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Multi-objective Spectrum Assignment in Heterogeneous Cognitive Radio Networks for IoTs

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Summary

Internet of Things (IoT) applications have massively increased in the last few years. Future-generation IoTs are going to be massive in number, heterogeneous in nature, and extremely demanding in terms of computation and communication requirements. Therefore, effective techniques are needed to optimize the use of scarce communication resources. This work proposes a novel multi-objective framework to investigate the channel assignment problem in cognitive radio network (CRN)-based IoT applications. The multi-objective optimization framework comprises three objective functions. The first objective aims to maximize the overall system throughput fairness, the second objective aims to maximize the overall system residual energy, and the third objective aims to increase the user satisfaction level by maximizing the overall priority index. The problem of channel assignment is modeled and solved using Mixed Integer Linear Programming (MILP) and ϵ-constraint technique. This technique generates a set of Pareto efficient solutions and an optimal solution among these solutions is selected using a fuzzy logic decision mechanism. Moreover, power level selection is incorporated by solving the problem multiple times for different power levels and obtaining a preferred solution for each power level. The simulations are conducted to unveil an interesting trade-off between the conflicting system design objectives i.e., the overall throughput and the overall residual energy while incorporating the significance of Primary User (PU) activity when preforming channel assignment in CRN.

KEYWORDS:
Internet of Things, Cognitive Radio Network, Multi-objective Optimization, Fuzzy Logic

1 | INTRODUCTION

Over the last few years, Internet of Things (IoT) applications have seen massive growth. IoT-based applications have changed the way human beings look at and accomplish their daily tasks. The presence of IoTs in human life is only going to get more ingrained with the passage of time[1]. In the future, IoT-based applications are projected to enter the realm of holographic communications, which require real-time data transmission in the range of gigabits per second or even terabits per second[2]. Another possible future application of IoT is in the domain of Wireless Brain Computer Interface (WBCI). WBCIs will provide the interface between the human brain and external IoTs, and they will allow humans to control devices in their smart homes, smart cities, and medical systems in a simple yet more intelligent and powerful way[3]. Fully autonomous driving[4], smart cities, and smart education[2] are few of the numerous possible applications that are projected to disrupt the way humans look at their daily lives in the future. The current and future IoT applications are not only compute- and data-intensive, they also require massive connectivity, where everything is required to be connected to the internet; hence the concept of "Internet of Everything (IoE)[5]. In the future, IoT devices will see their deployment expanded from smart homes and smart cities to deep into the sea, earth, and even space[6].

As mentioned above, the current and future applications of IoTs are going to put a huge pressure on wireless communication technologies in terms of connectivity and data rates, eventually resulting in a huge increase in the demands on the radio spectrum. This explosive demand for wireless communication services, driven by economic and technical forces, is going to lead to a tremendous solicitation of limited radio resources such as bandwidth and energy. Therefore, efficient sharing of radio resources in future wireless networks is a subject of paramount importance. Traditionally, the spectrum regulatory authorities employ a static spectrum assignment policy to share the radio resources in wireless communication systems. Although static spectrum assignment avoids interference by exclusively assigning different frequency bands to different wireless systems, it can lead to inefficient spectrum utilization. This problem is widely researched and has been addressed by scientists in industry and academia alike. The researchers are trying to address the issue of spectrum shortages, which are expected to arise in the future largely because of the ever-increasing number of wireless applications and devices. To mitigate this problem, cognitive radio networks (CRNs) have gained overwhelming recognition in the world of wireless networks in the past[7]. The CRN technology ensures the effective usage of underutilized frequency bands; hence satisfying the ever-increasing needs of IoT applications[8,9,10].

In CRNs, unlicensed/secondary users (SUs) are allowed to access an idle/unused portion (spectrum holes) of the licensed spectrum as long as they do not interfere with the licensed/primary users (PUs). Thus, it is necessary for SUs to be smart enough to be capable of sensing channel interference, learning from the environment, and having the capability to dynamically access the spectrum[11,12,13]. An SU should dynamically utilize the spectrum holes, and in order to do that, it should be able to adapt its operating parameters as per the requirements of the surrounding environment. During this whole process, it should not harm the interest of PUs. To be specific, the SU should constantly sense the operating frequency channel and it should never block access to the channel for a PU if required. So, in order to enable dynamic spectrum access (DSA), the operation of the CRN should address two essential issues. The first one is identifying spectrum holes by performing spectrum sensing and the second one is providing an efficient assignment of these spectrum holes among SUs[14]. Recently, several works have addressed the first issue of whether spectrum sensing is utilized in a cooperative or non-cooperative manner. As far as the second issue is concerned, it is largely an open research question and a challenging problem as it involves multiple users and multi-channel CRNs[15]. Therefore, in this work, our objective is to find an optimal channel assignment strategy that can efficiently utilize the radio resources provided that the SUs can sense the holes in the spectrum. By answering this question, we intend to address the issues faced by current and future IoT applications.

Channel assignment is a fundamental function that involves the assignment of the most appropriate frequency band to an SU that is seeking access to the channel. There are multiple criteria that determine the channel assignment. Some of them include maximizing the throughput, minimizing the energy consumption, and utilizing the channel resources in the most fair manner. Any channel assignment technique seeks to achieve one or multiple of the aforementioned objectives while minimizing the interference to PU's operation. The spectrum holes identified through spectrum sensing are used as inputs to the channel assignment. This helps in finding the optimum channel that SU can use according to its requirements[16]. The procedure for solving the channel assignment problem can be divided into following three steps: 1) defining the target objective function; 2) formulating the channel assignment problem; and 3) defining the technique to solve the channel assignment problem[17].

There are several works reported in the literature for channel assignment in CRN with different target objective functions. To the best of our knowledge, most of the approaches for channel assignment for CRN are considered single-objective, whereas the channel assignment problem with multi-objective functions has not been well investigated. The channel assignment techniques serving a single objective can be useful in scenarios where all the users are homogeneous in nature and have similar Quality of Service (QoS) requirements. In such a scenario, satisfying individual requirements leads to global optimality. However, in a scenario where users with heterogeneous requirements are involved, satisfying the global requirement may not satisfy the individual requirements, and vice versa. In such a scenario, individual requirements might even conflict with the global optimality, and individual requirements like throughput, energy efficiency, or fairness might have to be sacrificed in certain cases for the global optimality. Moreover, the system with a single objective function does not offer any flexibility in the trade-off between different conflicting design objectives; hence, a multi-objective framework considering different objectives for channel assignment in CRN is desired.

In this work, we propose a multi-objective framework for the optimization of the channel assignment problem in CRNs used by

IoT applications. For this problem, three target objective functions are considered:
Function 1 (F1): The sum of proportional fairness-based throughput achieved by all SUs.
Function 2 (F2): The sum of the expected residual energy of all SUs.
Function 3 (F3): The sum of the priority index dependent on the PU activity.
A framework comprising a lexicographic optimization-based augmented ε-constraint method to solve this problem is presented. The augmented ε-constraint method generates a set of efficient Pareto optimal solutions. Moreover, a decision-maker based on fuzzy logic is proposed to find the preferred solution among these Pareto optimal solutions. Furthermore, to incorporate the power level selection mechanism into this framework, an iterative approach is introduced in which the multi-objective problem is solved for different power levels. This procedure results in a set of preferred solutions, one for each power level. Finally, the most preferred solution (best compromise solution) is obtained by employing a fuzzy logic based multi-criteria decision maker on the set of preferred solutions. One of the practical applications of this work could be the creation of smart buildings that include a variety of home appliances and other systems like patient monitoring and security systems. When we consider various home appliances, we find that they typically do not require the transmission of large amounts of data, but at the same time, they need transmission methods that use the least amount of energy. On the other hand, the security system installed throughout the building requires a large amount of data to be communicated, which requires more bandwidth, whereas the patient monitoring systems must send critical data that requires integrity and urgency, which is why these devices should be prioritized in terms of network access. A point-wise summary of the main contributions of this work is given below

- Development of a novel multi-objective channel assignment framework for the multi-user and multi-channel heterogeneous CRN environment that is being used by end IoT devices.
- Proposing an augmented ε-constraint method to solve the multi-objective optimization problem and provide a set of Pareto efficient solutions.
- Application of a fuzzy logic-based multi-criteria decision maker that enables to obtain a preferred solution to satisfy diverse requirements of IoT devices.
- To make this work applicable to low-power devices, an iterative approach is developed to select the most preferred solution with a suitable power level.

In the rest of the paper, Section 2 details the work related to this paper and also highlights the difference between this work and the existing state-of-the-art work. Next, in Section 3, the system model used in this work is presented. This section also details multiple objective functions that we intend to optimize in this work. These objectives include throughput, residual energy, and priority index. This section also discusses a multi-objective problem formulation based on these objective functions and the constraints associated with this problem formulation. Section 4 presents details about our proposed augmented ε-constraint method. This section also discusses a decision-making process that is based on fuzzy logic. It is a multi-criteria process that solves the above mentioned multi-objective optimization problem. Section 5 presents the fuzzy logic and augmented ε-constraint method based framework to select the suitable power level and channel assignment for CRN. Section 6 presents the simulation framework and discusses the results obtained through this framework. This section also sheds light on the significance of the framework and the obtained results. Section 7 finally concludes this work with discussion on future work.

2 | RELATED WORK

Channel assignment is one of the most critical aspects of CRNs. Through efficient channel assignment, the effective operation of primary and cognitive radio networks is ensured. The aim of effective channel assignment is to assign channels to SUs in such a way that they do not interfere with the operation of PUs and at the same time ensure optimal performance of the spectrum. There are many surveys and existing studies on channel assignment in CRN[18]. In this section, we explore in detail the existing work on channel assignment in CRN. We discuss different research works that use various objective criteria to optimize the channel assignment in CRNs.

Throughput maximization is the most common criterion for channel assignment in any wireless network. Several studies have addressed the problem in CRNs, in which throughput maximization for channel assignment has been addressed in two ways. First, there are studies in the literature that look at the throughput locally and optimize the throughput of individual SUs with a disregard for the global network throughput. Then, there are studies in the literature that address the throughput optimization problem in a global manner and strive to maximize the global throughput of the whole network. Authors in[19] propose a channel assignment approach for multichannel CRN. The aim of the technique is to maximize the overall throughput of the network, with the constraint that each SU power must be lower than the maximum power. However, since the given target objective is to maximize the throughput, it is expected that every SU should transmit with the maximum allowed transmit power; hence, Li et al.'s approach may not work for energy constrained CRNs. Authors in[20] propose a distributed channel assignment algorithm in CRNs for throughput maximization that does not involve cooperation among SUs. Due to this lack of cooperation, the first SU may select the best channel to maximize its throughput without consideration of the other SUs, which may cause unfairness. Several other techniques that lack fairness or energy constraint considerations[21,22] have also been proposed. Since the objective function of maximizing throughput of individual SUs or of the overall network can create unfairness, to avoid such a case, a number of other works, such as[23,24,25], consider maximizing the throughput fairness among SUs. This is done either by maximizing the minimum average throughput per SU or using a fairness factor. However, there are a couple of limitations to these works: first, they do not consider the PU activity; second, they consider achievable bandwidth to be equal over every channel so that fairness can be measured by the number of channels allocated to each SU.

Energy efficiency is another important criterion for channel assignment in CRN and becomes even more critical for energy constrained CRN. Although a number of works exist with respect to channel assignment in CRN in general, there are relatively few of them that focus on the energy efficiency issue. Authors in[26] present a novel mechanism for SUs to access the CRN. The proposed mechanism optimizes the overall energy efficiency of the SUs. The proposed mechanism works in such a way that the SUs can sense the entire spectrum at the beginning of each slot. Then, based on the proposed channel selection and power allocation algorithms, the SUs select the slots that result in the overall optimized energy consumption of the system. The authors in[27] formulated the channel access mechanism as an optimization problem. The objective function of the mechanism is to maximize energy efficiency by minimizing the transmission power on the selected channel. Authors in[23] present another mechanism that dynamically allocates the spectrum to SUs. The underlying objective of this mechanism is to improve overall energy efficiency while maintaining fairness in the system. The proposed mechanism leverages modified game theory to centrally control the allocation of spectrum to SUs in such a way that the spectrum is utilized to its maximum while maintaining fairness in spectrum allocation. The work in[28] proposed an event detection and channel allocation scheme for an energy-constrained CRN. The channels are characterized based on parameters such as PU arrival rate, channel quality, collision, and congestion. The best channel is assigned to the highest-priority SU. The ultimate objective of the proposed scheme is to maximize the reward, which is calculated based on the priority of the matrix associated with the SU. A couple of limitations are there though. First limitation is the problem of maximizing energy efficiency. This limitation is transformed into minimizing the transmission power of the SUs. Second limitation is the overall network energy which is attempted to be maximized. This limitation may not care about the individual SU energy and may lead to depletion in network lifetime. To cope with these limitations, the authors of[29] presented a residual energy-aware channel assignment scheme for energy-constrained CRN. The objective of the scheme is to prolong the life of CRN nodes through energy optimization. For this purpose, the authors in[29] use the R-coefficient, which estimates the residual energy of the network. However, the major limitation of this work is that it ignores throughput. Another criterion is priority, which can be defined based on the spectrum/channel characteristics. Only a few works have considered this so far, such as[30,31,32], where the spectrum characteristics i.e., 802.11 bands or 3G, are the decisive factor defining the priority of an SU for a particular channel.

Cognitive radio is useful in several technologies, including wireless sensor networks (WSNs), machine-to-machine communication (M2M), the IoT, and long-term evolution (LTE). These technologies are in widespread use in a range of diverse applications, ranging from surveillance to healthcare[33]. Each application may have different requirements in terms of throughput, residual energy, or any other optimization objective[34]. For example, if we look specifically at CRN-based IoT applications, the authors in[8] present a framework that ensures reliability in channel assignment for IoT devices. Similarly, the authors in[11] present a technique that takes into account the heterogeneous nature of IoT devices and satisfies their diverse communication requirements through an enhanced spectrum reservation framework. Authors in[12] present another energy efficient channel assignment for distributed CRN-based IoT devices. Yet, none of the single objective problems presented in the previous studies for channel assignment in CRN allow for flexibility in the trade-off of the conflicting objectives. Hence, a framework is desirable that can offer flexibility in different objectives according to the needs of the application. In this work, we present a novel framework for channel assignment in CRN that includes multiple-objective optimization incorporating a number of target objective functions and constraints. These objective functions and constraints have never been considered collectively in any existing framework and they include throughput fairness maximization, residual energy maximization, priority maximization, power level selection, and ensuring a limit on interference to PU.

3 | SYSTEM MODEL AND PROBLEM FORMULATION

3.1 | Nomenclature

In this paper, we use a number of notations and symbols. These notations and symbols with explanation are given in Table 1.

3.2 | System Model

In CRN, the PUs and SUs exist in similar geographical regions. However, they do not talk to each other. Normally, the SUs sense the spectrum availability, and they share this information with other SUs in the vicinity. This spectrum sensing and sharing information is mainly used to improve the overall spectrum utilization and is usually performed in an opportunistic manner[35]. To access information about spectrum availability, SUs need access to a control channel[36]. CRNs normally span a lot of geographical areas, and having a common control channel that covers the entire CRN is not viable. This becomes particularly important when the devices in the CRN are low-powered. In such a scenario, it is good to have control channels that have restricted geographic boundary[37,38]. In this work, we term such a scenario a cluster-based configuration, where each cluster has a number of SUs. Furthermore, in this work, an entire CRN means a cluster of clusters.

An example of one such cluster-based CRN is shown in Figure 1. In this figure, a single cluster is presented, comprising various types of Cognitive Radio (CR) based IoT nodes, often referred to as Secondary Users (SUs), each with diverse requirements. Within this cluster, individual nodes exhibit distinct needs concerning throughput, latency, and energy consumption. Furthermore, this cluster incorporates a designated node acting as the cluster head. Moreover, in the proximity, there exists a primary network with numerous primary nodes. These SUs have to coexist along with these primary users. A complete CRN will consist of a number of such clusters. We call such CRN a cluster-based CRN, where it is assumed that a channel assignment in one cluster will lead to channel assignment in the entire network, thus resulting in cooperative channel assignment in a cooperative manner. In our system model, we assume that there are N+1 SUs in a cluster. Every cluster has a cluster head (CH) (ref Figure 1), who is responsible for assigning the channels to the SUs in the cluster. Furthermore, it is assumed that there are M+1 channels in the cluster, with one channel acting as the control channel. The control channel is assumed to be free at all times, with no activity by the PU on the control channel. Apart from the control channel, every other channel is available to be used by PU or SU at mutually exclusive times. This work specifically focuses on the channel assignment problem, and the discussion on the CH and control channel selection mechanisms is beyond the scope of this paper. As far as the SUs in a cluster are concerned, it is assumed that they are free to move within the cluster boundary and that they are just one hop away from the cluster head. Finally, the CH is assumed to have no constraints regarding energy consumption.

The overall system model can be divided into three parts: spectrum sensing, spectrum assignment, and data transmission. Figure 2 depicts the frame structure, where each frame contains the durations for three steps, i.e., spectrum sensing (SS), channel assignment (CA), and transmission (TX). In this figure, τ_s, τ, and T denote the durations of spectrum sensing, spectrum sensing and channel assignment, and whole frame length, respectively. In the spectrum sensing step, the SU discovers spectrum holes by detecting the presence of PU. In spectrum sensing, it is assumed that the behaviour of PU is consistent over M channels. In general, in most CRN studies, PU traffic is considered to be independent and is distributed identically through an OFF/ON process[39,40,41]. In this process, the ON and OFF states are indicative of whether the channel is in use or not. As evident, the OFF state means that the channel is not in use by PU, and an ON state indicates the contrary.

Let T_{on} and T_{off} be the exponential random variables, which denote the busy and idle duration of a channel, respectively. Given that, t_{on} and t_{off} denote the mean busy and idle durations, respectively, the probability of channel occupancy Pr_{on} and probability of PU absence Pr_{off} can be written as 1, 2.

$$Pr_{on} = \frac{t_{on}}{t_{on} + t_{off}} \tag{1}$$

$$Pr_{off} = \frac{t_{off}}{t_{on} + t_{off}} \tag{2}$$

In this work, we focus on the spectrum sensing and channel assignment problem. For this purpose, it is assumed that the SUs can sense all the M channels of the CRN through any of the spectrum sensing techniques. These techniques can be sensing through

TABLE 1 Notations and Definitions

N+1	Number of SUs in the cluster
M+1	Number of licensed primary channels
τ_s	Time duration of spectrum sensing
τ	Time duration of spectrum sensing and channel assignment
T	Time duration of a frame
Pr_{on}	Probability of channel occupancy by PU
Pr_{off}	Probability of PU absence over a channel
Ψ	Set of empty/idle primary channels available for SUs
K	Number of channel in Ψ
Ω_k^i	Throughput achieved by i^{th} SU over k^{th} channel
γ_k^i	SINR between ith SU and CH over k^{th} channel
p_{ik}^T	Transmission power of i^{th} SU over k^{th} channel
g_{ik}	Channel gain between i^{th} SU and CH over k^{th} channel
I_k	Interference temperature constraint on k^{th} channel
g_{mk}^i	Channel gain from i^{th} transmitter at location m in k^{th} channel
α	Path loss exponent
β_i	Proportional fairness weight assigned to i^{th} SU
R_i^c	Current residual energy of the i^{th} SU
R_i^k	Expected residual energy of i^{th} SU if assigned k^{th} channel
s_k^i	Priority value assigned to i^{th} SU over k^{th} channel
Ω^i	Data rate demand for i^{th} SU
Z	Set of efficient Pareto optimal solutions
Z'	Set of preferred solutions
W_i	Preference given to i^{th} objective function
P	The total power for a cluster
σ_k	Probability of PU re occupancy over k^{th} channel

a matching filter, measuring energy consumption[42], or feature detection[43]. Moreover, we also assume that no imperfections are associated with spectrum sensing and that the probability of spectrum misdetection and false alarm is less than 0.1. The spectrum sensing process is performed by the SUs in a collaborative manner, and the results of spectrum sensing are reported by the SUs to CH through the control channel of the cluster. The spectrum sensing process builds up a pool of available channels denoted

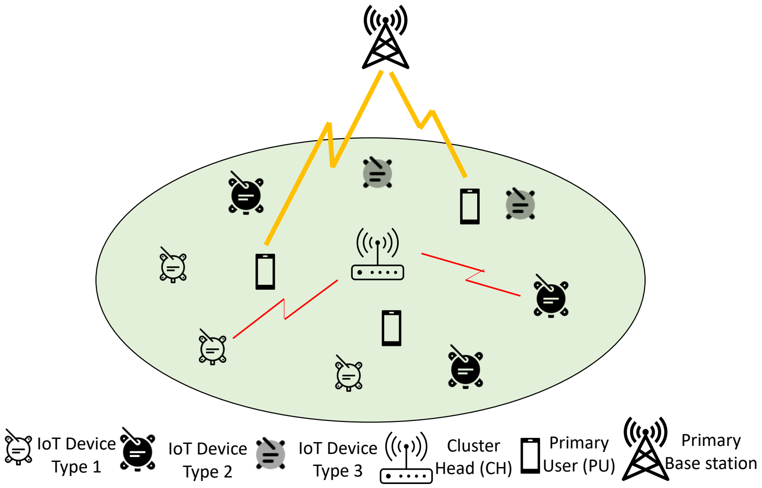


FIGURE 1 A Sample Cluster in a Cluster-based Cognitive Radio Network

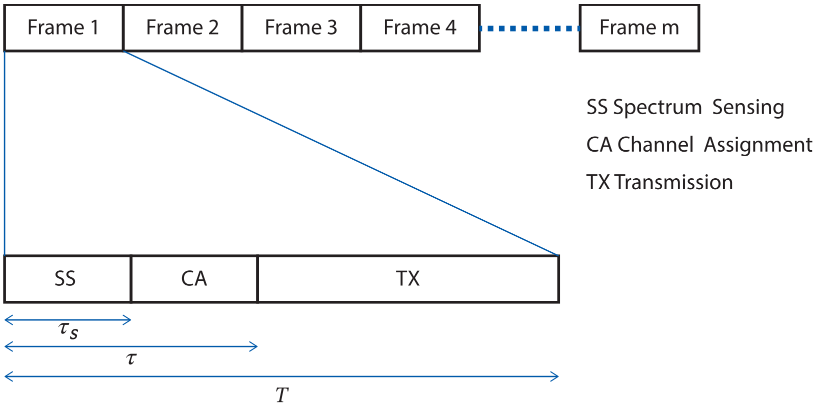


FIGURE 2 Frame Structure Describing Spectrum Sense, Channel Assignment, and Data Transmission Durations in Cognitive Radio Network

by ψ with K number of channels, where $K \leq M$.

During the spectrum sensing process, the CH has to continually assign ψ channels to N SUs. In order to complete the assignment, every SU that has data to send over the channel sends a request message to CH (i.e. $CA_Request$). This request message is sent to CH through the control channel. The request message also contains the desired QoS parameters, based on which the CH has to make a decision. The CH receives multiple request messages from SUs, and then, based on the QoS requirements, it broadcasts a reply message (i.e. CA_Reply). In response to the reply message, the concerned SU adjusts its parameters and broadcasts its message on the relevant channel. The whole process, starting from spectrum sensing to data transmission, is also depicted in Figure 3. It can be seen from this figure that SU first senses the spectrum. Secondary user then sends a channel assignment request. Upon receiving request, CH evaluates the parameters and broadcasts its reply. After receiving the reply, SUs adjust their parameters and the SU with the permission to access the channel sends the data over relevant channel.

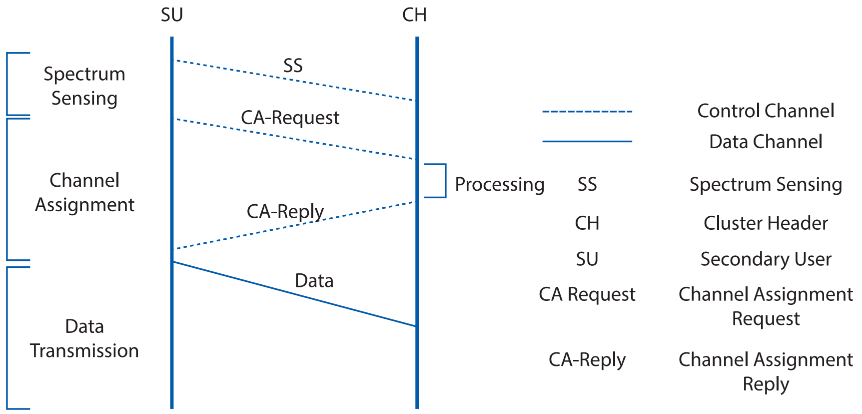


FIGURE 3 Channel Assignment Process Between Between Secondary User and Cluster Head

3.3 | Problem Formulation

The channel assignment problem in wireless networks can be divided into three steps. The first is the defining criteria, or the target objective function that is required to be achieved. The second step is the formulation of the problem through a model, and the third step is the way to solve the problem. Some of the most commonly used criteria that are used for channel assignment include maximization of throughput, reduction of interference, power optimization, optimizing the energy efficiency, and a fair use of channel resources. In this section, some of the relevant criteria are defined and problem formulation is done using them.

3.3.1 | Throughput/Data rate Maximization (F_1)

Throughput is the most important criteria in channel assignment for CRN. Throughput is a function of the signal-to-interference plus noise ratio (SINR). For an i^{th} SU communication with CH over channel k, the throughput denoted by Ω_k^i can be written as

$$\Omega_k^i = Blog_2(1 + \gamma_k^i)\left(\frac{T - \tau}{T}\right) \tag{3}$$

where B is the bandwidth of the channel in Hz, γ_k^i denotes the SINR, $T - \tau$ is the transmission duration. The γ_k^i can be determined as:

$$\gamma_k^i = \frac{p_{ik}^T g_{ik}}{N_o + \sum_{j=1, j\neq i}^{N} p_{jk}^T g_{jk}} \tag{4}$$

In the above equation p_{ik}^T is the transmission power of i^{th} SU over channel k, g_{ik} represents the channel gain over k^{th} channel, and N_o indicates the noise spectral density. In equation 4, the term $\sum_{j=1, j\neq i}^{N} p_{jk}^T g_{jk}$ indicates the interference caused by other users that are in the transmission range of the cluster head. The criteria of maximizing the throughput can create unfairness in the spectrum distribution among SUs, which, in the worst case, can even lead to starvation for some SUs. To avoid such a case, we have considered maximizing throughput fairness as one of the objective. The throughput fairness can be represented as $\beta_i \Omega_k^i$. To update β_i, we used the concept explained in[44], which can be mathematically expressed as:

$$\beta_i (r + 1) = \left(1 - \frac{1}{t_c}\right) \Omega^i(r) \tag{5}$$

Where r is the current frame $\Omega^i(r)$ is the average throughput of i^{th} SU in a past window of length t_c. CRN also has the constraint on interference that SUs should create no or limited interference to PU. Hence, interference is another important criterion for designing efficient channel assignments in CRN. To deal with such interference, many works[45,46,47] are based on the term Interference Temperature Limit (ITL). ITL is the RF power measured at a receiving antenna per unit bandwidth. For a given channel, for which the ITL limit is not exceeded, it can be made available to SUs. According to the work in[47], in order to satisfy the ITL constraint, the total received power at a specified measurement point over a channel k must satisfy $\sum_{i=1}^{N} p_{ik}^T g_k^i(m) \leq I_k$, where $g_k^i(m)$ is the channel gain from i^{th} SU to the measurement point m and $I_k > 0$ is a predefined threshold.

3.3.2 | Energy Efficiency (F_2)

Another important criterion is energy efficiency $\left(F_2\right)$, which becomes even more important in energy constrained CRN. In this work, the aim is to maximize the sum of the expected residual energy denoted by R_i^k of all SUs in order to prolong the lifetime of the network. According to[29], the expected residual energy computation of i^{th} SU R_i^k can be computed as:

$$R_i^k = R_i^c - E_i^k \tag{6}$$

In equation 6, R_i^c is the current residual energy and E_i^k is the energy consumed by i^{th} SU if assigned the k^{th} channel. E_i^k consists of four components. These components are the energy consumed in sensing the channel, transmitting and receiving the data, and the last one when nothing is being done. We denote here p_i^S as the power consumed in sensing the channel, p_i^R as the power consumed in receiving the data, and p_i^T as the power consumed while transmitting the data. The transmission power p_i^T can be represented as:

$$p_i^T = p_{RF} + p_A d_i^{\alpha} \tag{7}$$

In equation 7, p_{RF} gives the energy consumed by the radio frequency circuit. Next, the term p_A is the amplifying power required by the transmitter to transmit the data; d indicates the distance between i^{th} secondary user and the cluster head; and α represents the path loss exponent. Depending on the activity of the PU, the energy consumed by the SU can have two possible scenarios.

Case I

In the absence of PU, when no false alarm is generated, the energy consumed by i^{th} SU over k^{th} channel can be written as

$$E_k^i = p_i^s \tau_s + p_i^P(\tau - \tau_s) + p_i^T(T - \tau) \tag{8}$$

Case II

In the presence of PU, when SU is able to detect PU accurately, the energy consumed by i^{th} SU over k^{th} channel can be written as

$$E_k^i = p_i^s \tau_s \tag{9}$$

3.3.3 | Priority (F_3)

Another important criterion is the priority $\left(F_3\right)$, which can be defined in two ways: 1) by categorizing the available channels depending on the PU activity, and 2) by categorizing the SU in different classes depending on their application requirements. In this work, we categorized the channels depending on the level of PU activity. The priority of i^{th} SU over k^{th} channel denoted by s_k^i can be computed as

$$s_k^i = \frac{1}{\sigma_k} \tag{10}$$

where σ_k is the probability of PU re-occupancy over the k^{th} channel selected by SU. Since the idle time of k^{th} channel is expressed as exponential random variable $T_{off}(k)$, then the probability that a PU comes back over k^{th} channel is equal to Pr $\left(T_{off}\left(k\right) \leq \frac{T}{R}\right)$[30] and it can be expressed as

$$\sigma_k = 1 - e^{-\frac{T}{R(k) \times t_{off}(k)}} \tag{11}$$

Where R(k) is the data rate over k^{th} channel and $t_{off}(k)$ means off time over k^{th} channel.
In practice, all three objective function F_1, F_2, F_3 explained above are desirable from the QoS perspective of the SUs. Therefore, in this work, we considered them jointly and formed a multi-objective optimization problem for channel assignment in CRN. The mathematical representation of the problem is as follows:

Determine $x = \left[x_1^1, \ldots, x_1^N, \ldots., x_K^1, \ldots, x_K^N\right]^T$

To Maximize:

$F_1 = \sum_{k=1}^{K} \sum_{i=1}^{N} \Omega_k^i x_{ik},$
$F_2 = \sum_{k=1}^{K} \sum_{i=1}^{N} R_k^i x_{ik},$
$F_3 = \sum_{k=1}^{K} \sum_{i=1}^{N} s_k^i x_{ik}$

Subject to

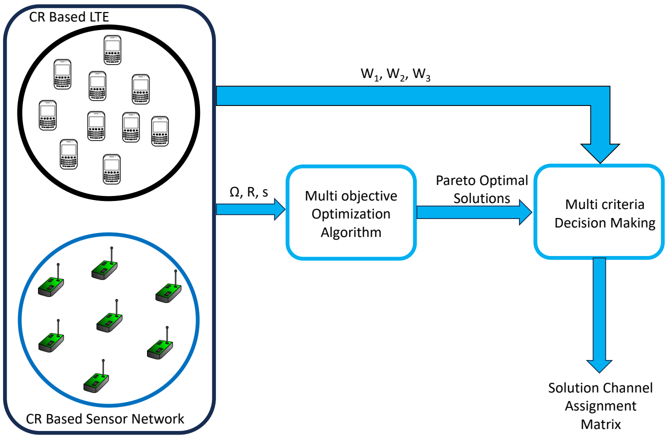


FIGURE 4 Process Diagram of Proposed Multi-objective Channel Assignment Framework in Cognitive Radio Network

$$\begin{aligned}
C1 &: \sum_{k=1}^{K} x_{ik} = 1, \sum_{i=1}^{N} x_{ik} = 1, \qquad \forall\, i, k for N = K \\
C2 &: \sum_{k=1}^{K} x_{ik} \leq 1, \sum_{i=1}^{N} x_{ik} = 1, \qquad \forall\, i, k for N > K \\
C3 &: \sum_{k=1}^{K} x_{ik} = 1, \sum_{i=1}^{N} x_{ik} \leq 1, \qquad \forall\, i, k for N < K \\
C4 &: \sum_{i=1}^{N} \left[p_k^i g_k^i (m)\right] x_{ik} \leq I_{max} \qquad \forall\, i, k \\
& x_{ik} \in \{0, 1\} \qquad \forall i, k
\end{aligned} \tag{12}$$

Here, constraints $C1, C2, and C3$ show the constraints on channel assignment for three cases. In the first case, if $N = K$, number of SUs is equal to the number of available channels. In the second case, if $N > K$ those K available channels are assigned to K selected SUs, whereas the remaining $N - K$ SUs cannot transmit in this frame. In third case, if $N < K$, the N selected channels get assigned to N SUs, and the remaining $K - N$ channels will not be used in this frame because each SU possesses a single antenna. In equation 12, C4 indicates the interference temperature constraint, and x_{ik} is the decision variable. Its value is either 0 or 1 where $x_{ik} = 1$ indicates that channel k is assigned to the i^{th} SU.

4 | PROPOSED MULTI-OBJECTIVE CHANNEL ASSIGNMENT FRAMEWORK

Figure 4 depicts the process diagram of the proposed multi-objective channel assignment framework in CRN. The CRN may consist of different CR-based networks. First, each network computes achievable throughput, expected residual energy, and priority index matrices denoted by Ω ,R, and S respectively. Each matrix has N × K dimensions, where N is the number of SUs and K is the number of available channels. Given Ω, R, S to the multi-objective optimization algorithm results in a set of Pareto optimal solutions. To select a particular solution among the Pareto optimal solutions, the network specifies its preference by using weights W_1, W_2, W_3 corresponding to different objective functions. In order to construct a channel assignment matrix that contains a single optimal solution, a multi-criterion decision making process is used, with the weights and the set of Pareto solutions serving as inputs. Through the utilization of multi-objective optimization and the utilization of trade-offs between those objectives, this method is able to provide flexibility across a variety of objective functions. This is accomplished by finding a set of Pareto solutions through the utilization of multi-objective optimization. In addition to this, it makes use of a weighted multi-criteria decision-making approach, which enables it to take into consideration the myriad of diverse requirements that are posed by heterogeneous networks.

Multi-objective optimization can be used to solve problems consisting of conflicting objective functions. The problem given in

Equation 12 falls under the scope of multi-objective optimization as it combines the maximization of overall throughput and overall residual energy, which by nature conflict with one another. To increase the overall throughput, more energy needs to be consumed, which may in turn lead to a decrease in residual energy. Conversely, to increase residual energy, total energy consumption needs to be reduced, which may lead to a decrease in overall throughput. Hence, a trade-off exists between overall throughput and residual energy which gives rise to multiple solutions and there is not necessarily a unique solution that is best with respect to both objectives. Problems such as this are thus said to have a set of non-dominated solutions (or Pareto optimal solutions). In terms of pareto optimal solutions, the non-dominated solutions are classified as pareto dominant, pareto optimal, efficient pareto optimal, and weak pareto optimal solutions. Further explanation about non-dominant solutions is as follows[48].
Following is the concept of Pareto optimality with the assumption that the entire L objective functions $F_i, i = 1, \ldots L$ in the considered multi-objective optimization problem are for maximization.

Pareto Dominance *(Definition)*: "A solution x is said to dominate a solution x', if the value of the entire L objective functions $F_1(x), \ldots, F_i(x), \ldots F_L(x), i = 1, \ldots L$, is at least the same as $F_1\left(x'\right), \ldots, F_i(x'), \ldots F_L(x'), i = 1, \ldots L, for L - 1$ objective functions and better with respect to one objective function".

Pareto Optimal Solution *(Definition)*: "A solution is said to be Pareto if it not dominated by any other solution in the solution space. The set of all the non-dominated solutions is known as Pareto front. The Pareto optimal solutions can be further categorized into weak and efficient Pareto solutions".

Efficient Pareto Optimal Solution *(Definition)*: "A solution to a multi-objective problem is Pareto efficient if no other feasible solution exists that is at least as good with respect to all objectives and strictly better with respect to at least one objective function".

Weak Pareto Optimal Solution *(Definition)*: "A solution to a multi-objective problem is weak Pareto solution if another feasible solution exists that is at least as good with respect to all objectives and strictly better with respect to at least one objective function".

The definitions given above can be further understood with the help of scenario given in Figure 5. Consider a simple example with two objective functions, $F_1 and F_2$. The feasible region of the two objective functions is shown in Figure 5. It can be noticed that among points A, B, and C, the point C dominates A and B because the value of F_1 is same for all three points, whereas the value of F_2 for C is greater than A and B. Therefore, A and B represent the weak Pareto optimal solutions, and C represents the efficient Pareto optimal solution. Likewise, between E and D, D is the efficient Pareto optimal solution, and E is the weak Pareto optimal solution because F_1 value for D is greater than E. The segment CD represents the efficient Pareto front. Since the efficient Pareto optimal solution dominates the weak efficient solution, in multi-objective optimization weak efficient solutions are not usually pursued[49].

Remark: To solve the problem in 12, it will be necessary to generate a set (Z) containing the Pareto efficient solution, which provides a set of Pareto optimal resource allocation solutions/policies. Then, depending on preference, a proper resource allocation policy can be selected for implementation.

4.1 | Generation of Pareto Optimal Solution Set Z

Various methods exist in the literature that are used to generate the Pareto optimal solution. Among the existing solutions, the most commonly used are the weighted method and the ϵ-constraint method. In the weighted method, different objective functions are assigned different weights. Then, through various combinations of different objective criteria weights, the combination that gives the best results is chosen. Contrary to the weighted method, in ϵ-constraint method, one objective function is optimized at a given time while other objective functions are treated as constraints. There are several advantages to the ϵ-constraint method over the weighting method. For example, for linear problems, the weighting method only generates extreme solutions, whereas the ϵ-constraint method can be used to generate both extreme and non-extreme solutions by altering the feasible region. Furthermore, for integer and mixed integer problems, the weighted method cannot produce unsupported solutions (e.g., point Q in Figure 5 indicates the unsupported solution) whereas the ϵ-constraint can. Lastly, with the weighted method, it is necessary to scale the different objective functions whereas with ϵ-constraint method this is not required. Since the multi-objective problem given in Equation 12 is a Mixed Integer Linear Programming (MILP) problem, in this paper we adopted ϵ–constraint to solve it. The

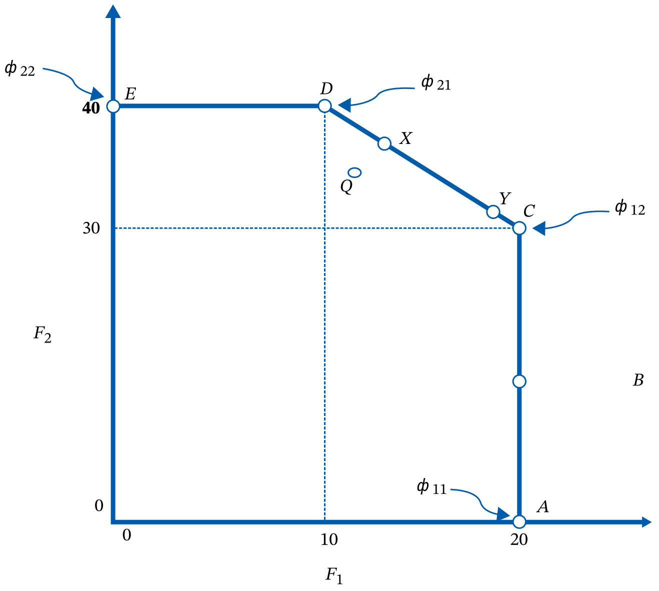


FIGURE 5 Pictorial Explanation of Various Pareto Optimal Solutions for Two Objective Function

problem in 12 can be written in ε–constraint form as follows:

$$\begin{gathered}
\text{Maximize} F_1(x) \\
\text{Subject to} \\
F_2\,(x) \geq \varepsilon_2 \\
F_3\,(x) \geq \varepsilon_3 \\
\dots \\
F_L\,(x) \geq \varepsilon_L \\
C1 - C4 \\
x_{ik} \in 0, 1
\end{gathered} \tag{13}$$

In order to solve a problem using equation 13, one must have the values of $\varepsilon_2, \varepsilon_3, \dots \varepsilon_L$. This means that at least the range of the (L-1) objective function needs to be determined. The easiest and most common way to find these ranges is using payoff table[50]. In this paper, the lexicographic optimization to construct the payoff table is presented. Mathematically, the payoff table denoted by ϕ can be written as a matrix.

$$\phi = \begin{bmatrix} F_1^* & \cdots & F_1^i & \cdots & F_1^L \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ F_i^1 & \cdots & F_i^* & \cdots & F_i^L \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ F_L^1 & \cdots & F_L^i & \cdots & F_L^* \end{bmatrix}$$

The optimum value of F_i is indicated by F_i^*. Practically, the lexicographic method for calculating the payoff table is performed as follows. First, the individual optima for each objective are calculated. Next, with the solution that optimizes $F_i, i = 1 \dots L$, $(F_i^*, theoptimalvalueof F_i)$, the value of other objective functions represented as $F_1^i, \dots, F_{i-1}^i, F_{i+1}^i, \dots F_1^i$ are calculated. In this way, repeat this process for every objective function. Finally, come up with a payoff table (ϕ) with a number of rows and columns that equal the number of objectives (i.e., L). The i^{th} row of the payoff table can be written as $F_1^i, \dots, F_{i-1}^i, F_i^*, F_{i+1}^i, \dots F_1^i$. The maximum and minimum values of the j^{th} column of the payoff table indicate the range of the j^{th} objective function (i.e., Fj) for the ε-constraint method.

For the sake of clarity, consider the example given in Figure 5 with two objective functions F_1 and F_2. The payoff table ϕ will be a 2 × 2 matrix and can be written as

$$\phi = \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix}$$

First, the first objective function F_1 will be optimized obtaining $\phi_{11} = F_1^* = 20$. Then, the second objective function, i.e., F_2 is optimized by adding F_1^* in the constraint $(i.e.F_2(x) \geq \varepsilon_2$, where $\varepsilon_2 = \phi_{11} = 20$ in 13 to obtain$\phi_{12} = F_1^2 = 30$. Then, this procedure is iterated for the second row of ϕ. First, the second objective function i.e. F_2 will be optimized to obtain $\phi_{22} = F_2^* = 40$. Now adding F_2^* in the constraint $(i.e.F_1(x) \geq \varepsilon_1, where \varepsilon_1 = \phi_{22} = 40 in (13))$ optimize the first objective function, i.e., F_1 to obtain $\phi_{21} = F_2^1 = 10$. Therefore, the obtained payoff table ϕ will be

$$\phi = \begin{bmatrix} 20 & 30 \\ 10 & 40 \end{bmatrix}$$

The points $\phi_{11}, \phi_{12}, \phi_{21} and \phi_{22}$ are also indicated on the Figure 5. The range of the first and second objective function $F_1 and F_2$ can be calculated as the difference in the first and second columns of ϕ matrix which is 10 for both $F_1 and F_2$ respectively.

In order to guarantee that Z contains only efficient solutions for problems in Equation 12, at least (L-1) objective function constraints should have binding[51]. Otherwise, there may exist an alternate solution that may improve one of the non-binding constraints belonging to one of the objective functions; hence, the solution to the problem is not in fact efficient. To overcome this ambiguity, the objective function constraint needs to be changed into equalities by including slack variables. The problem in Equation 13 will become as follows:

$$\begin{gathered} \text{Maximize } F_1(x) + \rho \times \left(s_2 + s_3 + \ldots s_L\right) \\ \text{Subject to} \\ s_2 = F_2(x) - \varepsilon_2 \\ s_3 = F_3(x) - \varepsilon_3 \\ \ldots \\ s_L = F_L(x) - \varepsilon_L \\ C1 - C4 \\ x_{ik} \in 0, 1 \end{gathered} \tag{14}$$

Theorem: The problem formulation in (12) produces only efficient solutions.

Proof: Assume a solution x' of 11 dominates a solution x of 12, and then $(F_1, \varepsilon_2 + s'_2, \varepsilon_3 + s'_3, \ldots, \varepsilon_L + s'_L)$ dominates $(F_1, \varepsilon_2 + s_2, \varepsilon_3 + s_2, \ldots, \varepsilon_L + s_L)$. As the value of F_1 is same for both cases

$$\begin{gathered} \varepsilon_2 + s_2 \leq \varepsilon_2 + s'_2 \\ \varepsilon_3 + s_3 \leq \varepsilon_3 + s'_3 \\ \ldots \\ \varepsilon_L + s_L \leq \varepsilon_L + s'_L \end{gathered} \tag{15}$$

with one strict inequality. Taking the sum of both sides of 15 and based on the fact that there exists at least one strict inequality, it can be deduced that

$$\sum_{i=2}^{L} s_i < \sum_{i=2}^{L} s'_i \tag{16}$$

However, this contradicts the basic assumption of 14 that it maximizes summation of s_i. Hence, no solution x' exists that dominates the solution x; thus, the solution x obtained from 14 is an efficient solution.

Considering F_1 as the main objective function, the range of remaining objective functions, i.e., $F_2, F_3, \ldots, F_L$ are computed. Then, the ranges of these objective functions are divided into an equal number of δ_i intervals resulting into $\delta_i + 1$ points, where each point represents a subproblem. Obtaining $\delta_i + 1$ points for (L-1) objective functions will result in $(\delta_2 + 1) \times \left(\delta_3 + 1\right) \ldots \times$

$(\delta_L + 1)$ sub problems. Each subproblem (j, k,…, l)

$$\begin{gathered}\text{Maximize } F_1(x) + \rho \times \left(s_2 + s_3 + \ldots + s_L\right)\\ \text{Subject to}\\ s_2 = F_2(x) - \varepsilon_{2j} = F_2(x) - \max\left(F_2(x)\right) - \left(\frac{\max\left(F_2(x)\right) - \min\left(F_2(x)\right)}{\delta_2}\right) \times j, \quad j = 0, 1, \ldots \delta_2\\ s_3 = F_3(x) - \varepsilon_{3k} = F_3(x) - \max\left(F_3(x)\right) - \left(\frac{\max\left(F_3(x)\right) - \min\left(F_3(x)\right)}{\delta_3}\right) \times k, \quad k = 0, 1, \ldots \delta_3\\ \ldots\\ s_L = F_L(x) - \varepsilon_{Ll} = F_L(x) - \max\left(F_L(x)\right) - \left(\frac{\max\left(F_L(x)\right) - \min\left(F_L(x)\right)}{\delta_l}\right) \times l, \quad l = 0, 1, \ldots \delta_L\\ C1 - C4\\ x_{ik} \in 0, 1\end{gathered} \tag{17}$$

Solving each subproblem will give an efficient Pareto solution. Some of these $(\delta_2 + 1) \times \left(\delta_3 + 1\right) \ldots \times (\delta_L + 1)$ subproblems may have an infeasible solution and will be discarded. Hence, the final outcome is a set of efficient solutions Z.

4.2 | Decision Making Using Fuzzy Logic

First, a set of pareto-optimal solutions is obtained through the solution of sub-problems of the main multi-objective optimization problem. Next, a fuzzy logic-based decision maker needs to choose the best trade-off among the available pareto-optimal solutions. The decision-maker makes decisions on the basis of specified objective criteria for various kinds of applications. In this work, a fuzzy approach is proposed for the decision-making process where linear memberships function $(\mu F_i^k(x))$ for $i = 1, ...L and k = 1, ..., S$, where S is the number of rows/solutions in Z. The fuzzification process can be defined as

$$\mu F_i^k = \begin{cases} 0 & F_i^k \le min\left(F_i\right) \\ \frac{F_i^k - min\left(F_i\right)}{max\left(F_i\right) - min\left(F_i\right)} & min\left(F_i\right) \le F_i^k \le max\left(F_i\right) \\ 1 & F_i^k \ge max\left(F_i\right) \end{cases} \tag{18}$$

The defined membership function μF_i^k gives the degree of optimality for the i^{th} objective of the k^{th} Pareto optimal solution from set Z. The whole membership function of k^{th} Pareto optimal solution μ^k can be calculated based on its individual membership function as follows:

$$\mu^k = \frac{\sum_{i=1}^{L} W_i . \mu F_i^k}{\sum_{s=1}^{S} \sum_{i=1}^{L} W_i . \mu F_i^k} \tag{19}$$

Where W_i is the weight value of the i^{th} objective function. The solution k with the maximum membership function μ^k is the preferred solution denoted by $\bar{x}$ based on the adopted weight factors and so is selected as the optimal solution of the problem. For the sake of clarity, considering the example given in Figure 5 with two objective functions F_1 and F_2, let's assume that after applying the method for generating efficient Pareto optimal solutions, two alternative solutions X and Y are obtained as indicated in Figure 5. Let's assume the entries corresponding to this solution in the Z matrix are as follows:

$$Z = \begin{bmatrix} 13 & 37 \\ 19 & 32 \end{bmatrix}$$

The first row of Z indicates the value of F_1 and F_2 for the solution point X, and the second row of Z indicates the value of F_1 and F_2 for the solution point Y. Now, we will compute the μF for the Z matrix. Since there are two solutions X and Y and two objective functions, the matrix μF can be represented as

$$\mu F = \begin{bmatrix} \mu F_1^1 & \mu F_2^1 \\ \mu F_1^2 & \mu F_2^2 \end{bmatrix}$$

Each element of matrix μF will be computed using Equation 18. For instance, take μF_1^1, where $(i, k) = (1, 1)$ indicates the fuzzy membership function for the first objective function, i.e., F_1 and the first solution point, i.e., X, or in other words, the first element of the Z matrix, i.e., Z_{11}. Using 18, it can be seen that Z_{11} i.e., 13 is greater than the min $\left(F_1\right)$ and less than the max $\left(F_1\right)$, therefore, μF_1^1 will be computed as

$$\mu F_1^1 = \frac{F_1^1 - min\left(F_1\right)}{max\left(F_1\right) - min\left(F_1\right)} = \frac{13 - 10}{20 - 10} = \frac{3}{10}$$

Similarly, by computing other elements of μF, we will finally obtain

$$\mu F = \begin{bmatrix} \frac{3}{10} & \frac{7}{10} \\ \frac{9}{10} & \frac{2}{10} \end{bmatrix}$$

Next, the μ matrix will be computed, which can be written as

$$\mu = \begin{bmatrix} \mu^1 \\ \mu^2 \end{bmatrix}$$

where μ^1 and μ^2 indicate the membership functions for solutions X and Y, respectively. Let's assume $W_1 = W_2 = 1/2$, which means the same preference is assigned to both objective functions F_1 and F_2. Using 19, the μ^1 and μ^2 can be computed as

$$\mu^1 = \frac{W_1 \times \mu F_1^1 + W_2 \times \mu F_2^1}{\left(W_1 \times \mu F_1^1 + W_2 \times \mu F_2^1\right) + \left(W_1 \times \mu F_1^2 + W_2 \times \mu F_2^2\right)} = \frac{\frac{1}{2} \times \frac{3}{10} + \frac{1}{2} \times \frac{7}{10}}{\left(\frac{1}{2} \times \frac{3}{10} + \frac{1}{2} \times \frac{7}{10}\right) + \left(\frac{1}{2} \times \frac{9}{10} + \frac{1}{2} \times \frac{2}{10}\right)} = \frac{10}{21}$$

$$\mu^2 = \frac{W_1 \times \mu F_1^2 + W_2 \times \mu F_2^2}{\left(W_1 \times \mu F_1^1 + W_2 \times \mu F_2^1\right) + \left(W_1 \times \mu F_1^2 + W_2 \times \mu F_2^2\right)} = \frac{\frac{1}{2} \times \frac{9}{10} + \frac{1}{2} \times \frac{2}{10}}{\left(\frac{1}{2} \times \frac{3}{10} + \frac{1}{2} \times \frac{7}{10}\right) + \left(\frac{1}{2} \times \frac{9}{10} + \frac{1}{2} \times \frac{2}{10}\right)} = \frac{11}{21}$$

Since $\mu^2 > \mu^1$, therefore, the solution represented by point Y will be selected as the preferred solution.

4.3 | Computational Complexity Analysis

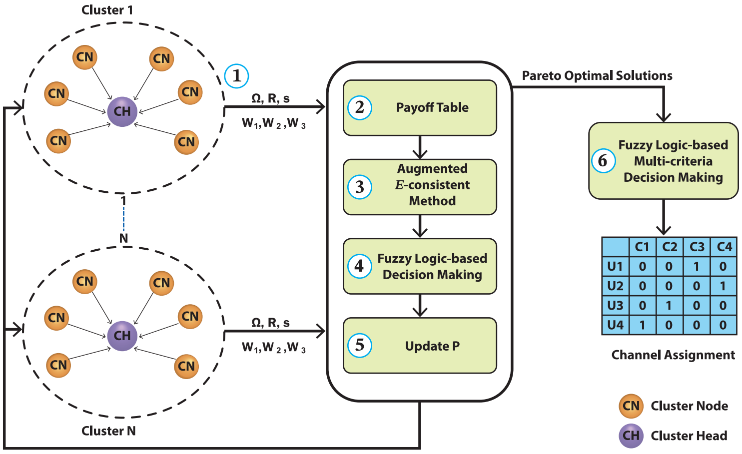
Solving the multi-objective problem given in 12 can be divided into three phases: payoff table generation, generation of efficient solutions, and selection of the preferred solution. In this subsection, we compare the computational complexities of the exhaustive search and our proposed method up to finding the efficient solution set, as the rest (the selection of the preferred solution) is the same for both.

To generate the payoff table, a lexicographic optimizer is employed. First, for each i^{th} objective function $F_i\left(x\right), i = 1, \ldots, L$ single objective problem P is solved to get its optimum value. Then, solve multi-objective for each i^{th} objective function $F_i\left(x\right)$ making the rest of $L - 1$ objectives constraints. Hence, for the generation of a payoff table in total 2 times L (the number of objective functions) the optimization problem is solved. In this work, we interfaced Matlab 2021 with GAMS 24.2 to solve the assignment problem. GAMS invokes Gurobi/CPLEX for solving the optimization problem. The algorithm options available for solving mixed integer linear assignment problems are the primal or dual simplex methods. Let the dimensions of the assignment problem be $N \times K$ where N is the number of SUs and K is the number of channels. According to[52] the complexity of the Primal Simplex algorithm is $O\left(n^3\right)$ where $n = max(N, K)$. Hence, the complexity of the payoff phase will be $O\left(2L\left(n^3\right)\right)$. In the generation of efficient solution phase $\left(q_2 + 1\right) \times \left(q_3 + 1\right) \times \ldots \times \left(q_L + 1\right)$ multi-objective optimization problem are solved. Given the complexity of solving each optimization problem is $O\left(n^3\right)$ and $q_i = q, i = 1, \ldots, L$, the complexity of generating an efficient solution by the proposed scheme is $O((q + 1)^{L-1}(n^3))$. Therefore, the overall complexity for the generation of efficient solutions by the proposed scheme is $O((q + 1)^{L-1} + 2L)(n^3))$.

According to[53], the exhaustive search complexity for solving a problem of $N \times K$ dimension assignment matrix is $O\left(\frac{N!}{N-K}\right)$. Solving the ϵ-constraint problem for L number of objectives by iteratively optimizing one function turn by turn and taking others as constraints will reduce the complexity of the exhaustive search to $O\left(L\left(\frac{K!}{K-N}\right)\right)$. Given a wireless (cognitive radio) network that usually has more channels than users, i.e., $K \gg N$ and $n = max(N, K)$, the complexity of an exhaustive search can be written as $O\left(L\left(n!\right)\right)$. Table 2 shows the computational complexity of both the proposed technique and the exhaustive search for efficient solutions.

TABLE 2 Complexity Comparison

Technique	Complexity
Exhaustive Search	$O(L(n!))$
Proposed Method	$O((q+1)^{L-1}+2L(n^3))$



	C1	C2	C3	C4
U1	0	0	1	0
U2	0	0	0	1
U3	0	1	0	0
U4	1	0	0	0

FIGURE 6 Process Flow Diagram of the Proposed Technique

5 | FUZZY LOGIC AND ε-CONSTRAINT METHOD BASED PROPOSED FRAMEWORK

Figure 6 shows the process flow diagram of the proposed multi-objective channel assignment framework for CRN. The whole process has been divided into six steps. Following is a step-by-step description of the proposed technique.

Step 1: Initialize P, the total power budget for the CH, which allocates the transmission power p_i^T to the SUs such that $\sum_{i=1}^{N} p_i^T \leq P$ and calculate Ω_k^i, R_k^i, and S_k^i using equations 3, 6 and 10 which are $N \times K$ matrices.

$$\Omega_k^i = \begin{bmatrix} \Omega_1^1 & \cdots & \Omega_K^1 \\ \vdots & \ddots & \vdots \\ \Omega_1^N & \cdots & \Omega_K^N \end{bmatrix}, \; R_k^i = \begin{bmatrix} R_1^1 & \cdots & R_K^1 \\ \vdots & \ddots & \vdots \\ R_1^N & \cdots & R_K^N \end{bmatrix}, \; s_k^i = \begin{bmatrix} s_1^1 & \cdots & s_K^1 \\ \vdots & \ddots & \vdots \\ s_1^N & \cdots & s_K^N \end{bmatrix}$$

Step 2: Using Ω_k^i, $R_k^i and\ s_k^i$ apply lexicographic optimization to obtain the payoff table ϕ which is an $L \times L$ matrix.

$$\phi = \begin{bmatrix} F_1^* & \cdots & F_1^L \\ \vdots & \ddots & \vdots \\ F_L^1 & \cdots & F_L^* \end{bmatrix}$$

The maximum of the j^{th} column of ϕ represent the maximum value for the j^{th} objective function, and the minimum of the j^{th} column of ϕ represents the minimum value for the j^{th} objective function. The range of the j^{th} objective is the difference between the maximum and the minimum value of the j^{th} objective function.

Step 3: Obtain Z, by applying augmented ε-constraint method for solving the problem in 10.

$$Z = \begin{bmatrix} F_1(x_1) & \cdots & F_L(x_1) \\ \vdots & \ddots & \vdots \\ F_1(x_S) & \cdots & F_L(x_S) \end{bmatrix}$$

Z is $S \times L$ matrix; each row of Z represents an efficient Pareto optimal solution. The set $x_1, \ldots, x_S$ represents the set of efficient solutions, and Z contains the values of the objective function corresponding to these solutions.

Step 4: To obtain the preferred solution $\bar{x}$, apply fuzzy logic-based decision-making process. First, calculate the membership degree function matrix μF_i^k using 14 for the Z matrix.

$$\mu F_i^k = \begin{bmatrix} \mu F_1^1 & \cdots & \mu F_L^1 \\ \vdots & \ddots & \vdots \\ \mu F_1^S & \cdots & \mu F_L^S \end{bmatrix}$$

μF_i^k is $S \times L$ matrix; each row of μF_i^k represents a degree of membership of each objective function for the k^{th} Pareto efficient solution. The degree of membership value represents the value obtained for that objective solution for a particular Pareto-efficient solution based on how close it is to the maximum value and how far it is from the minimum value of that objective function. Now compute μ^k using 15, the combined membership degree function for the k^{th} Pareto optimal solution. The Pareto efficient solution with the largest value of μ^k is selected as the preferred Pareto optimal solution $\bar{x}$ and stored in Z^*, where each row of Z^* corresponds to the best solution for a given power level P and contains the value of $F_1, F_2, and F_3$ for $\bar{x}$.

Step 5: Update $P = P - \left(\frac{P_{max}-P_{min}}{Q}\right)$, where Q is the maximum number of power levels. If $\left(P \geq P_{min}\right)$, go to step 2.

Step 6: Now a matrix Z* of size $Q \times L$ is obtained.

$$Z^* = \begin{bmatrix} F_1\left(\bar{x}_1\right) & \cdots & F_L\left(\bar{x}_1\right) \\ \vdots & \ddots & \vdots \\ F_L\left(\bar{x}_Q\right) & \cdots & F_L\left(\bar{x}_Q\right) \end{bmatrix}$$

Each row of Z* corresponds to an efficient solution for a particular power level and contains the objective function value corresponding to the preferred solution selected in step 4 for that power level. Calculate the membership degree function matrix $\mu \bar{F}_i^k$ using 14 for the Z* matrix and $\bar{\mu}^k$ using 15. The solution with the largest value of $\bar{\mu}^k$ represents the most preferred solution, denoted by x*.

6 | SIMULATION RESULTS

6.1 | Parameter Setting

To evaluate the proposed scheme, we considered a geographical service area of size 500×500 m^2 in which CRN is deployed. The service area is divided into clusters. A CH is deployed at the center of each cluster to serve SUs within the cluster. The simulation is conducted within a cluster of size 10×10 m^2. The cluster consists of N SUs and M licensed channels to be used by SUs. The SUs are uniformly distributed within the cluster, with the minimum distance between CH and SU equal to 1 m. All the SUs are assumed to be active and have the data to send to the CH. SU position remains fixed during frame duration; otherwise, SU are mobile within the boundary of the cluster. Each channel has the same bandwidth of 1 MHz. It is assumed that SU employs binary orthogonal frequency shift keying (FSK) modulation on a frequency selective fading channel with a path loss exponent equal to 3.5. Moreover, each cluster has a total power P, which is distributed among SU based on a water filling mechanism discussed in[54]. Regarding PU activity consideration in the geographical region, a PU can occupy any channel with an occupancy probability of Pr_{on} which is set to be 0.1 unless specified. Table 3 lists the parameters used in the simulation. In order to show the trade-off between the achieved overall throughput and the residual energy, we simulated two cases:

1. Varying W_1, the preference weight associated with objective function F1 (throughput fairness maximization) from 0.1 to 0.8 and fixing W_2 (weight associated to residual energy maximization) and W_3 (weight associated with priority index maximization) to 0.1.
2. Varying W_2 from 0.1 to 0.8 and fixing W_1 and W_3 to 0.1.

For each case, two different scenarios are considered.

1. Effect of varying numbers of SUs.
2. Effect of varying numbers of licensed channels.

The simulation is carried out for the channel assignment in a single frame. We simulated 100 different topologies for each scenario and reported their average overall system throughput, residual energy, and priority index. In addition to showing the significance of considering priority index as a third objective function, we considered two more cases: without PU activity consideration, each channel is assigned the same priority index irrespective of PU appearance probability during SU communication,

TABLE 3 Parameters Setting

Symbol	Definition	Quantity
f_c	operating frequency band	2.4 GHz
B	channel bandwidth	1 MHz
T	frame duration	400 ms
τ	Sensing and assignment process time	100 ms
α	Path loss exponent	3.5
Pr_{on}	PU occupancy probability	0.1
I_{max}	Maximum level of interference	0.3
R_i	Initial residual energy of ith SU	100 J
P	Total transmission power of cluster	10 ~ 1 Watt
W_i	Preference to ith objective function	0.1 ~ 0.8

and with PU activity consideration, each channel is assigned a priority index according to the probability of PU appearance over that channel. The performance of these cases is compared in terms of spectral and energy efficiency.

6.2 | Varying SUs with Fixed Channels

To show the effect of varying the number of SUs, we performed the simulation by fixing the number of channels (M) to 5 and varying the number of SUs (N) from 3 to 7. The results are represented in the form of overall throughput, overall energy consumption, and the overall priority index across different scales.

Figure 7 shows the effect of varying the number of SUs while varying W_1 and fixing W_2 and W_3 to 0.1. By increasing W_1, the overall throughput increases, whereas the overall residual energy decreases. For the sake of clarity, instead of overall residual energy, we plotted the overall energy consumption. It is clear that the overall energy consumption and the overall throughput increase with increasing N until N is less than or equal to M (i.e., $N \leq M$). However, overall energy consumption and throughput become constant with further increase in N beyond M (i.e., $N \geq M$).

Figure 8 shows the simulation results for varying W_2 and fixing W_1 and W_3 to 0.1. By increasing W_2 the overall throughput decreases, whereas the overall residual energy increases (shown by decrease in the overall energy consumption). Analogous to Figure 7, the throughput for N>M becomes constant; however, it decreases with decreasing N, and similarly, overall energy consumption increases with increasing N unless N is less than or equal to M in which case it becomes constant. Concerning the overall priority index in Figures 7 and 8 its value depends on N, but it does not change with changing weight preferences as every channel is assigned the same priority index.

6.3 | Varying Channels with Fixed SUs

To show the effect of varying the number of licensed channels, we fixed N and varied M from 3 to 7. In this section, the results are also presented in the form of overall throughput and overall energy consumption on different scales to show their trade off. Figure 9 shows the result of varying W_1, in different scenarios with M = 3, 5 or 7. With increasing W_1, the throughput increases and overall residual energy decreases, as shown by an increase in overall energy consumption. It is evident that the overall throughput increases with increasing number of channels, even beyond M = 5, although no SU can occupy more than one channel because having more channels results in the selection of a better channel. The overall energy consumption increases with increasing M until N<M. For $N \geq M$ the overall energy consumption becomes almost constant.

Figure 10 shows the simulation result of increasing W_2 with fixed N = 5. With increasing W2, the overall energy consumption decreases, leading to an increase in overall residual energy and a decrease in overall throughput. The behaviour of different performance metrics in relation to different values of M is analogous to that described in for Figure 9.

6.4 | Considering PU Activity

To show the impact of incorporating the PU activity in the channel assignment in CRN, we considered the third objective function based on the PU activity. Each k^{th} channel is ranked based on the probability of PU occupancy. The overall objective

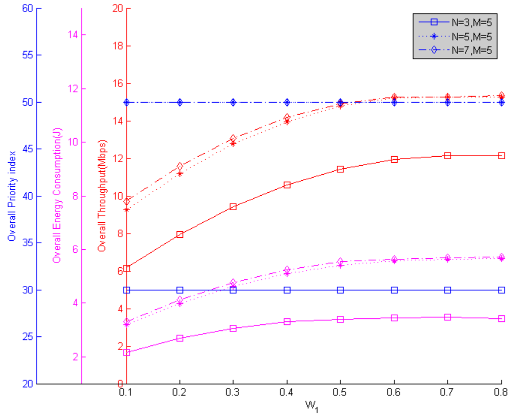


FIGURE 7 Overall throughput, energy consumption, priority index curves for changing W_1 from 0.1 to 0.8 while keeping $W_2 = W_3 = 0.1$ for varying SUs and fixed channels

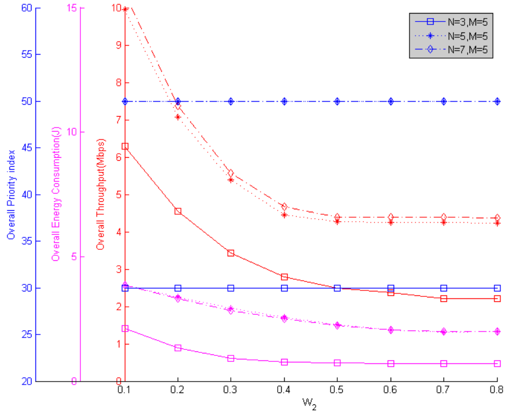


FIGURE 8 Overall throughput, energy consumption, priority index curves for changing W_2 from 0.1 to 0.8 while keeping $W_1 = W_3 = 0.1$ for varying SUs and fixed channels

is to maximize the sum of the priority values of the assigned channels. To show its significance, we compared two performance metrics, i.e., spectral efficiency η_{SE} and energy efficiency η_{EE}, with and without considering the PU activity. In this work, we define spectral efficiency as the ratio of throughput and the bandwidth observed over the duration of frame T, i.e., $\eta_{SE} = \frac{R}{B}$ bits/Hz, where R is the accumulated achieved data rate of all SUs and B is the accumulated bandwidth of all available channels. Furthermore, in this work, we define energy efficiency as the ratio of throughput and energy consumed during the duration of a frame T, i.e., $\eta_{EE} = \frac{R}{E}$ where R is the accumulated achieved data rate of all SUs and E is the overall energy consumed by all SUs. We set a value of $Pr_{on}(k)$ between 0.1 and 0.4 for each available channel. For this case, without consideration of PU activity, each channel is ranked the same; however, for PU activity-aware channel assignment, the ranks are computed using the formula, i.e., $s_k^i = \frac{1}{Pr_{on}(k)}$. A channel with higher PU activity will be ranked lower than a channel with lower PU activity.

Figure 11 shows the impact of varying the number of channels and considering PU activity on the energy efficiency of the channel assignment in CRN. The number of channels varies from 3 to 7, while the number of SUs is kept fixed at 5. The preference weight

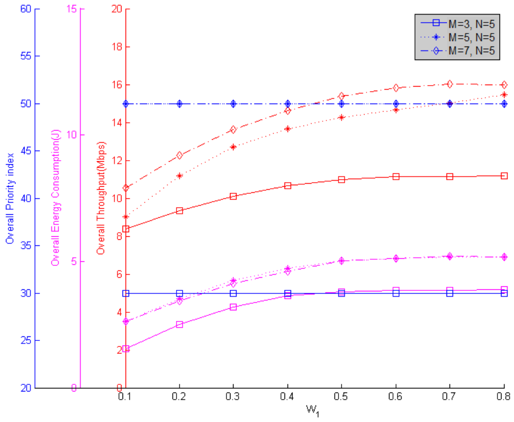


FIGURE 9 Overall throughput, energy consumption, priority index curves for changing W_1 from 0.1 to 0.8 while keeping $W_2 = W_3 = 0.1$ for varying channels and fixed SUs

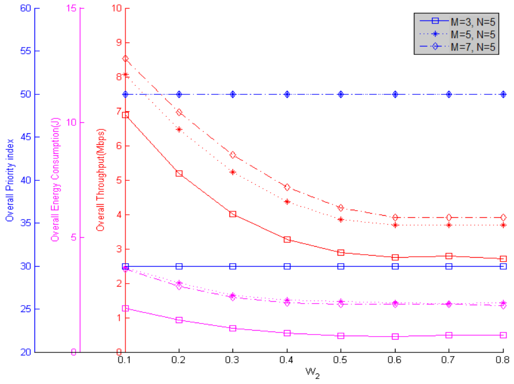


FIGURE 10 Overall throughput, energy consumption, priority index curves for changing W_2 from 0.1 to 0.8 while keeping $W_1 = W_3 = 0.1$ for varying channels and fixed SUs

values are set to be $W_1 = W_2 = W_3$=1/3. The overall success probability will increase when more empty channels are added to the pool for the transmission of SUs, which will lead to increased energy efficiency. This can be accomplished by adding more empty channels to the pool. For $N \geq M$, energy efficiency for both cases without PU consideration is almost the same; however, for $N < M$, a significant advantage in terms of gains in energy efficiency is achieved while considering the PU activity. For the scenarios having $N \geq M$, the energy efficiency for both cases with and without PU activity consideration is almost the same, as every channel is being used and assigned to one SU as ensured by constraints C1 and C3. For the scenario having $N < M$, the gain in energy efficiency for considering PU activity is significant as compared to without PU consideration. Each of the SUs is supposed to be given one channel, which means that N channels must be chosen out of M channels. Because of this, selecting channels that have less expected PU activity results in a higher chance of successful transmission, which consequently contributes significantly to the increase in energy efficiency.

Figure 12 shows the effect of varying the number of channels on the spectral efficiency for both cases, i.e., with and without PU activity consideration for a fixed number of SUs. This figure shows how the spectral efficiency changes as the number of

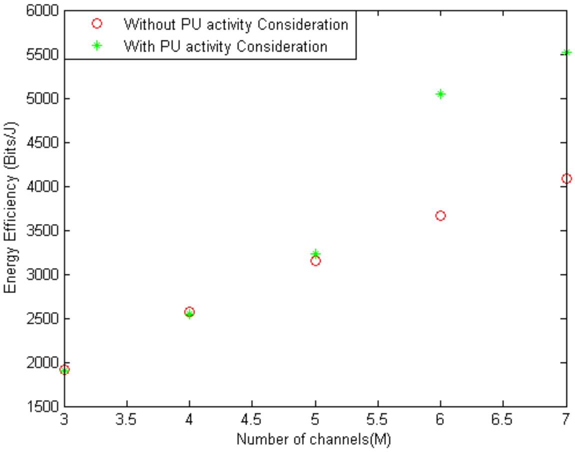


FIGURE 11 Energy efficiency vs varying number of channels (M) with and without PU activity consideration for fixed number of SUs N=5 and $W_1 = W_2 = W_3$=1/3

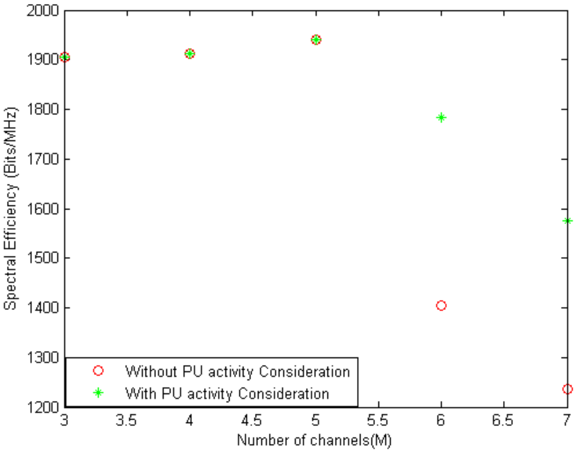


FIGURE 12 Spectral efficiency vs varying number of channels (M) with and without PU activity consideration for fixed number of SUs N=5 and $W_1 = W_2 = W_3$=1/3

channels changes. The number of channels is varied from 3 to 7, while the number of SUs is kept fixed at 5. The preference weight values are set to be $W_1 = W_2 = W_3$=1/3. With increasing numbers of channels, for the $N \geq M$ scenario, only a slight increase in spectral efficiency is observed because all the available channels are already being assigned; this increase is due to an increase in the probability of successful transmission. On the other hand, for the $N < M$ the spectral efficiency decreases as only N channels out of M available channels will be assigned to SUs. The spectral efficiency is the same for both cases with and without PU activity consideration for $N \geq M$ as all the available channels are being used. However, for $N < M$ the gain in spectral efficiency for PU activity consideration is greater than when there is no PU activity taken into consideration. This is due to the fact that only N channels out of M are to be selected.

6.5 | Discussion

Within the proposed framework that we have developed, we have implemented three objective functions: overall throughput, overall residual energy, and overall priority. By assigning different preference values (represented by weight) to each objective function, we were able to demonstrate the trade-off that exists between the various functions of the evaluation. Cognitive radio can be helpful in a variety of technological contexts, such as wireless sensor networks (WSNs), machine-to-machine communication (M2M), the internet of things (IoT), and long-term evolution (LTE). These technologies are extensively used in a wide variety of applications, ranging from surveillance to healthcare. The preference values (weights assigned to various objective functions) can be adjusted in the proposed framework. This allows the framework to be tailored to the requirements of both the underlying application and the technology. In addition to this, we incorporated a priority objective function, the weight of which is modifiable or replaceable depending on the particulars of the technology and the activity that needs to be performed. According to the results of our investigation, the number of available channels (K) for SUs is the most significant factor responsible for determining the channel assignments in CRNs. Additionally, the characteristics of those channels are also a significant factor. The maximum number of channels that can be utilized is determined by a number of different factors, one of which is the reliability and efficiency of the spectrum sensing technique and architecture. PU activity is another important factor that significantly affects the performance of channel assignment in CRNs and must be incorporated during the process of channel assignment. As a result of this, it is imperative that PU activity be taken into consideration during the process of channel assignment. In order to accomplish this, we used the priority objective function to sort the available channels in descending order of priority for use. A channel that had a lower percentage of peak utilization (PU) activity was given a higher priority for use than a channel that had a higher percentage of peak utilization (PU) activity. By utilizing channels that had a lower level of PU activity, we were able to see significant improvements in both the spectral and energy efficiencies of our system. Therefore, significant enhancements in the performance of channel assignment in CRNs can be accomplished by utilizing the suggested framework and solution in conjunction with an appropriate sensing architecture and accurate modelling of PU activity. This will allow for significant improvements in both the spectral and energy efficiency performance of channel assignment.

7 | CONCLUSION

In this paper, we considered the channel assignment and power level selection problem for CRN and presented a multi-objective framework to solve it. The framework presents an iterative approach to selecting the power level, ϵ-constraint method to solve the multi-objective problem, and a fuzzy logic-based method for multi-criteria-based decision making is employed. The proposed framework determines the most preferred Pareto optimal solution by considering the relative importance of the numerous objective functions included in the application environment. Furthermore, the framework that we have proposed can accommodate a wide range of different objective functions. In this study, we investigated the trade-off between several objective functions by varying the weights (preferences) assigned to them, and we demonstrated the importance of these weights in the channel assignment process in CRN. In this study, we make the assumption that CRN will be free of spectrum sensing errors. However, in the future, we can investigate the impact of sensing errors in multi-objective channel assignment in CRN on various objective functions.

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