that the excellent propagation characteristics in TV spectrum is enough trigger for proliferation in the deployment of *heterogeneous*-WSO, thus, making the heterogeneous environment denser and more complex to manage.

Coexistence in heterogeneous environment is already considered a complex task due to signal propagation characteristics in TV spectrum and disparity in network technologies [49]. The scarcity in TV spectrum, especially in highly congested urban areas, makes it even more challenging to perform channel allocation in heterogeneous environment satisfactorily. The satisfactorily here refers to a state where each *heteroge-*

neous-WSO is allocated its desired channel demands. Some TVWS sharing algorithms like in [49], adapt the WSO channel demand satisfaction in the channel allocation process. However, such allocation creates discrepancy in allocation as some WSOs get their desired channel demand while others do not get the channel. Considering the free to use status, each WSO has a right to access the TVWS for its data offloading. On the other hand, some algorithms like in [11] focus on improving fairness in allocation by equally distributing the available whitespace bandwidth among coexisting WSOs. The algorithm in [11] underllok the effective utilization of the scarce TV spectrum. Similarly, some other TVWS sharing algorithms also have some issues in their channel allocation process, as discussed in Section 2.1 and Section 3.1.

In this chapter, we propose a TVWS sharing mechanism with an aim to accommodate as many as WSOs on the available TVWS while optimizing some other performance parameters like system throughput, and TVWS utilization. Accommodating as many as WSOs in the TVWS shall improve fairness in allocation among *heterogeneous*-WSOs. The channel sharing in TVWS is modeled as a multiobjective optimization problem (MOP) where each objective function tackles an important coexisting requirement, such as interference and disparity in network technologies, fairness in allocation, system throughput optimization. In order to solve the defined MOP and to share the TVWS among WSOs, we proposed an evolutionary algorithm. The The proposed algorithm also takes care of the channel occupancy requirements of the WSOs in the TVWS sharing process. The simulation results show that the proposed scheme achieves a higher fairness in allocation and a better satisfaction in WSOs' fraction of channel occupancy requirements as compared to the state-of-the-art related works.

3.1 Background and Contributions of this Chapter

Bahrak and Park modeled the spectrum-sharing problem as a multiobjective optimization problem, which was then scalarized using a weighted-sum approach and formulated using a modified Boltzmann machine [49]. A CDM algorithm called FACT [49] is then designed to solve the MOP [49]. However, the main issue with the weighted-sum approach is its inability to find Pareto-optimal solution points in the non-convex region of the solution space boundary [50]. Another issue with the FACT is its discrepancy in allocation. It allocates the available spectrum to WSOs until a WSO's channel demand is satisfied. However, in highly congested areas, the available spectrum may be insufficient to accommodate the channel demands of all the collocated WSOs. Similarly, some other work like in [51], [14], [26], implements a CDM procedure that fully satisfy the channel demands of *heterogeneous*-WSOs. However, such channel allocation policy may cause some of the WSOs to get the channel while rest of them do not. This situation is intensified in a highly-congested area where a limited TV spectrum is available for secondary user activities due to the active presence of licensed operator. Hessar and Roy [14] have discussed the TVWS sharing problem, but in the secondary cellular networks. They have used two different formulations. Heuristic approaches are then adopted, and greedy algorithms are designed for each of these formulations. Within these greedy algorithms, brute force search is applied to find the solution that maximizes the throughput under the minimum fairness in allocation. However, search over the space of a possibly very large number of network and channel collocation combinations leads to a high runtime complexity to find an optimal solution.

Similarly, some genetic algorithms (GA), defined for implementing the channel sharing problem, also exist in the literature. For example, the authors in [52] use a GA-based reliability model to assign channels to mobile hosts based on the reliability of the base station and the channels to enhance the overall reliability of the mobile network system. The results show that this method requires higher number of iterations and generally higher number of available channels than the number of mobile hosts in order to achieve higher reliability. Similarly, Shrestha et. al., proposes a GA-based joint out-of-band spectrum sensing and channel allocation scheme for cognitive radio networks [53]. The joint sensing and resource allocation optimization problem has been formulated using fitness functions of sensing utility and the data transmission utility. Jao and Joe consider a new cognitive radio network model with heterogeneous primary users operating simultaneously via multi-radio access technology [54]. It focuses on energy efficient resource allocation and use a GA-based scheme to obtain an optimal solution in terms of power and bandwidth. Zhang et al., [55] adapt ecology based species competition model to develop a coexistence mechanism called ecological Species Competition based HEterogeneous networks coexistence MEchanism (SCHEME). The SCHEME enables each coexisting network to adjust achieved bandwidth per its QoS requirements dynamically. However, the SCHEME requires the number of channels to be larger than the number of coexisting networks. Such condition cannot be fulfilled in highly congested urban areas where a limited number of TV channels is available for unlicensed use.

In this chapter, we discuss the CDM system that performs TVWS sharing among coexisting WSOs with an aim to accommodate as many as WSOs in the available TVWS. Note that the coexisting WSOs operating in heterogeneous network technologies are referred to as *heterogeneous*-WSOs in this thesis. The main contributions of the proposed work are summarized as follows.

1. A CDM procedure is implemented as a process of sharing a set of TV channels of predetermined bandwidth among a set of *heterogeneous*-WSOs. Unlike existing CDM formulations in the TVWS sharing domain [49], [26], [14], the proposed formulation accommodates as many as *heterogeneous*-WSOs on the available TVWS by relaxing their channel demand.

2. The proposed CDM system transforms the nonconvex, nonlinear multiobjective function in the TVWS sharing MOP (Section 3.2.2) into a max-min optimization formulation, using a binary epsilon indicator function (Section 3.2.5). Such formulation enables the CDM system to achieve a true multiobjective optimization as it does not require a priori articulation of preferences of the decision maker nor does it need to scalarize the multiobjective function in the TVWS sharing MOP. Consequently, a better approximation of global minima of the TVWS sharing MOP is achieved as compared to the existing CDM systems in [49], [26].

3. An evolutionary algorithm, called EvCo is proposed to obtain a feasible Pareto-optimal solution for the TVWS sharing MOP. Our evaluation studies show the

superiority of the EvCo over existing TVWS sharing algorithms in [49], [26] regarding scalability, fairness and WSOs' satisfaction from the allocation.

3.2 TVWS Sharing Problem Formulation

In this section, we formulate the TVWS sharing problem as an energy minimization MOP and transform it into a max-min optimization problem using a binary indicator function. In order to tackle the defined optimization problem, a CDM system is designed in the following section.

3.2.1 Modeling the CDM System

A centralized CDM system, as shown in Fig. 2.1, is defined as follows,

$$\mathbf{O}^{*} = TVWS(\mathcal{W}, \mathcal{J}, \mathcal{T}, \mathcal{D}), \tag{3.1}$$

where $\mathcal{W} = \{1, 2, \ldots, W\}$, $\mathcal{J} = \{1, 2, \ldots, J\}$, and $\mathcal{T} = \{T_1, T_2, \ldots, T_J\}$ represent a set of *heterogeneous*-WSOs, a set of available TV channels and a channel window time set, respectively. The window time is defined as a slot duration of a scheduling repetition period that satisfies the essential system quality of service (QoS) performance, as discussed in Section (2.3.1). The parameter, $\mathcal{D}$ represents a set of channel-demands of *heterogeneous*-WSOs, defined as,

$$\mathcal{D} = \Big\{ [n_w]_{W\times 1}, [O_w]_{W\times 1}, [p_w]_{W\times 1}, [SINR_{w,j}]_{W\times J} \Big\}.$$

The system parameters in (3.1) are defined using information clauses defined in 902.19.1 [11]. In [11], an abstraction is provided that allows WSOs to send their channel demands to their CM. We exploit such information available at CM to formulate the channel demands set as follows. Let n_w represents the number of TV channels desired by WSO w. The value of n_w depends upon the network technology employed by the WSO, defined as follows. Let $\mathcal{M} = \{1, 2, 3\}$ be a set of network technologies where the number 1, 2, and 3 refers to the technologies defined in 802.19.1 like 802.11af, 802.22, and ECMA392, respectively. The standard definitions of these technologies specify a single channel of regulatory defined bandwidth, e.g., 6 MHz in the US, as a compulsory requirement of TVWS operations. An 802.11af type WSO can operate on 1, 2 or 4 TV channels [56]. However, allocating more than one channels to such a WSO is defined as optional in [56]. The proposed CDM system, thus, supports the channel allocation among WSOs requesting for one TV channel, or multiple, non-contiguous TV channels. Channel allocations which are continuous in frequency slots are also promoted in the proposed system; however, such an allocation is not guaranteed. The $O_w \in \mathcal{D}$ translates to the amount of time that the WSO $w \in \mathcal{W}$ desires to use its desired channel to radiate electromagnetic waves using a pre-allocated transmission power p_w. A WSO's desired bandwidth is defined as, $b_w = n_w b$[MHz] where b represents the bandwidth of a TV channel. The CDM system then solves the following TVWS sharing problem.

TVWS Sharing Problem Definition

Given input parameters in the system Eq. (3.1), the TV channels must be shared among a set of coexisting WSOs such that the following objectives are satisfied:

- Allocation among WSOs is fair,

- System throughput is maximized,
- WSOs are satisfied regarding their channel demands.

The objectives of the TVWS sharing problem are formulated in the following functions.

Fairness in Allocation

Fairness, from a spectrum allocation perspective, is regarded as equity in access to radio resources. It is defined in terms of a fraction of demand serve metric as,

$$R_w := \begin{cases} \dfrac{r_w}{d_w}, & \text{if } r_w < d_w \\ 1, & \text{otherwise} \end{cases}. \tag{3.2}$$

The $d_w = \sum_{j=1}^{n_w} O_w b_j \log_2 (1 + SINR_{w,j})$ represents the amount of data that the WSO w desires to transmit while $r_w = \sum_{j=1}^{n_w} O_{w,j} b_j \log_2(1 + SINR_{w,j})$ represents the amount of data that the WSO w can transmit using its allocated timeslot $O_{w,j}$. Optimizing $\mathbf{R} = (R_1, R_2, \ldots, R_W)'$ by maximally equalizing $R_w \approx R_m, \forall w, m \in \mathcal{W}$ results in fair allocation among *heterogeneous*-WSOs. A fairness function is thus defined as an energy minimization function based on Jain's fairness index [46] as follows,

$$\bar{f}_F(\mathbf{O}) = \left[1 - \frac{\left[\sum_w R_w(\mathbf{O})\right]^2}{W \sum_w R_w(\mathbf{O})^2} \right]. \tag{3.3}$$

System Throughput Maximization

The gain in system throughput depends on multiple factors. Some common factors are formulated as follows.

Contiguous Channel Allocation: Contiguous channel allocation allows a network to have adaptive channel widths that can increase system throughput by more than 60% compared to a fixed-width configuration [57]. The contiguous channel allocation is promoted as follows. Let A=(0,T_j], and an allocation of a channel j to a WSO w be defined using an indicator function, as follows:

$$\mathbf{1}_A(O_{w,j}) := \begin{cases} 1, & \text{if } O_{w,j} \in A \\ 0, & \text{otherwise} \end{cases}. \tag{3.4}$$

For each block of channels, a monotone increasing cost function is defined as, $(\mathbf{1}_A(O_{w,j}) - \mathbf{1}_A(O_{w,j+1}))$. The function adds a cost of two for each block of channels. The contiguous channel allocation then becomes the energy minimization function, defined as,

$$\bar{f}_C(\mathbf{O}^{'}) = \sum_w \left[\sum_j \left(\mathbf{1}_A(O_{w,j}) - \mathbf{1}_A(O_{w,j+1})\right)^2 \right] I_w, \tag{3.5}$$

where the updated solution metric, $\mathbf{O}^{'}$, is defined by concatenating a zero column on both, the leading and trailing end of the solution matrix $\mathbf{O}$, i.e., $\mathbf{O}^{'} := [[0]_{W\times 1}||\mathbf{O}||[0]_{W\times 1}]$. The function, I_w, forces the cost of channel allocations to w^{th} WSO to be zero if a single channel or a single block of contiguous channels is allocated, defined as follows,

$$I_w := \begin{cases} 0, & \text{if } \sum_j \left(\mathbf{1}_A(O_{w,j}) - \mathbf{1}_A(O_{w,j+1})\right)^2 \leq 2 \\ 1, & \text{otherwise} \end{cases}. \tag{3.6}$$

WSO Homogeneity: In this subsection, we aim to discuss how a set of WSOs with the same MAC technologies are encouraged to share a TVWS channel, referred to as WSO *homogeneity* in this thesis. Homogeneity in MAC technology is a merit to pursue because sharing a channel among WSOs with incompatible MAC technologies results in higher switching delay and error rates due to unresolved synchronization issues [49]. The *homogeneity* in MAC technology is promoted using the control overhead in the technologies in $\mathcal{M}$, defined as follows. Let a variable $C_{w,m(w)}$ be defined as the cost of sharing a channel between two WSOs, $w, m \in \mathcal{W}$, where *m(w)* represents a WSO m sharing a channel with WSO w. Let $\tau_w \in \mathcal{M}$ represent MAC technology of WSO w and β_w represent its control overhead. The control overhead is defined as the amount of time required by a WSO to perform control signaling while operating in the TVWS. This value is fixed and predetermined based on the underlying network technology of the WSO. For example, if a 802.22 WSO employs OFDMA, one OFDM symbol is used for both the frame preamble and the frame header; except for the first frame in the superframe which consumes two additional symbols (1/4 cyclic prefix mode). If we consider two OFDM symbols per frame as a control region then using a symbol duration, T_{Sym}=0.3733 ms [22], the control overhead per frame is computed as, 0.7466 ms. Other settings may generate different overhead. Similarly, if a WSO m operates in a different network technology than that of the WSO w, its control overhead will be different from that of WSO w. The total overhead in a channel varies as the channel is shared among *heterogeneous*-WSOs. The value of the parameter $C_{w,m(w)}$ is then defined simply by adding the control overhead of all WSOs sharing a channel as follows:

$$C_{w,m(w)} := \begin{cases} \beta_w + \beta_m, & \text{if } \tau_w \neq \tau_m \forall (w,m) \in \mathcal{W} \\ 0, & \text{otherwise} \end{cases} . \tag{3.7}$$

Let sharing a channel j between *heterogeneous*-WSOs w and m be expressed using an indicator function as,

$$I_{w,m(w)}(j) := \begin{cases} 1, & \text{if } O_{w,j}O_{m,j} > 0 \\ 0, & \text{otherwise} \end{cases}. \tag{3.8}$$

The homogeneity function then becomes an energy minimization function, defined as follows:

$$\bar{f}_H(\mathbf{O}) = \sum_{w=1}^{W}\sum_{j=1}^{J} I_{w,m(w)}(j)C_{w,m(w)}, \forall m \in \mathcal{W}, m \neq w. \tag{3.9}$$

SINR: Let $\mathcal{S}_j \subseteq \mathcal{W}$ be a set of WSOs with a maximal gain on channel j. The $\mathcal{S}_j$ is selected such that the total occupancy time of WSOs sharing channel j does not exceed the window time T_j as,

$$\mathcal{S}_j = \Big\{ w \in \mathcal{W} | \max\left([SINR_{w,j}]\right) : \sum_{w \in \mathcal{S}_j} O_{w,j} \leq T_j \Big\}, \forall j \in \mathcal{J}. \tag{3.10}$$

Let $T^0 := \sum_{\forall j \in \mathcal{J}} \sum_{\forall w \in \mathcal{S}_j} O_{w,j} b_{w,j} \log_2 \left(1 + SINR_{w,j}\right)$ be the maximum throughput that can be achieved if available TV channels are allocated to WSOs with maximal channel gain. The throughput optimization then becomes an energy minimization function, defined as follows:

$$\bar{f}_T(\mathbf{O}) = \left(T^0 - \sum_{w=1}^{W} r_w \right). \tag{3.11}$$

To optimize system throughput, the functions in (3.5), (3.9), and (3.11) must be optimized concurrently.

WSO Satisfaction from the Allocation

A WSO w is satisfied from the allocation if it achieves its desired data volume d_w. A quantifiable satisfaction can be defined regarding an energy minimization function as follows.

$$\bar{f}_S(\mathbf{O}) = \frac{1}{W}\sum_{w=1}^{W}\left(\frac{d_w - r_w}{d_w}\right)^2. \tag{3.12}$$

3.2.2 TVWS Sharing MOP Formulation

To achieve the TVWS sharing objectives in Section (3.2.1), the CDM system needs to optimize objective functions in (3.3), (3.5), (3.9), and (3.11), and (3.12) simultaneously. Let $\mathcal{J}_w := \{j | O_{w,j} > 0, \forall j \in \mathcal{J}\}$ be a set of channels allocated to WSO w, and let $\mathcal{J}^c := \mathcal{J} \backslash \mathcal{J}_w$. Let $\mathcal{R} = \{\beta_w, \forall w \in \mathcal{W}\}$ be a set of WSOs' control overheads. The TVWS sharing problem in Section (3.2.1) then becomes a MOP defined as follows:

$$\begin{aligned}
\underset{\mathbf{O}}{\text{minimize}} \quad & \bar{\mathrm{F}}(\mathbf{O}) = \left(\bar{f}_F(\mathbf{O}), \bar{f}_T(\mathbf{O}), \bar{f}_S(\mathbf{O}), \bar{f}_C(\mathbf{O}), \bar{f}_H(\mathbf{O})\right)^T \\
\text{subject to} \quad & \sum_{w=1}^{W} O_{w,j} \leq T_j, \quad \forall j \in \mathcal{J}, && (3.13a) \\
& \sum_{\forall j \in \mathcal{J}} O_{w,j} \leq n_w O_w, \ \forall w \in \mathcal{W}, && (3.13b) \\
& \sum_{\forall j \in \mathcal{J}} O_{w,j} > \beta_w, \quad \forall w \in \mathcal{W}, && (3.13c) \\
& \beta_w < O_{w,j} \leq O_w, \quad \forall j \in \mathcal{J}_w, \forall w \in \mathcal{W}, && (3.13d) \\
& O_{w,j} = 0, \qquad \forall w \in \mathcal{W}, \forall j \in \mathcal{J}^c && (3.13e)
\end{aligned}$$

The constraint in (3.13a) ensures that the total occupancy time of all allocated WSOs on channel j does not exceed the channel window time T_j . The constraint (3.13b) ensures that the total occupancy time of a WSO w on all allocated channels does not exceed its total desired channel occupancy time. The constraint in (3.13c) ensures that each WSO gets allocation on at least one channel, ensuring a minimum fairness in allocation. The constraint in (3.13d) ensures that for each allocated channel to WSO w, the occupancy time of the WSO satisfies the minimum and the maximum allocation constraints, $\beta_w \in \mathcal{R}$, and O_w, respectively. The constraint in (3.13e) sets all the variables $O_{w,j}$ to zero where the WSO w is not scheduled in the TV channels, i.e., $\mathcal{J}^c$. This constraint, in conjunction with (3.13d), allows the optimization routine to adjust the channel occupancies of *heterogeneous*-WSOs such that the CDM system can accommodate as many as *heterogeneous*-WSOs in the system.

3.2.3 Pareto-optimality in MOP in (3.13)

In multiobjective optimization, like in (3.13), it often happens that the objective functions conflict each other. For example, optimizing the fairness function in MOP in (3.13) diminishes the effect of throughput function. Thus, the solution point $\mathbf{O} \in \mathcal{P}$ which optimizes one of the functions may diminish the effect of the other function(s) in $\bar{\mathbf{F}}$. Consequently, a single solution point $\mathbf{O}$ that could optimize all objectives in $\bar{\mathbf{F}}$ in (3.13) is not possible. They need to be balanced by applying Pareto-optimality concept, defined as follows.

Let $\mathcal{P}$ be a feasible solution set defined on the domain of the MOP in (3.13), $\Omega = [0, 1]$. Then, finding a Pareto-optimal solution requires establishing a preference relation on the solution points in $\mathcal{P}$, as follows. Let $\mathbf{O}^1, \mathbf{O}^2 \in \mathcal{P}$, and corresponding objective functions are $\bar{\mathbf{F}}\left(\mathbf{O}^1\right), \bar{\mathbf{F}}\left(\mathbf{O}^2\right)$; then, $\mathbf{O}^1$ is preferable to $\mathbf{O}^2$ if $\bar{\mathbf{F}}\left(\mathbf{O}^1\right)$ dominates $\bar{\mathbf{F}}\left(\mathbf{O}^2\right)$. Thus, the dominance concept regarding MOP in (3.13) can be defined as follows.

Definition 2. $\bar{\mathbf{F}}\left(\mathbf{O}^1\right)$ *dominates* $\bar{\mathbf{F}}\left(\mathbf{O}^2\right)$ *if and only if* $\bar{f}_m\left(\mathbf{O}^1\right) \leq \bar{f}_m\left(\mathbf{O}^2\right)$, *for every* $m \in \{F, T, S, C, H\}$ *and* $\bar{f}_n\left(\mathbf{O}^1\right) < \bar{f}_n\left(\mathbf{O}^2\right)$ *for at least one index* $n \in \{F, T, S, C, H\}$.

Formally, the Pareto-optimal solution to MOP in (3.13) is defined as follows [58].

Definition 3. *A solution point* $\mathbf{O}^* \in \mathcal{P}$ *is Pareto-optimal to* (3.13) *if and only if there is no other solution point* $\mathbf{O} \in \mathcal{P}$ *such that* $\bar{\mathbf{F}}(\mathbf{O})$ *dominates* $\bar{\mathbf{F}}(\mathbf{O}^*)$.

This definition states that, for a Pareto optimal point, any improvement in an objective must deteriorate in at least one other objective. Note that $\mathbf{O}^*$ is Pareto optimal, meaning that it is preferable to any other solution point in $\mathcal{P}$. Thus, finding a Pareto optimal solution requires an ordering of solution points in $\mathcal{P}$ by establishing a Pareto dominance relation on corresponding points in objective function space, $\mathcal{Z} = \left\{\bar{\mathbf{F}}(\mathbf{O}) | \mathbf{O} \in \mathcal{P}\right\}$. For example, to illustrate the Pareto dominance concept, let's consider an example scenario shown in Fig. 3.1, as defined in [58]. For simplicity, let's assume $\mathcal{P} = \left\{\mathbf{O}^1, \mathbf{O}^2, \mathbf{O}^3, \mathbf{O}^4\right\}$ is finite and $\mathcal{Z}$ is a 2D objective space, i.e., m=2, as shown in Fig. 3.1. The pareto dominance for the optimization scenario in Fig. 3.1 is then defined as follows.

Let $\preceq$ denotes the weak Pareto-dominance relation by establishing a component wise order relation on two vectors. For example, in Fig. 3.1, $\bar{\mathbf{F}}\left(\mathbf{O}^1\right) \preceq \bar{\mathbf{F}}\left(\mathbf{O}^2\right)$ means $\bar{f}_m\left(\mathbf{O}^1\right) \leq \bar{f}_m\left(\mathbf{O}^2\right)$, $\forall m = 1, 2$, which shows that $\bar{\mathbf{F}}\left(\mathbf{O}^1\right)$ weakly dominates $\bar{\mathbf{F}}\left(\mathbf{O}^2\right)$. The weak dominance relation can be extended to Pareto-dominance relation as fol-

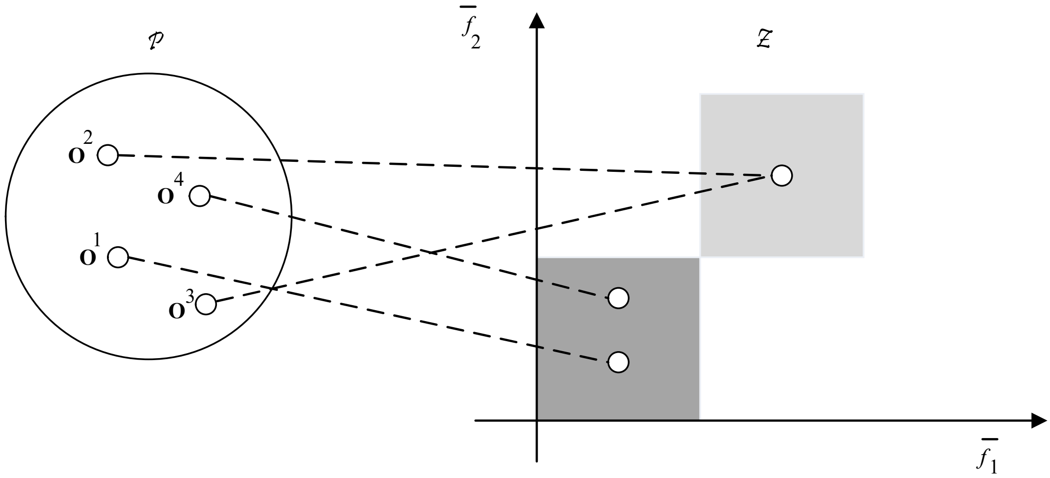

Figure 3.1: Optimization scenario with $\mathcal{P} = \left\{\mathbf{O}^1, \mathbf{O}^2, \mathbf{O}^3, \mathbf{O}^4\right\}$ and m=2. The shaded regions in objective space $\mathcal{Z}$ represents locations where objective points $\bar{\mathbf{F}}\left(\mathbf{O}\right) \in \mathcal{Z}$ in dark dominate to objective points $\bar{\mathbf{F}}\left(\mathbf{O}\right) \in \mathcal{Z}$ in the light.

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lows: $\bar{\mathbf{F}}\left(\mathbf{O}^1\right) \preceq \bar{\mathbf{F}}\left(\mathbf{O}^2\right)$ and $\bar{\mathbf{F}}\left(\mathbf{O}^2\right) \npreceq \bar{\mathbf{F}}\left(\mathbf{O}^1\right)$. For optimization in Fig. 3.1, the Pareto-dominance relation is established as follows: $\bar{\mathbf{F}}\left(\mathbf{O}^1\right) \preceq \bar{\mathbf{F}}\left(\mathbf{O}^a\right)$ and $\bar{\mathbf{F}}\left(\mathbf{O}^a\right) \npreceq \bar{\mathbf{F}}\left(\mathbf{O}^1\right),\ \forall a \in \{2, 3, 4\}$, which represents $\bar{\mathbf{F}}\left(\mathbf{O}^1\right)$ dominates $\bar{\mathbf{F}}\left(\mathbf{O}^a\right), \forall a \in \{2, 3, 4\}$ as shown in Fig. 3.1. This shows that $\mathbf{O}^1$ is preferable to any other point in $\mathcal{P}$, i.e., $\mathbf{O}^1$ is Pareto optimal for the optimization case in Fig. 3.1. Finding Pareto-optimal to MOP in (3.13) is not easy as the MOP in (3.13) has nonconvex, nonlinear property, as discussed in the following section.

3.2.4 Non-convergence Issue

Let $\mathcal{P} \subseteq \mathbb{R}^{W \times J}$ be a closed, nonempty subset of $\mathbb{R}$ consisting of all feasible solution points defined in the domain on the MOP in (3.13). If $\mathcal{P}$ is a convex set, we refer to variable $\mathbf{O} \in \mathcal{P}$ a convex variable, if $\mathcal{P}$ is a nonconvex set, the variable $\mathbf{O} \in \mathcal{P}$ is considered as a nonconvex variable.

Theorem 3.2.1. *For a nonconvex $\mathcal{P}$, the function $\bar{\mathbf{F}}$ in* (3.13) *is a nonconvex function.*

Proof. See Appendix B.

If $\mathcal{P}$ is a nonconvex set, the optimization problem like MOP in (3.13) can be hard in general [59]. Moreover, step function in (3.5) makes the MOP in (3.13) as nonlinear function. In such a case, no algorithm can converge to a global Pareto-optimal solution, at least in a polynomial time [59]. There exist some methods that converge to such a solution. For instance, when $\mathcal{P}$ is a nonconvex finite set, a simple brute force method, a branch-and-bound method and a branch-and-cut method, all are guaranteed to converge to the global Pareto-optimal solution [59]. However, these and such methods have non-polynomial worst-case run time [59]. It is often burdensome to use them for optimizing the TVWS sharing problem where a shorter run time is desirable. Our aim is to give up the accuracy and use a method that can find a good approximate of a global Pareto-optimal point in a shorter run time. The evolutionary strategy (ES) based heuristic technique can provide such a solution quickly [60], [61]. It is specifically suitable for a nonconvex, non-differentiable optimization problem [60] like MOP in (3.13). Moreover, the computational costs of optimization techniques in the ES are lower as ES does not require complex gradient or hessian calculations. Therefore, we adopt ES technique to design an algorithm (3.1) to tackle the TVWS sharing MOP in (3.13).

An evolutionary algorithm, like the EvCo in Section (3.3.1), requires a fitness function to rank the solution points. Therefore, we define an indicator based optimization function and use it as a fitness function. Before we define the indicator function, the objective functions in (3.3), (3.5), (3.9), and (3.11), and (3.12) are normalized for following reason. The objective functions' values are defined in different intervals, e.g., $0 \leq \bar{f}_F \leq 1, \bar{f}_T \in \mathbb{R}_0^+,\ 0 \leq \bar{f}_C \leq W \times J,\ 0 \leq \bar{f}_S \leq 1, \bar{f}_H \in \mathbb{R}_0^+$. The larger valued functions like $\bar{f}_T,\ \bar{f}_C,$ and $\bar{f}_H$ may diminish the effect of small valued functions like $\bar{f}_F$ and $\bar{f}_S$. To get an equal effect of these objective functions in the indicator function, we normalize them as follows,

$$f_\alpha(\mathbf{O}) = \frac{\bar{f}_\alpha(\mathbf{O}) - \bar{f}_\alpha^{\min}}{\bar{f}_\alpha^{\max} - \bar{f}_\alpha^{\min}}, \forall \alpha \in \{F, T, S, C, H\} \tag{3.14}$$

where $\bar{f}_\alpha^{\min}$ and $\bar{f}_\alpha^{\max}$ represent the minimum and maximum objective function values over all solution points in $\mathcal{P}$, respectively, defined as follows.

$$\begin{aligned} \bar{f}_\alpha^{\min} &= \text{minimum}\{f_\alpha(\mathbf{O}),\ \forall \mathbf{O} \in \mathcal{P}\}, \\ \bar{f}_\alpha^{\max} &= \text{maximum}\{f_\alpha(\mathbf{O}),\ \forall \mathbf{O} \in \mathcal{P}\}. \end{aligned} \tag{3.15}$$

The TVWS sharing MOP in (3.13) is then redefined using normalized objective functions as follows.

$$\begin{aligned} \underset{\mathbf{O}}{\text{minimize}} \quad & \mathrm{F}(\mathbf{O}) = (f_F(\mathbf{O}), f_T(\mathbf{O}), f_S(\mathbf{O}), f_C(\mathbf{O}), f_H(\mathbf{O}))^T \\ \text{subject to} \quad & \text{constraints in (3.13a to (3.13e).} \end{aligned} \tag{3.16}$$

3.2.5 Problem Formulation using Binary Epsilon Indicator Function

A binary epsilon indicator function measures the quality of two sets of solution points with respect to each other [62]. In our case a set of solution points is called a cluster; the clustering method is defined in Section (3.3.1). The indicator function performs preference ordering on a set of clusters, by establishing Pareto-dominance on the corresponding objective function vector defined as follows.

Let $C_k = \{\mathbf{O} \in \mathcal{P}\}$ be a cluster then, $\forall \mathbf{O} \in \mathcal{P}$ a set of K clusters is defined as, $\mathcal{C} = \{C_1, C_2, \ldots, C_K\}$. Let $k, l \in \{1, 2, \ldots, K\}$ be the indices to the cluster set $\mathcal{C}$ then a binary epsilon indicator function applied to the $\mathbf{F(O)}$ in (3.16) can be defined as follows [62]:

$$\begin{gathered} \mathcal{I}_{\varepsilon^+}(C_k, C_l) = \min_\varepsilon \Big\{ \forall \mathbf{O}^q \in \mathcal{C}_l \; \exists \mathbf{O}^p \in \mathcal{C}_k : \\ f_\alpha(\mathbf{O}^p) - \varepsilon \leq f_\alpha(\mathbf{O}^q), \; \alpha = \{F, T, S, C, H\} \Big\}. \end{gathered} \tag{3.17}$$

According to the definition in (3.17), $\mathcal{I}_{\varepsilon^+}(C_k, C_l)$ denotes the minimum amount, ε, which is required to improve each objective function $f_\alpha(\mathbf{O}^p), \forall \alpha \in \{F, T, S, C, H\}$ for each member of C_k such that C_k is weakly preferable to C_l. The indicator function in (3.17) is redefined as max-min optimization formulation [63] as follows:

$$\mathcal{I}_{\varepsilon^+}(C_k, C_l) = \max_{\mathbf{O}^q \in \mathcal{C}_l} \min_{\mathbf{O}^p \in \mathcal{C}_k} d_\varepsilon(\mathbf{O}^p, \mathbf{O}^q) \tag{3.18}$$

where a distance function is $d_\varepsilon(\mathbf{O}^p, \mathbf{O}^q) = \max_\alpha (f_\alpha(\mathbf{O}^p) - f_\alpha(\mathbf{O}^q)), \; \forall \alpha \in \{F, T, S, C, H\}$. A small example in Appendix D illustrates how the function in (3.18) finds a pareto-optimal solution by establishing Pareto-dominance on a given set of solution points. Thus, the TVWS sharing MOP in (3.16) is transformed into a max-min optimization problem in (3.18) for which an evolutionary algorithm is designed in the following section.

3.3 Solution to the TVWS Sharing Problem

In this section, we design an evolutionary algorithm that solves the TVWS MOP in 3.15. The EvCo algorithm in 3.1, is an update procedure that runs on the CDM system, proposed in Section (3.2.1). The EvCo uses its inputs – CDM system input parameters defined in (3.1), population size P, a number of generations M, generation indicator threshold δ_g and MOP domain $\Omega = \left[0, T_j\right]$ – to progressively improve the solutions in the set $\mathcal{P}$ using the optimizing function in (3.18). The EvCo output a solution $\mathbf{O}^* \in C_k^*$ that represents the best approximation of the Pareto-optimal point, as shown in the output section in the algorithm in 3.1. The detailed discussion on the algorithm is provided in the following section.

3.3.1 EVCO: An Evolutionary Algorithm for Coexistence Decision Making in TVWS

EvCo algorithm commences its execution using a predefined initial population; a set of randomly generated solution points

$$\mathcal{P} = \left\{\mathbf{O}^1, \mathbf{O}^2, \ldots, \mathbf{O}^P\right\}.$$

Each solution point $\mathbf{O} \in \mathcal{P}$ uniformly distributes the WSOs in the available TVWS, as follows. Let $\mathcal{W}_j \subseteq \mathcal{W}$ be the subset of WSOs sharing the channel j. Then, for each WSO in the set $\mathcal{W}_j$, the EvCo generates the channel occupancy time, $\forall O_{w,j} \in \mathbf{O}, \forall w \in \mathcal{W}_j, \forall j \in \mathcal{J}$, randomly and uniformly distributed in the domain Ω. The WSOs, not scheduled in channel j, get zero occupancy time, i.e., $O_{w,j} = 0, \forall w \in \mathcal{W} \setminus \mathcal{W}_j, \forall j \in \mathcal{J}$. The random generation of the occupancy time values, $\forall O_{w,j} \in \mathbf{O}$,

Algorithm 3.1: An Evolutionary algorithm for Coexistence decision making in TVWS (EvCo)

Algorithm Input: $\mathcal{W}, \mathcal{J}, \mathcal{T}, \mathcal{D}, M, P, \delta_g, \Omega = [0, T_j]$;

Algorithm Output: $\mathbf{O}^* \leftarrow \mathbf{O} : \text{minimum}\left(\mathbf{F}\left(\mathbf{O}\right) \in \mathcal{O}\right) \forall \mathbf{O} \in C_k^*$;

Algorithm Steps

1: ***initialization*:** generate an initial population $\mathcal{P}$ as follows,

a) Define a rule to select a WSO subset, $\mathcal{W}_j \subseteq \mathcal{W}$, sharing a channel j, $\forall j \in \mathcal{J}$.

b) Define $O_{w,j} \forall w \in \mathcal{W}_j, \forall j \in \mathcal{J}$ randomly and uniformly distributed on Ω.

c) Define $O_{w,j} = 0, \forall w \in \mathcal{W} \setminus \mathcal{W}_j, \forall j \in \mathcal{J}$.

2: ***population engineering*:** for each solution points $\mathbf{O} \in \mathcal{P}$ do:

a) For each channel $j \in \mathcal{J}$, set $O_{w,j} = \beta_w, \forall w \in \mathcal{W}_j$ if (3.13c) or (3.13d) is violated.

b) If (3.13a) is violated, reduce allocated occupancy time $\forall O_{w,j} \in \mathbf{O}$, using Eq. (3.19).

c) If (3.13b) is violated, reduce allocated occupancy time $\forall O_{w,j} \in \mathbf{O}$, using Eq. (3.23).

3: ***clustering*:** for each solution points $\mathbf{O} \in \mathcal{P}$: Form a set of clusters $\mathcal{C}$ defined by $\mathcal{P}$ using cosine similarity as, $C_k = \left\{\text{max}.S\left(\mathbf{O}^p, \mathbf{O}^q\right), \forall \left(\mathbf{O}^p, \mathbf{O}^q\right) \in \mathcal{P}\right\}$.

Algorithm 3.1: EvCo(continued)

4: ***calculations*****:**

a) $\forall \mathbf{O} \in C_k, \forall C_k \in \mathcal{C}$, compute $\mathcal{O} = \big\{\mathbf{F}\big(\mathbf{O}^p\big)\big\}$, using Eq. (2.3), (3.5), (3.9), and (3.11) and (3.12).

b) For each ordered pair cluster $(C_k, C_l) \in \mathcal{C}$, compute indicator function, $\mathcal{I}_{\varepsilon^+}(C_k, C_l)$, using Eq. (3.18) and store in an indicator table $\mathcal{K}$.

c) Compute g^{th} generation indicator value as, $I_g = \sum\limits_{k,l \in \{1,\ldots,K\}, k \neq l} \mathcal{I}_{\varepsilon^+}(C_k, C_l)$.

5: ***Elitism and Replacement*****: While** $g > M$ or $\big|I_g - I_{g-1}\big| > \delta_g$ **do:**

a) Identify an elite cluster set as, $\{C_k^*\} \leftarrow \min\big(\mathcal{I}_{\varepsilon^+}(C_k, C_l) \in \mathcal{K}\big)$, and define suboptimal cluster set as, $\mathcal{C}' \leftarrow \mathcal{C} \setminus \big\{C_k^*\big\}$.

b) For each suboptimal cluster $C_k \in \mathcal{C}'$, generate an offspring cluster as: $C_k^{\downarrow} = \{\mathbf{O}\}$, randomly on the domain $\Omega = [0, 1]$ such that $\big|C_k^{\downarrow}\big| = |C_k|$.

c) For all offspring clusters, $C_k^{\downarrow}$, apply Step 2 and Step 4.

d) For every $C_k^{\downarrow}$, **if** $\sum\limits_{l \in \{1,\ldots,K\} \setminus k} \mathcal{I}_{\varepsilon^+}\left(C_k^{\downarrow}, C_l\right) < \sum\limits_{l \in \{1,\ldots,K\} \setminus k} \mathcal{I}_{\varepsilon^+}(C_k, C_l)$ **then**

i. Define next generation indicator value as: $I_{g+1} = I_g - \sum\limits_{l \in \{1,\ldots,K\} \setminus k} \mathcal{I}_{\varepsilon^+}(C_k, C_l) + \sum\limits_{l \in \{1,\ldots,K\} \setminus k} \mathcal{I}_{\varepsilon^+}\left(C_k^{\downarrow}, C_l\right)$

ii. Next generation cluster set as, $\mathcal{C} \leftarrow C_k^{\downarrow} \bigcup \{\mathcal{C}\} \setminus C_k$

iii. Update $\mathcal{K}$ as, $\mathcal{K} \leftarrow \mathcal{I}_{\varepsilon^+}\left(C_k^{\downarrow}, C_l\right) \bigcup \mathcal{K} \setminus \mathcal{I}_{\varepsilon^+}(C_k, C_l), \forall l \in \{1, \ldots, K\} \setminus k$.

6: ***return*****:**$C_k^* \leftarrow C_k : \min\big(\mathcal{I}_{\varepsilon^+}(C_k, C_l) \in \mathcal{K}\big)$

may result in violating the constraints in (3.13). In such a case, the EvCo applies the population engineering to update the solution point $\forall \mathbf{O} \in \mathcal{P}$, as follows. If constraint in (3.13c) or (3.13d) is violated, the EvCo updates the occupancy time $\forall O_{w,j} \in \mathbf{O}$ of each allotted WSO w on channel j, using its minimum allocable occupancy time, $\beta_w \in \mathcal{R}$. If constraint in (3.13a) is violated, the EvCo computes an over-allocation as, $\sum\limits_{w \in \mathcal{W}} O_{w,j} - T_j$, and calculates $\frac{O_{w,j}}{\sum\limits_{w \in \mathcal{W}} O_{w,j}}$ to compute normalized allocation. Next, the occupancy time of each WSO sharing a channel j is updated as,

$$O_{w,j} \longleftarrow O_{w,j} - \left(\sum_{\forall w \in \mathcal{W}_j} O_{w,j} - T_j \right) \frac{O_{w,j}}{\sum\limits_{w} O_{w,j}}, \forall j \in \mathcal{W}. \tag{3.19}$$

If constraint in (3.13b) is violated, the over-allocation, $\sum\limits_{\forall j \in \mathcal{J}_w} O_{w,j} - n_w O_w$, is reduced in proportion to channel occupancy demand of WSO w, O_w, as follows,

$$O_{w,j} \longleftarrow O_{w,j} - \left(\sum_{\forall j \in \mathcal{J}_w} O_{w,j} - n_w O_w \right) \frac{O_{w,j}}{O_w}, \forall w \in \mathcal{W}_j. \tag{3.20}$$

The EvCo then forms a cluster of solution points in $\mathcal{P}$ with enough similarity. Clustering the solution points helps the EvCo to rank a set of non-comparable solution points rather than a single solution point. This property improves the convergence speed of the algorithm, as discussed in Section (3.3.2). The similarity among solution points in $\mathcal{P}$ is measured using a cosine similarity function. Briefly, the cosine similarity measures the angular similarity between two vectors as [64],

$$S\big(\mathbf{O}^p, \mathbf{O}^q\big) = \frac{\langle \bar{\mathbf{O}}^p, \bar{\mathbf{O}}^q \rangle}{\|\mathbf{O}^p\| \|\mathbf{O}^q\|}, \forall \mathbf{O}^p, \mathbf{O}^q \in \mathcal{P} \tag{3.21}$$

where $\bar{\mathbf{O}}^p$ and $\bar{\mathbf{O}}^q$ represent the one-dimensional transformation of 2-D vectors $\mathbf{O}^p$ and $\mathbf{O}^q$, respectively. The solution points with the maximum cosine similarity are grouped in the same cluster, e.g., C_k. A cluster set is then defined as, $\mathcal{C} = \{C_1, C_2, \ldots, C_K\}$. The EvCo then computes the fitness function of each cluster in $\mathcal{C}$ as define in Step 4 in Algorithm (3.1). In the fitness function calculation, an indicator value is calculated for every ordered cluster pair $(C_k, C_l) \in \mathcal{C}$ and stored in an indicator table $\mathcal{K}$.

The EvCo then iterates for a number of generations to improve the quality of the solution points. This process is achieved through elitism and replacement operators of the evolutionary theory. In elitism, a set of clusters with the best indicator value in generation g, denoted as $\{C_k^*\}$ is identified and passed to the next generation cluster set. The elite set size is defined as, $\left|\{C_k^*\}\right| = |\mathcal{C}| - \left|\mathcal{C}\right|^{\alpha}$where $\alpha \in [0,1]$ is a scaling factor to control the rate of elitism. The elitism can increase the performance of the EvCo because it prevents losing the best-found solutions in the current generation. The EvCo then generates an offspring cluster, $C_k^{\downarrow}$ against all worst valued clusters in the set $\mathcal{C}' = \mathcal{C} \setminus \{C_k^*\}$. Next, the EvCo applies hill-climbing based replacement operator for each offspring cluster as follows. It computes an indicator function value $\mathcal{I}_{\varepsilon^+}(C_k^{\downarrow}, C_l)$ for an ordered cluster pair, $(C_k^{\downarrow}, C_l), \forall C_l \in \mathcal{C}$. If the indicator value of the offspring cluster $C_k^{\downarrow}$ is lower than that of the corresponding cluster $C_k \in \mathcal{C}'$, the $C_k^{\downarrow}$ replaces C_k in the next generation cluster set and indicator table is updated with the indicator value of $C_k^{\downarrow}$, otherwise C_k is passed to the next generation cluster set and indicator table remains unchanged. The elitism selection and hill climbing replacement process continues until a stopping criterion, as defined in Step 5.

3.3.2 Complexity Analysis of EvCo

In this section, we make some comments about the computational cost of the EvCo. Let W, J, $P=|\mathcal{P}|$ be the number of WSOs, the number of channels and the population size, respectively. Generating an initial population, performing population engineering and computing objective functions in (2.3), (3.5), (3.9), and (3.11), (3.12), (3.14), (3.19), and (3.23) all are linear operations in W, J, and P having complexity, $O\left(PWJ\right)$. The cosine similarity in (3.21) is defined by computing the Euclidean dot product and Euclidean distance operator, both of which have a computational complexity of the order of population size P, defined as $O\Big(\frac{P(P-1)}{2}\Big)$. Computing an indicator function involves finding a minimum epsilon so that a cluster C_k becomes weakly Pareto-optimal to cluster C_l for each ordered pair of clusters $\big(C_k, C_l\big) \in \mathcal{C}$. It requires to compute functions in (3.3), (3.5), (3.9), and (3.11),(3.12), and (3.14) each of which requires $O\left(PWJ\right)$ complexity.

In the elitism step, EvCo identifies an elite cluster C_K^* in an arbitrary array (indicator table) of length $K \times K$ which is a linear time operation requiring $O\Big(M\big|\{C_k^*\}\big|\Big)$ complexity where M is the total number of generations. Let $N \leq P$ be the number of solution points of all offspring clusters $C_k^\downarrow$ then, population generation, population engineering, objective function calculations, and the indicator function in (3.18) all require $O\big(MNWJ\big)$ computational complexity. The cosine similarity function and clustering the N solution points require $O\Big(\frac{MN(N-1)}{2}\Big)$ and $O\big(M(N-1)^2\big)$ complexity, respectively. Finally, the overall computational complexity of the proposed algorithm is a function of the number of generations, M, the elitism rate, N , the number of WSOs, W, and the number of channels J, defined as, $O\big(MNWJ\big)$.

3.4 Performance Analysis

In this section, we describe our simulation setup, the summarized allocation policies of comparative algorithms, and the comparative results of the simulation.

3.4.1 Simulation Setup

Consider an 802.19.1 coexistence system deployed in a geographic region. The number of coexisting WSOs in the area is W=32 and the number of available TV channels in the area varies as, J=$\{5, 6, \ldots, 16\}$. The system has eight CMs, each serving four WSOs. The MATLAB is used as a simulation platform to model the WSOs and their channel demand parameters as follows. Each WSO is defined as a group of unlicensed TV band devices. These devices are modeled using FCC regulations. The FCC defines four types of TV band devices, such as fixed, portable Mode 1, portable Mode 2 and sensing only [3]. In this simulation, we model first three types of devices. The channel demands and channel characteristics of WSOs are randomly generated. For example, the additive white Gaussian noise channels are considered. The transmission power of each WSO is generated randomly on $\big(0, P_{\max}\big]$ where $P_{\max}$ is the maximum allowed transmission power which is set based upon WSO type. For example, a WSO with fixed transmitter like AP in IEEE 802.22 network can radiate at a maximum of 4 W. A WSO comprising portable mode devices like in IEEE 802.15.4 can transmit at a maximum of 100 mW. An initial population of 50 solution points,$\mathcal{P}\{\mathbf{O}^1, \mathbf{O}^2, \ldots, \mathbf{O}^{50}\}$

is randomly generated in the domain of (3.13), $\Omega = \left[0, T_j\right]$, using rand function in MATLAB, where $T_j = 1, \forall j \in \mathcal{J}$. The solution points in $\mathcal{P}$ are then grouped into 25 clusters based on maximal cosine similarity values. The worst fitness valued chromosome in each generation is replaced with randomly generated new offspring cluster. The number of generations is set as, M=300.

3.4.2 Comparative Algorithms

The proposed algorithm is compared to FACT [49] and Share [26]. The TVWS sharing mechanism of FACT is summarized in Section (3.1). Note that for comparative purposes; the channel allocation strategy is the same as that defined in [49]; however, the objective functions used to evaluate the FACT performance are as defined in (3.3), (3.5), (3.9), and (3.11), and (3.12).

The TVWS sharing problem in [26] is modeled as a lexicographic ordering of throughput of coexisting networks, as summarized in Section (3.1). The *Share* algorithm in [26] operates in three phases. In the first phase of allocation, *Share* orthogonalizes the WSOs in the available TV channels. In the second phase, channel sharing is performed mutually among allotted WSOs of the first phase under the condition that their throughputs achieved in the first phase do not decrease. The fairness is improved in the third phase by sharing the channel with WSOs that do not obtain channels in the previous phases such that lexicographically ordered throughputs does not decrease. We show graphs of the simulation results of the three algorithms in Fig. 3.2 to Fig. 3.5. The dashed, dotted, and solid lines in the figures represent the behaviors of EvCo, FACT, and *Share*, respectively, as explained in the following subsection.

3.4.3 Results and Discussions

The three allocation algorithms are compared using the following performance metrics: fairness in allocation, system throughput, WSO satisfaction in terms of percentage of their demand served, and resource utilization in terms of spectral efficiency (SE).

Fairness in Allocation

Fig. 3.2 shows the fairness in sharing the TVWS, measured by the function in (3.3). A higher index value indicates fairer allocation. As can be seen in Fig. 3.2, the EvCo achieves a higher fairness index value. This is due to the flexible allocation policy of EvCo. In this policy, the channel occupancy allocation of WSOs sharing a channel is adjusted such that their normalized throughput are equalized maximally, i.e., $T_w \approx T_m, \forall w, m \in \mathcal{W}$, as defined in Section (3.2.1). FACT also considers the normalized throughput as a fairness metric; however, it's strict allocation policy is discriminating, as explained in Section (3.1). As a result, a decreased fairness index value is observed, especially when the number of TV channels in the system is low, as shown in Fig. 3.2.

The *Share*, on the other hand, achieves a better fairness index value than the FACT. This improvement is because it does not strictly satisfy the channel occupancy demand of each allotted WSO. Rather it enables WSOs to share a channel in second and third phase of allocation. However, a channel is shared among coexisting WSOs only if the system throughput is improved. This constrained sharing reduces the fairness in allocation among coexisting WSOs. As a result, the fairness in allocation of *Share* is

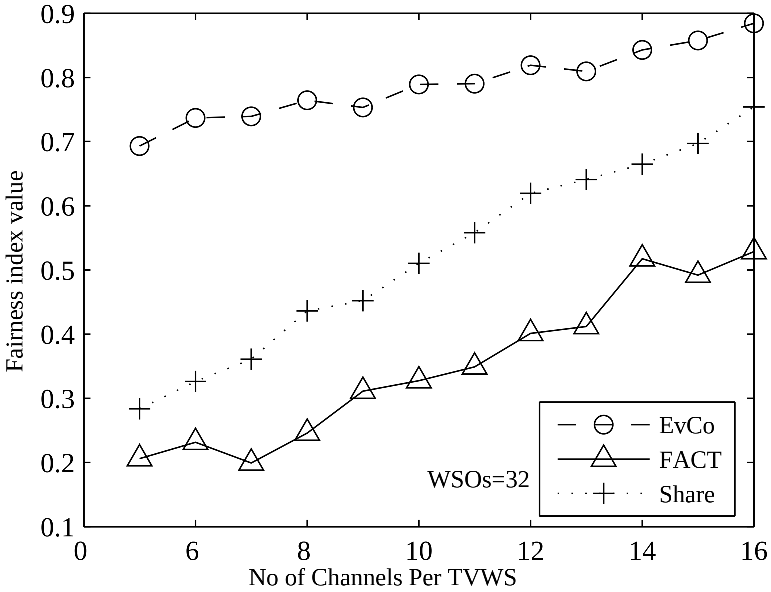

Figure 3.2: Fairness index value of coexisting WSOs for a variable number of TV channels in the system.

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comparatively lower than the EvCo algorithm as shown in Fig. 3.2.

WSO Satisfaction from Allocation

WSO satisfaction is defined in terms of their fraction of channel demand served, defined as, $\frac{1}{W}\sum_{w\in\mathcal{W}}\frac{r_w}{d_w}$. Fig. 3.3 shows that the EvCo achieves the highest average WSO satisfaction as compared to the comparative algorithms. This improvement is due to maximally satisfying the channel demands of the WSOs by optimizing their achieved data rates, as defined in (3.12). Moreover, the EvCo readjusts the channel occupancy time of WSOs to schedule a greater number of WSOs in a channel. These allocation steps improve the fraction of the demand served to the WSOs in the system. On the other hand, the FACT achieves the least WSO satisfaction from the allocation as shown

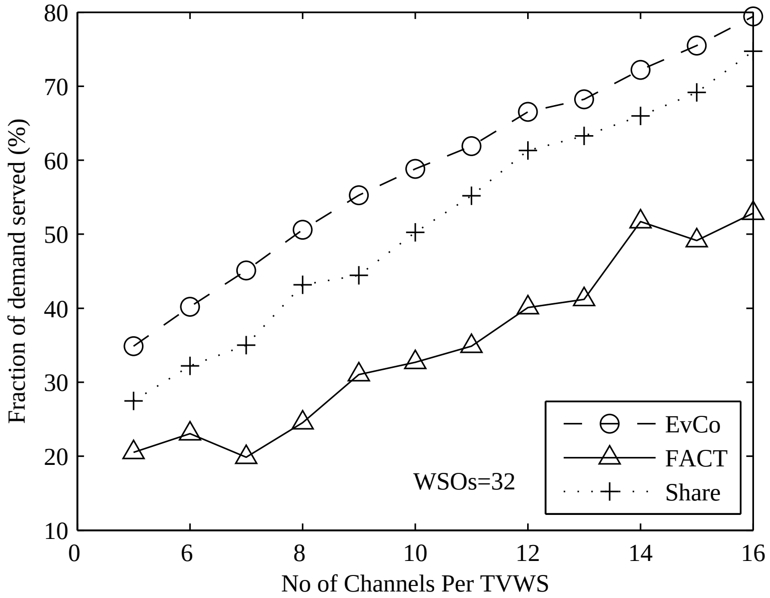

Figure 3.3: WSO satisfaction from TVWS allocation in terms of WSO fraction of channel demands for a variable number of TV channels in the region.

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in Fig. 3.3. This decrease in satisfaction is due to it's an unequal channel slot allocation among WSOs sharing a channel, as discussed in Section (3.1). Consequently, a higher variation in WSO fraction of demand serve is observed which leads to a lower overall WSO satisfaction in the system. The *Share*, however, achieves a higher WSO satisfaction from the allocation than that of the FACT as shown in the figure. This is because the *Share* enables the coexisting WSOs to share the channels during the second and third phase of allocation. This sharing process improves their fraction of channel demand serve thus, leading to a comparatively higher WSO satisfaction in the system as shown in Fig. 3.3.

System Throughput

Fig. 3.4 shows the system throughput achieved by the three algorithms. The system throughput (ST) is measured using the Shannon-Hartley capacity theorem [47] as follows.

$$ST = \sum_{j \in \mathcal{J}} \sum_{w \in \mathcal{W}} O_{w,j} b_{w,j} \log_2\big(1 + SINR_{w,j}\big) \tag{3.22}$$

Fig. 3.4 shows that the EvCo and FACT exhibit competitive behavior. At some instance of the number of TV channels in the system, the EvCo results in higher system throughput while in some other cases, the FACT gives higher throughput. The reason is that both algorithms make use of optimization parameters such as homogeneity and contiguous channel allocation in their MOP formulation. These optimization steps result in lower scheduling delays in sharing the channel among the WSOs and help the WSOs to use adaptive channel widths. These achievements improve the channel utilization thus, leading to a higher system throughput. On the other hand, *Share* gives a lower system throughput than the EvCo and the FACT, as shown in Fig. 3.4, which is due to an orthogonal channel allocation in the first phase of allocation. In such allocation, it is quite possible that if a WSO with poor signal to interference and noise ration (SINR) happen to get a channel and the WSOs with good SINR value may not able to share the channel in the second or third phase due to the constraint of maintaining the lexicographic ordering of throughput. Consequently, the system throughput achieved by the *Share* is decreased, as shown in Fig. 3.4.

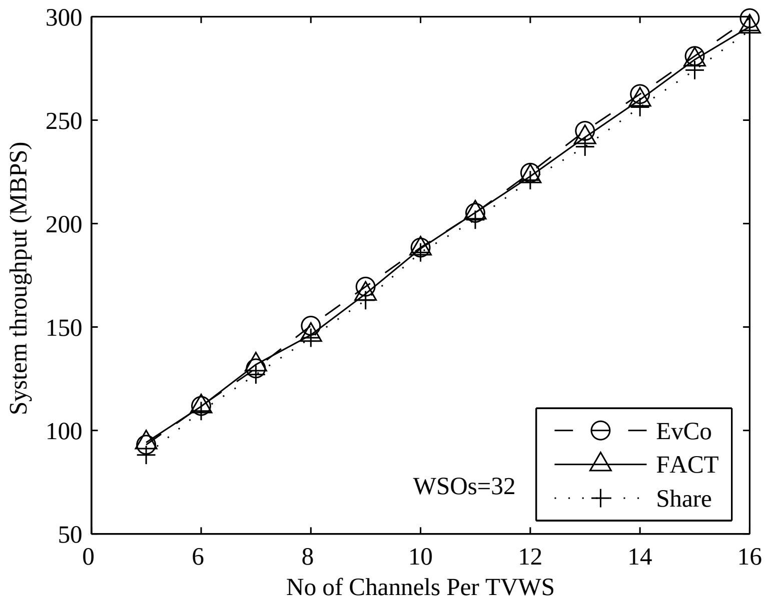

Figure 3.4: System throughput for 32 WSOs on a varying number of TV channels.

Spectral Efficiency

According to ITU-R [65], the SE of a radio communication system can be defined as follows:

$$\eta = \frac{M}{B \times S \times T} \tag{3.23}$$

where M is the amount of information transferred over distance S using spectrum width B in time T. Keeping all other parameters constant, we define M as the data rate achieved by WSOs sharing available TVWS, as described in (3.22), and the distance is taken as one without loss of generality. The parameter T is set equal to the window time of the channel which is taken as one without loss of generality, and the channel width is 6 MHz. Fig. 3.5 shows the effect of heterogeneity on resource utilization regarding the SE of the three algorithms. In the figure, the bps/Hz value is averaged over the

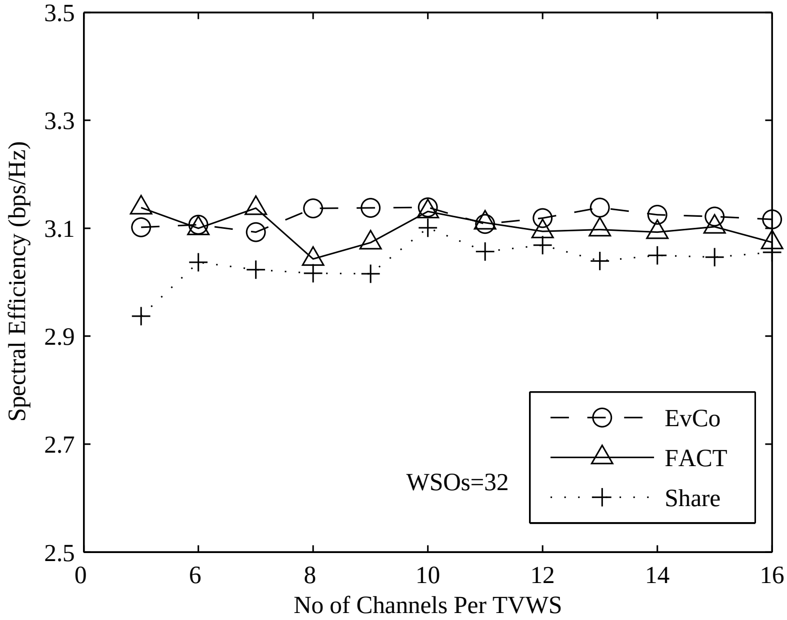

Figure 3.5: The spectral efficiency of coexisting WSOs averaged over a number of available TV channels in the system.

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number of channels in the system.

Fig. 3.5 shows that both EvCo and FACT show competitive behavior. However, as compared to *Share*, EvCo yields a better SE result. This improvement is due to optimizing SINR and contiguous channel allocation parameters in the MOP formulation in EvCo, as defined in (3.5), and (3.9), respectively. Fig. 3.5 also shows that the SE values, especially those of FACT, are higher when the number of channels in the system is small and gradually decrease as the number of channels increases. The reason is that when the number of available channels is low, the WSOs with optimal channel utilization are prioritized in channel allocation over the WSOs with suboptimal channel utilization. However, as the number of available channels increases, suboptimal WSOs

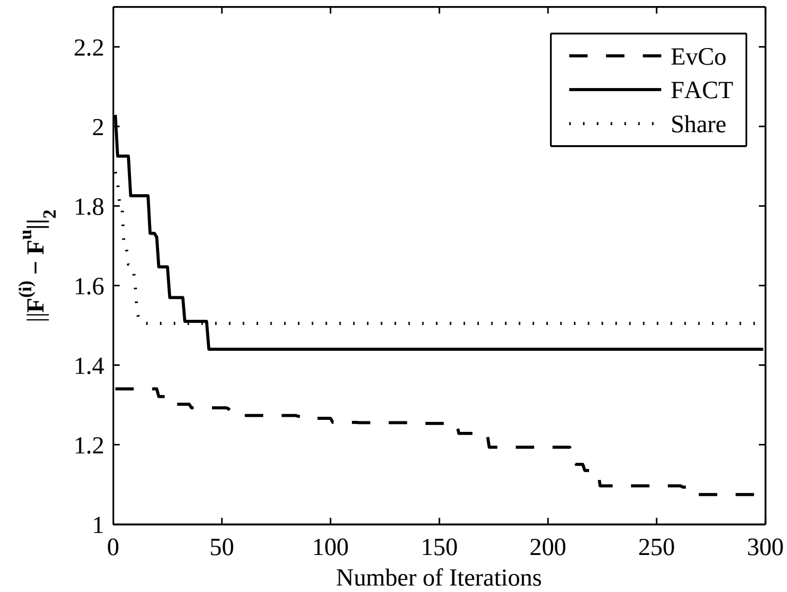

Figure 3.6: Accuracy in the solution obtained at each iteration.

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can get a larger share of the channels. These suboptimal WSOs have a detrimental effect on achievable SE due to the poor channel conditions. This effect intensifies as the number of available channels exceeds 19. At this point, almost all coexisting WSOs in the system obtain a plentiful share of the available spectrum, leading to a sharp decline in the SE values of the three algorithms.

3.4.4 Complexity Graph of EvCo, FACT, and Share

In this section, we empirically compare the performance of the three algorithms using performance metrics like accuracy and speed. The performance study is done by measuring how well each algorithm approximates an utopia point. An utopia point in multiobjective optimization is a point where every objective function achieves an optimal value. As the objective functions $f_\alpha \in \mathbf{F}, \forall \alpha \in \{F, T, S, C, H\}$ in (3.16) are

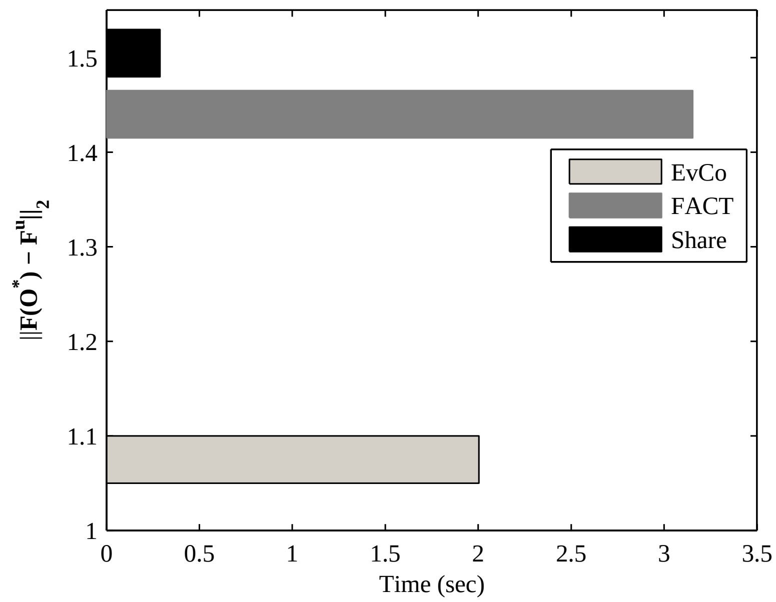

Figure 3.7: Run-time of the three algorithms to identify the best solution.

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contradicting, therefore, a single solution point $\mathbf{O}^*$ cannot optimize all of them. An optimal solution $\mathbf{O}^{\alpha*}$ is obtained. It is point where an objective function f_α is individually optimized. Let $\mathbf{F}^{\mathrm{u}}$ be an utopia point for $\mathbf{F}$ in (3.16) defined as,

$$\mathbf{F}^{\mathrm{u}} = \Big[f_F\big(\mathbf{O}^{F*}\big), f_T\big(\mathbf{O}^{T*}\big), f_S\big(\mathbf{O}^{S*}\big), f_C\big(\mathbf{O}^{C*}\big), f_H\big(\mathbf{O}^{H*}\Big]^T.$$

Since, each objective functions in $\mathbf{F}$ in (3.16) is a non-negative minimization function, as defined in Section (3.2.4), therefore, we define the utopia point for MOP in (3.16) as, $\mathbf{F}^{\mathrm{u}} = [0, 0, 0, 0, 0]$. Then, using $\mathbf{F}^{\mathrm{u}}$, the accuracy and the convergence test of the three allocation algorithms are performed as follows.

In the accuracy test, we compute measurement error to determine how good each of the three comparative algorithms approximates the Utopia point. The measurement error function is defined as, $\left\|\mathbf{F}^{(\mathrm{i})} - \mathbf{F}^{\mathrm{u}}\right\|_2$ where $\mathbf{F}^{(\mathrm{i})}$ is the the i^{th} iteration objective function value of each algorithm. The lower is the measurement error, the better is the solution point. The result of the accuracy study is shown in a graph in Fig. 3.6. The figure shows that the proposed algorithm gives the least measurement error. The difference between lines of the EvCo and the comparative algorithms in Fig. 3.6 attributes to the true multiobjective optimization property of the proposed CDM system, as discussed in the Introduction section (3.1). Moreover, although the EvCo converges to an optimal point at a much higher number of iterations, more than 250 in Fig. 3.6, yet, it is faster than the FACT as shown in Fig. 3.7, as discussed follows.

In the convergence test, we measure how quickly the three algorithms converge to an optimal solution point. The convergence test results shown in Fig. 3.7 and Fig. 3.8 are defined as follows. Let $\left\|\mathbf{F}\left(\mathbf{O}^*\right) - \mathbf{F}^{\mathrm{u}}\right\|_2$ gives measurement error, defined on function $\mathbf{F}$ using an optimal solution point, $\mathbf{O}^*$. The time taken to identify $\mathbf{O}^*$ by each algorithm is shown in Fig. 3.7. The result in the figure shows that the *Share* finds $\mathbf{O}^*$ quickly than the comparative schemes. The reason is that the complexity of *Share* is a function of the number of WSOs getting a channel in the first phase of allocation. Since, the allocation process in *Share* is orthogonal in the number of channels. Since, the maximum number of channels in the simulation setup is small, i.e., 16, therefore, the *Share* run-time is considerably short. However, as the number of WSOs in the system increases, the *Share* takes the comparatively higher time to identify $\mathbf{O}^*$ as shown in Fig. 3.8. On the other hand, the FACT takes the highest time to identify a solution point $\mathbf{O}^*$ as shown in Fig. 3.8. The reason is that computing the weight of neurons in this scheme requires high run-time complexity of $O\left(J^2W^2T\right)$ where T is the number of

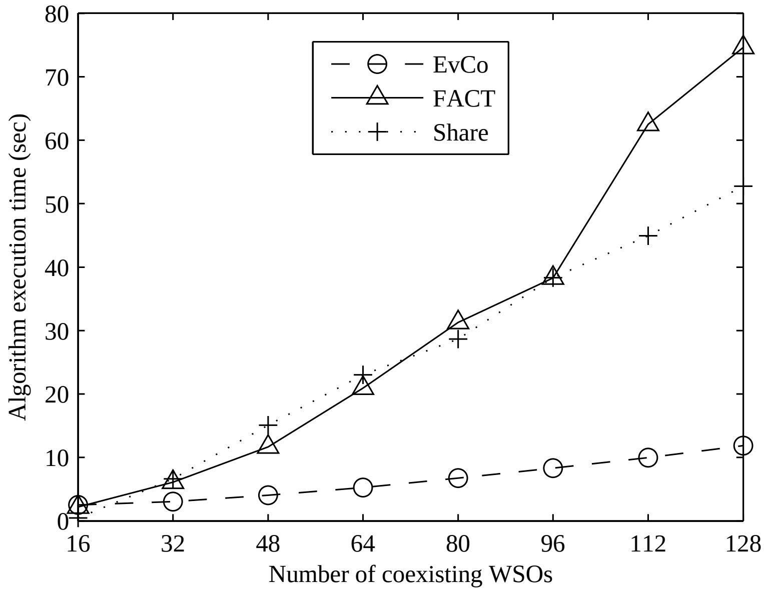

Figure 3.8: Runtime of the three algorithms to identify an optimal solution for larger denser networks.

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time slots per channel. Moreover, as the number of WSOs or the number of channels in the system increases, the complexity of FACT increases quadratically as shown in Fig. 3.8. On the other hand, the EvCo outputs optimal solution $\mathbf{O}^*$ more quickly because computing an indicator function is fast. Moreover, the EvCo finds the optimal solution point by simply calculating the functions defined in (3.3), (3.5), (3.9), and (3.11), and (3.12). Such computations require linear time complexity. Thus, these results conclude that the EvCo is highly versatile in highly congested areas and completes the TVWS scheduling process in a quick run-time for larger, denser networks.

3.5 Conclusion

In this work, we have proposed a CDM system to perform TVWS sharing in heterogeneous coexistence environment. The proposed system implements the TVWS sharing problem as a multiobjective optimization problem for which an evolutionary algorithm called as, EvCo is also designed. We evaluate the performance of the EvCo on 802.19.1-compliant CDM system and compare its performance with existing TVWS sharing algorithms. Our evaluation results show that the EvCo is superior to the comparative algorithms in [49] and [26], regarding fairness and WSO satisfaction from the allocation. Moreover, the EvCo can be readily implemented in an 802.19.1-based CDM system without requiring any significant changes to the baseline architecture of the coexistence system in IEEE 802.19.1.

Chapter 4

Conclusions and Future Research Directions

In this thesis, we have introduced methods to perform TV channel allocation among WSOs operating in heterogeneous coexisting environments. The channel allocation in heterogeneous environments is considered a complex and challenging task due to signal propagation characteristics in TV spectrum and disparity in network technologies employed by the coexisting WSOs.

4.1 Summary of Contributions

The improvements and reductions in performance as a result of using our proposed channel allocation mechanisms are summarized in Table 4.1. The Table 4.1 shows summary of the simulation results in Section 2.6.3 and Section 3.4.3. Note that the simulation setup consists of 32-WSOs with each WSO being modeled using FCC regulations, as discussed in Section 3.4.1. The number of TV channels in the system varies as, $J=\{5, 6, \ldots, 16\}$.

The performance metrics like fairness index (FI) system throughput (ST) and spectral efficiency (SE) show percentage of improvement, calculated over the average values of these metrics, achieved by the proposed channel allocation scheme vs the comparative channel allocation Schemes, defined in Section 2.6.1 and 3.4.2. While the performance metric, WSO satisfaction is measured for the maximum improvement of the allocation

Table 4.1: Summary of Contributions

Work	**Constraint Implementation**	**WSO Demand Domain**	**FI (%)**	**ST (%)**	**WSO Sat. (%)**	**SE(%)**
[16],[18]	QoS Provisioning	Low	3.33	S	4.81	N/A
		Medium	4.15	1.82 D	5.67	N/A
		High	17.2	6.42	17.79	N/A
[17],[18]	WSO Accommodation	Fixed	48.89	1.31	N/A	2.70

labels: S, D represents similar and decline in performance, respectively. N/A is for not applicable

scheme proposed in section 2.4 over the comparative allocation schemes. Note that the label "S" in Table 4.1 shows that the proposed scheme is similar in performance in terms of the pertinent performance metric, as compared to the closet comparative allocation scheme. Similarly, the label "D" represents that the proposed scheme observes decline in performance of the pertinent performance metric, as compared to the closet comparative allocation scheme. For example, the Table 4.1 shows that, for medium subdomain cases, the ST gain of the proposed channel allocation scheme, defined in Section 2.4 decreases, as compared to the allocation scheme in [14]. This happens when the number of channels in the system are low, as shown in Fig. 2.4. However, as the number of channels in the system increases, the ST gain of the proposed scheme improves over the Scheme in [14], as shown in Fig. 2.4. Similarly, the not applicable label represents that the proposed allocation scheme is not analyzed for the pertinent performance metric. For example, the performance of the allocation scheme defined in section 2.4 is not measured for the SE metric. While the scheme proposed in section 3.3 achieves, on average, 3.29 percent improvement in SE over the scheme in [49]. Note that the reason for such improvements are defined in Section 2.6.3 and Section 3.4.3

4.2 Future Research Direction

4.2.1 Channel Allocation in Heterogeneous Coexisting Environment

In Chapter 2 we discussed a coexistence scenario where WSOs have stringent QoS requirements while in Chapter 3 we perform TVWS sharing among WSOs with an aim to accommodate as many as WSOs in the available TVWS. However, the WSO coexistence environment could be potentially more complicated. Since, multiple of wireless standards have adopted PHY and MAC layers extensions for operations in TVWS, therefore, WSOs operating on these standards may be deployed for different traffic needs, and for different traffic types. For example, a set of coexisting WSOs may require strict bandwidth to be allocated while others may require fix delay. Therefore, a mix of WSOs with variable channel requirements may coexist in TVWS.

The channel sharing problem in heterogeneous mix of WSOs' scenario is defined as mixed integer programming (MIP) problem. The channel requirement deemed necessary for the WSO could be modelled as a binary integer variable while the requirement with flexible allocation could be defined as a real valued assignment variable. The solution finding method depends upon how the TVWS sharing problem is formulated. In case the objective function and constraints are linear, the problem becomes linear MIP which is comparatively easy to solve. The non-linear MIP, on other hand, is the one in which either of the objective function or constraints or both are non-linear. In most of the cases the non-linear MIP combines the combinatorial difficulty of optimizing over discrete variable sets with the challenges of handling nonlinear functions.

Appendices

Appendix A

Linearization Using Tangent Plane Approximation

In this section, we apply tangent plane approximation to linearize the objective function defined in (2.22a).

Let for some given points on the graph, $\left(q_1 = x^c_{1,j},\ q_2 = x^c_{2,j}\right)$, and $F = log\,(q+1)$, where $q = \frac{q_1 r^c_{1,j}}{O^c_{1,j}+\delta_{O^c_{1,j}} 0} + \frac{q_2 r^c_{2,j}}{O^c_{2,j}+\delta_{O^c_{2,j}} 0}$. If $\log\left(\mathcal{U}_{c,j}+1\right)$ is differentiable at (q_1, q_2), then the surface has tangent plane at (q_1, q_2, F). The equation of tangent plane at (q_1, q_2, F) is given by,

$$\frac{\partial y}{\partial x^c_{1,j}}\left(q_1, q_2\right)\left(x^c_{1,j} - q_1\right) + \frac{\partial y}{\partial x^c_{2,j}}\left(q_1, q_2\right)\left(x^c_{2,j} - q_2\right) - \left(F - \mathrm{F}\right) = 0$$

where y denotes multivariate objective function $\log\left(\mathcal{U}_{c,j}+1\right)$ and $F = \log\left(\mathcal{U}_{c,j}+1\right)$.

The tangent plane equation is rearranged as,

$$F = \mathrm{F} + \frac{\partial y}{\partial x^c_{1,j}}\left(q_1, q_2\right)\left(x^c_{1,j} - q_1\right) + \frac{\partial y}{\partial x^c_{2,j}}\left(q_1, q_2\right)\left(x^c_{2,j} - q_2\right)$$

where $\frac{\partial y}{\partial x^c_{1,j}} = \frac{r^c_{1,j}}{\left(\mathcal{U}_{c,j}+1\right)\left(O^c_{1,j}+\delta_{O^c_{1,j}} 0\right)}$ denotes partial derivative of log function at $x^c_{1,j}$. Thus, if F is differentiable at (q_1, q_2), then the tangent plane to the surface at (q_1, q_2) provides a good approximation to F near (q_1, q_2),

$$F \approx \mathrm{F} + \frac{\partial y}{\partial x^c_{1,j}}\left(q_1,\ q_2\right)\left(x^c_{1,j} - q_1\right) + \frac{\partial y}{\partial x^c_{2,j}}\left(q_1,\ q_2\right)\left(x^c_{2,j} - q_2\right)$$

which is called as linear approximation of y near (q_1, q_2).

For a general case with $|\mathcal{W}^c| = n$, and near to some given point, $\mathbf{q} = q_1 = x^c_{1,j}, \cdots, q_n = x^c_{n,j}$, we define linear approximation of y as,

$$F \approx \mathrm{F} + \frac{\partial y}{\partial x^c_{1,j}} (\mathbf{q}) \left(x^c_{1,j} - q_1 \right) + \cdots + \frac{\partial y}{\partial x^c_{n,j}} (\mathbf{q}) \left(x^c_{n,j} - q_n \right).$$

Appendix B

Convergence Property of the Subgradient Algorithm 2.1

In this section, we aim to discuss the convergence property of the algorithm in 2.1. Note that our discussion here closely follows the discussion on the convergence of subgradient algorithm defined in [66]. Interested readers are referred to [66] for seeking knowledge beyond what is presented in this short discussion.

Given $\lambda^0 \in \mathrm{E}^W$ and the sequence $\{t_k\}$ of positive scalars, called *step sizes*, in Algorithm 2.1, define the sequence $\left\{\boldsymbol{\lambda}^k\right\}$ as defined in Step 5-b) in Algorithm 2.1,

$$\lambda^{k+1} = \max\left\{\boldsymbol{\lambda}^k + t_k \nabla h\left(\boldsymbol{\lambda}^k\right),\ 0\right\}.$$

For any $\boldsymbol{\lambda}$, the maximum of (17) is assumed for at least one value of the index k. Since (17) is piecewise linear, there then exists at least one point $\boldsymbol{\lambda}^*$ such that $h\left(\boldsymbol{\lambda}^*\right) = h^* = \max P\left(\mathbf{X}, \boldsymbol{\lambda}^*\right)$. Then, $h\left(\boldsymbol{\lambda}^k\right)$ will converge to its optimum h^* under the conditions,

$$\lim_{k\to\infty} t^k \to 0,\ \sum_{k=0}^{\infty} t_k = \infty.$$

For the proof of the convergence of subgradient algorithm, the interested readers are encouraged to consult [66].

Appendix C

Non-Convexity of F in 3.13

In this section, we show that the objective function in (3.13) is non-convex on $\mathcal{P}$.

Definition 4. *The function* $\mathbf{F}$ *in* (3.13) *is considered convex if and only if* $f : \mathbb{R}^{W \times J} \rightarrow \mathbb{R}, \forall f \in \mathbf{F}$, *is convex,* $\mathcal{P}$ *is convex set, and* $\forall \mathbf{O}^p, \mathbf{O}^q \in \mathcal{P}$ *using* $\theta \in [0, 1]$ *if the following inequality holds:* $f\big(\theta\mathbf{O}^p + (1-\theta)\mathbf{O}^q\big) \leq \theta f\left(\mathbf{O}^p\right) + (1-\theta) f\left(\mathbf{O}^q\right)$.

Using a counterexample, we show that function $\mathbf{F}$ is not a convex function. The set $\mathbf{P}$ is convex if $\forall \mathbf{O}^p, \mathbf{O}^q \in \mathcal{P}$ implies that $\big(\theta\mathbf{O}^p + (1-\theta)\mathbf{O}^q\big) \in \mathcal{P}$ with $0 \leq \theta \leq 1$. Let $\exists \mathbf{O}^p, \mathbf{O}^q \in \mathcal{P}, \theta = 0.95$ and the parameters like d_w and SINR, as shown in Table C.1, we compute $f_F\big(0.95\mathbf{O}^p + 0.05\mathbf{O}^q\big) = 0.349$ and $\left(0.95 f_F\left(\mathbf{O}^p\right) + 0.05 f_F\left(\mathbf{O}^q\right)\right) = 0.346$. These results show that $f\big(\theta\mathbf{O}^p + (1-\theta)\mathbf{O}^q\big) > \theta f\left(\mathbf{O}^p\right) + (1-\theta) f\left(\mathbf{O}^q\right)$, which violates the inequality defined in Definition 2. An MOP is convex if all objective functions and feasible regions are convex [67], [68]. However, f_F has been shown to be a non-convex function; therefore, $\mathbf{F}$ is non-convex.

Table C.1: Input Parameters

WSO No.	$\mathbf{O}^p$	$\mathbf{O}^q$	d_w	SINR
1	0.2240	0.1634	10.6420	2.7287
2	0.1763	0.4756	48.7117	2.5371
3	0.5997	0.3610	9.4433	1.9674

Appendix D

Pareto-optimality Applied to MOP in 3.13

Following example shows how the EvCo, schedules a set of WSOs $\mathcal{W} = \{1, 2, \ldots, 5\}$, on a set of channels, $\mathcal{J} = \{1, 2\}$. Let the input parameters to the CDM system be initialized, as shown in Table D.1. Let $\mathcal{P} = \left\{\mathbf{O}^1, \ldots, \mathbf{O}^4\right\}$ be a randomly generated set of four solution points, as shown in Table D.2. These solution points are arranged into two clusters, $C_1 = \left\{\mathbf{O}^3, \mathbf{O}^4\right\}$ and $C_2 = \left\{\mathbf{O}^1, \mathbf{O}^2\right\}$, based upon maximal cosine similarity values calculated using function in 3.21. Then, for all solution points in Table D.2, the function $\mathbf{F}$ in (13) is computed as, $\mathbf{F}\left(\mathbf{O}^1\right) = (0, 1, 0, 0, 1)^{\mathrm{T}}$, $\mathbf{F}\left(\mathbf{O}^2\right) = (1, 0, 0.4908, 0, 1)^{\mathrm{T}}$, $\mathbf{F}\left(\mathbf{O}^3\right) = (0.72, 0.1271, 1, 0, 0)^{\mathrm{T}}$, $\mathbf{F}\left(\mathbf{O}^4\right) = (0.2851, 0.1750, 0.5664, 0, 0)^{\mathrm{T}}$. Then, the distance function for each solution point pair $\left(\mathbf{O}^p, \mathbf{O}^q\right) \forall \mathbf{O}^p \in C_1, \forall \mathbf{O}^q \in C_2$ is computed using (15) as, $d_\varepsilon\left(\mathbf{O}^p, \mathbf{O}^q\right) = \max\left(\mathbf{F}\left(\mathbf{O}^p\right) - \mathbf{F}\left(\mathbf{O}^q\right)\right)$. For example, $d_\varepsilon\left(\mathbf{O}^3, \mathbf{O}^1\right) = 0.2806$, $d_\varepsilon\left(\mathbf{O}^3, \mathbf{O}^2\right) = 0.1429$, $d_\varepsilon\left(\mathbf{O}^4, \mathbf{O}^1\right) = 0.1590$, $d_\varepsilon\left(\mathbf{O}^4, \mathbf{O}^2\right) = 0.1234$, $d_\varepsilon\left(\mathbf{O}^1, \mathbf{O}^3\right) = 0.6153$, $d_\varepsilon\left(\mathbf{O}^1, \mathbf{O}^4\right) = 0.5816$, $d_\varepsilon\left(\mathbf{O}^2, \mathbf{O}^3\right) = 0.4530$, $d_\varepsilon\left(\mathbf{O}^2, \mathbf{O}^4\right) = 0.4530$.

The indicator function value for an ordered pair cluster (C_1, C_2) is then defined using function in 3.18 as, $\mathcal{I}_{\varepsilon^+}(C_1, C_2) = \min\{0.2806, 0.1429, 0.1590, 0.1234\} = 0.1234$. Similarly, for ordered pair (C_2, C_1), indicator function value is calculated as, $\mathcal{I}_{\varepsilon^+}(C_2, C_1) = \min\{0.6153, 0.5816, 0.4530, 0.4530\} = 0.4530$. Since, $\mathcal{I}_{\varepsilon^+}(C_1, C_2) < \mathcal{I}_{\varepsilon^+}(C_2, C_1)$ thus C_1 Pareto-dominates C_2. The EvCo next iterates for the number of generations M=300 and produces an optimal solution $\mathbf{O}^*$. The rate achieved by each WSO, $w \in \mathcal{W}$ is then calculated using $\mathbf{O}^*$ as shown in Table D.1.

Table D.1: EvCo Input Parameters

WSO Number(w)	Input parameters to the EvCo				Achieved rate
	O_w	n_w	$\mathrm{SINR}_{w,j}$	d_w (mbps)	r_w (mbps)
1	0.95	1	6.7799	16.8706	10.1353
2	0.50	1	6.5284	8.7370	3.8802
3	0.40	2	7.8409	15.0921	10.4611
4	0.70	1	4.8911	10.7459	3.7024
5	0.90	1	5.4754	14.5528	6.4049

Table D.2: Solution Points

WSO Number(w)	C_1				C_2			
	Solution $\mathbf{O}^3$		Solution $\mathbf{O}^4$		Solution $\mathbf{O}^1$		Solutino $\mathbf{O}^2$	
	$O_{w,1}$	$O_{w,2}$	$O_{w,1}$	$O_{w,2}$	$O_{w,1}$	$O_{w,2}$	$O_{w,1}$	$O_{w,2}$
1	0.6979	0	0.5757	0	0.4972	0	0.3418	0
2	0	0.1672	0	0.2223	0	0.3161	0	0.3766
3	0.3021	0.2235	0.4243	0.1352	0.1591	0.2442	0.3066	0.3655
4	0	0.2424	0	0.2462	0	0.4397	0	0.2579
5	0	0.3669	0	0.3963	0.3437	0	0.3516	0

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Curriculum Vitae

Name	:	Muhammad Asif Raza
Birth Date	:	Jul 7, 1979
Birth Place	:	Vehari, Punjab, Paksitan
Permanent Address	:	Asif and Co., khaniwal road graha more, Distt. vehari, Pakistan

Education

2011.09–2018.02 **Ph.D.** Electrical Engineering and Computer Science, Gwangju Institute of Science and Technology (GIST), Gwangju, South Korea.

2004.11–2006.07 **M.S.** Master of Science (Information Technology), National University of Science and Technology (NUST), Islamabad, Pakistan.

2000.01–2003.11 **B.S.** Computer Science, University of Central Punjab (UCP), Lahore, Pakistan.

Work Experience

2011.09–present **Research Assistant**, GIST, Gwangju, South Korea.

2006.08–2011.04 **Sr. Research Associate**, Al-khawarizmi Institute of Computer Science, UET, Lahore, Pakistan.

Achievements and Awards

1. Received the scholarship for M.S. study at NUST.
2. Received the award of Korean Government Scholarship for Ph.D. study at GIST.

Publications

SCI Journals:

1. **M. Asif Raza**, Zafar Iqbal, Sang-Seon Byun, Hyunduk Kang, and Heung-No Lee, "A Versatile Coexistence Decision-Making System for Efficient TV Whitespace Sharing among Whitespace Objects," *Accepted for Publication in Wireless Communications and Mobile Computing, Hindawi*, Aug. 2017.

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