Journal of Universal Computer Science, vol. 30, no. 11 (2024), 1595-1623
submitted: 20/11/2023, accepted: 12/5/2024, appeared: 28/10/2024 CC BY-ND 4.0

An Intelligent Distributed Channel Selection Framework with Hybrid Mode Selection for Interference Mitigation in D2D based 5G Networks

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Abstract: Device-to-device (D2D) communication is an essential part of the 5G system used in cellular networks, which enables devices to communicate with each other without passing the base station BS. It is likely to aid in satisfying increasing capacity and effectively offloading traffic from the BS by distributing the transmission between D2D users from one side and cellular users and the BS from the other side. It results in improved throughput, energy efficiency, and other parameters. At the same time, the introduction of D2D communication in cellular networks creates new technical challenges to be addressed. One of the major issues is the mitigation of interference between device users (D_{Us}) and primary users (P_{Us}). This issue leads to performance degradation if it is not managed properly. In this paper, an intelligent distributed channel selection framework (IDCSF) in D2D communication for 5G networks with hybrid selection modes of D2D is proposed to help DUs select the best channel for transmission to mitigate interference. This channel selection framework classifies the available sensed channels using self-organizing map (SOM) learning technique into four classes considering channels with sensing errors false alarm (FalsA) and miss detection (MissD) to prevent using occupied channels. Furthermore, P_U activity model is adjusted to aid in recovering from bad channel selection decisions. Moreover, fuzzy logic technique is utilized to determine the reliable channels which can help the D_U along with channel selection algorithm to find channel's weight values. The channel with highest weight value is selected as the best channel. Simulation results show that the proposed framework IDCSF enhances selecting the best channel, improves throughput and spectral utilization, and reduces average delay, interference and search time compared to other approaches.

Keywords: 5G, D2D communication; device-to-device; cognitive radio; underlay.
Categories: C.2
DOI: 10.3897/jucs.116026

1 Introduction

Generally, 5G is a collection of many technologies such as cognitive radio networks (CRN), device-to-device (D2D) communication, millimeter wave (Mm-wave) communi-

cation, massive multiple input multiple output (MIMO), and visible light communication [Hashima et al., 2021].

D2D communication is an essential part of the 5G system used in cellular networks. It enables devices to communicate with each other without using the infrastructure of the network or the base station BS, which is required in traditional cellular networks despite the communicating devices being close to each other.

There are two types of D2D techniques in terms of spectrum usage: in-band and out-band D2D communications. In-band D2D can be further categorized into overlay and underlay D2D modes. In the underlay mode, both D2D and cellular users share the same spectrum resource. For the overlay mode, a dedicated portion of the available spectrum is utilized for D2D communication, and the remainder is used for cellular communication. To efficiently utilize network resources, we must choose the type of D2D communication mode that best fits the current network situation [Kamruzzaman et al., 2022].

D2D in 5G technology is considered a two-tier network [Nagapuri et al., 2022] comprised of device and macro cell tiers. Although devices in the device tier allow direct D2D communication, the BS may have full or partial control over the communication among the devices. Therefore, cellular network communication and D2D communication are similar; the only difference is that the devices at the edges of the cell and those in the interference areas within the cell can undergo effective services. Thus, in the device tier, D2D communication is classified into four classes [Gismalla et al., 2022]: the first one is direct communication between devices, with the BS controlling link establishment (underlay D2D), device relaying with the BS controlling link establishment, device relaying with the device itself controlling link establishment and the direct communication among devices, with the device itself controlling link establishment.

Since the D2D communication has several advantages in terms of improving performance in cellular networks, several main issues need to be effectively addressed to get the full advantage of D2D communication. Some of these are mode selection, device discovery, security, mobility management and interference mitigation. An intensive work has been conducted to address these issues. One of the important issues is interference mitigation which has been studied from some authors and utilize channel decision strategy to select the best channel to mitigate the interference. Hence, the paper focus on selecting the best channel strategy to mitigate interference.

A lot of studies have been conducted with the goal of demonstrating the most efficient methods for developing an effective and trustworthy D2D-enabled cellular system as a result of the aforementioned issues. Adjusting the transmit power of D2D transmitters below a predetermined threshold while achieving the SINR intended for cellular communication is one of the most popular interference avoidance strategies [Khoueiry and Soleymani, 2015, Araújo et al., 2016]. In [Duong and Shin, 2013], an algorithm for power control and distance-based interference mitigation has been carried out. The approach reduces the interference signal from the D2D transmitters to the eNB by limiting the maximum transmit power in accordance with the eNB's minimum acceptable SINR target. In [Song et al., 2015], power control algorithms and radio resource management are used to mitigate interference and improve the overall network throughput. The authors in [Gu et al., 2011] study the effect of dynamic power control and resource allocation where the eNB first assigns resources to CUE, then to D2D users, and at the end reuses cellular user equipments (CUE's) resources to D2D users when the demand is robust. The goal is to avoid interference when both D2D and CUE share the same resources.

This paper proposes an intelligent distributed channel selection framework (IDCSF) with hybrid modes of D2D communication in 5G networks which helps to encounter the problem of sensing errors that reduce the performance of the network and aids device users

(D_{Us}) in selecting the best channel in an intelligent way. This can improve the performance of the network by mitigating the interference and helping D_{Us} to select the best channel in a reasonable time. This leads to improve the performance of transmissions for D_{Us} and enhances throughput and spectrum utilization. The improvements that occur depend on our contributions, including using the self-organizing map (SOM) unsupervised learning technique to reduce sensing errors, adjusting the primary user (P_U) activity model, and applying the fuzzy inference system (FIS) and channel selector algorithm in an intelligent way. Based on the simulation results, the proposed framework ensures that the best available channel is selected with less P_U interference and less search time compared to other approaches.

The organizing of paper is summarized as follows: Section 2 presents the related works. In Section 3, the system model and assumptions are introduced. Section 4 the proposed framework is studied, and Section 5 analyzes the performance and simulation results are discussed. At the end, a conclusion and future work are provided in Section 6.

2 Background and Literature Study

Interference management in D2D communication in mobile networks can be analyzed and designed in different ways, using different schemes. Much research has been and continues to be conducted using theories in mathematics such as graph theory, game theory, and queueing theory to analyze and design interference management schemes. The interference relationships among D2D and cellular communication links can be represented by a graph, and graph theory can be used to address the sharing of resource problems. It has also been used to manage interference in underlay D2D communication mode in several recent works, such as [Han et al., 2014]. In [Su et al., 2013], the authors consider the mode selection MS and resource allocation (RA) in underlay D2D communication cellular networks, where different pairs of D2D links and many cellular users exist. The authors formulate the problem to maximize throughput with minimum requirements for data rate, and they use the particle swarm optimization technique to derive the solutions. Many researchers use graph theory in underlay mode, which means D_{Us} share the same resources of C_{Us} at the same time, but this method is not realistic in mobile devices, nor can it be updated at runtime and still remain static. Other works use game theory to analyze distributed RA schemes.

The intelligent interference coordination technique is also important, and more research has been produced to cope with most situations for D2D devices. Utilizing spectrum splitting is the best way to organize and minimize the cross-tier interference between the C_U and D_U. In [Ye et al., 2014], the authors utilize a time-frequency hopping method to randomize the co-tier interference among D_{Us} for a large cellular network. The time is split into slots, and each slot is consecutively assigned to D_{Us}, which can be in either D2D or cellular mode.

Another way to manage the interference is to control the power to address the cross-tier interference between D_{Us} and C_{Us} for both uplink (UL) and downlink (DL) cases as well as the co-tier interference between D_{Us} themselves in a combined cellular network and D2D communication. The authors in [Shalmashi et al., 2013] utilize power control (PC) to control interference where multiple D_{Us} share the resources of one C_U at the same time. The results indicate that multiple D_{Us} can share the spectrum with one C_U without affecting performance. PC is used to address the interference in some works, but this approach is not optimal to solve co-tier and cross-tier interference; it should be employed in combination with RA and/or MS.

The appropriate mode selection MS algorithm can also be utilized to mitigate cross-tier interference or co-tier interference. Many works employ MS with different criteria to address interference issues using path loss, the distance between D_{Us}, and the strength of the received signal over a D2D link; however, these schemes do not reflect the interference issues, such as the work in [ElSawy et al., 2014], which focuses on the distance between D_{Us} in sharing mode only. Some studies consider joint MS and PC and/or RA to achieve the full potential of D2D communication and to minimize interference.

They focus on the control and management of interference between D2D and cellular links, and they reuse the resources when the interference is small. The authors in [Della Penda et al., 2016] study the PC jointly with MS in a D2D underlying cellular network in a single cell scenario to meet a specific rate requirement while reducing energy consumption from a system and device perspective. In terms of mixed-integer nonlinear programming, radio resource management issues are formulated. Despite the fact that they are generally recognized to be nondeterministic polynomial time hard (NP-hard), they take advantage of the problem structure to develop effective algorithms that effectively resolve a variety of problem cases. In [Zhong et al., 2014], the authors consider joint channel allocation, PC in MIMO uplink enabled for a D2D mobile network to minimize cross-tier interference between C_{Us} and multiple D_{Us} pairs share the radio resources of multiple C_{Us} in this scheme. A random search is used to obtain the optimal RA, PC, and precoding. They decompose the optimization into two parts - one for PC for both D_{Us} and the other for MS and RA jointly for each D_{Us} and solve them individually. The joint MS and RA is NP-hard, and the authors propose two algorithms to address the problem. In [Huang et al., 2016], the authors suggest a centralized framework for decision-making at the BS for underlay D2D communication with a two-tier cellular network. The proposed solution includes mode selection, RA, and power control in reuse mode within a single framework. For reuse mode, the authors produce a geometric vertex search approach to address the problem of power allocation. They show that for cellular and dedicated modes, the frequency sharing increasing sum rate and solve the RA problem in closed form. In [Tang and Ding, 2015], the authors study mixed mode and node switching approaches, where several modes are used at once. Once a mode is chosen, the network must address RA to meet the network requirements.

In summary, existing research on D2D communications has generally considered mode selection, RA, and control of power subproblems either separately or collectively for single and multitier cellular networks [Wang et al., 2014]. In [Li et al., 2017], [Yu et al., 2014] the authors suggest a joint MS and RA algorithm and they studied only a single mode which is underlay mode but when the distance increase or be great than the distance threshold and D_U want to send with more power, in underlay mode there is transmission power constraint where the power does not increase than a limit but this is not appropriate for many applications and also the user's behavior is dynamic and move from location to location thus determining the distance is not practical along time since the distance will increase based on the user movement. While the work used underlay mode, the D_U power does not exceed than a particular limit to avoid interference with C_U. In this works they used joint and control the D_U power to avoid interference of C_U using underlay mode, here the optimization is not used only controlling the connection between channel selection and D2D which work as shared with C_U to control the power not to exceed a threshold.

In [Yu et al., 2014], the authors study only a single mode, namely the underlay mode. However, when the distance increases or is greater than the distance threshold and a D_U wants to send packets with more power, in underlay mode there is a transmission power constraint where the power does not increase above a limit. This is not appropriate for

many applications. Moreover, the user's behavior is dynamic and moves from location to location; thus, the distance is not practical over time since the distance will increase based on the user's movement. While the work uses the underlay mode, the D_U power does not exceed a particular limit to avoid interference with C_U. In this work, the authors used joint and control the D_U power to avoid interference of C_U using underlay mode, here the optimization is not used only controlling the connection between channel selection and D2D which work as shared with C_U to control the power not to exceed a threshold.

The work in [Li et al., 2018] combines D2D technology with traditional cellular networks to create a hybrid network to enhance the experience of video subscribers in long term evolution (LTE) networks. The proposed scheme is developed as a joint mode selection, RA, and power allocation problem based on the mitigation of interference, which is proven to be NP-hard. The authors present a greedy algorithm and a heuristic algorithm to address the problem, and the capacity of system users is increased, the overall system throughput is improved, and the video quality is enhanced.

In a hybrid network, mutual allocation of resource and mode selection to reduce the interference of D2D users enhances the throughput of a conventional cellular network. In [Song et al., 2019], a joint uplink and downlink allocation of resource scheme is suggested to maximize the total capacity of the system and guarantees the SINR of both C_U and D2D pairs. The problem of optimization is conceived as a nonlinear mixed-integer problem that is usually NP-hard. The optimization problem is divided into two subproblems, namely power allocation and channel assignment, to achieve a fair allocation of resources. The objective function of power control is proven to be a convex function in which the optimum power of transmission can be obtained. The Hungarian algorithm was designed to achieve the mutual uplink and downlink allocation of channels to enhance system capacity and maximize the efficiency of the spectrum. In reference [Lee et al., 2017], using various optimization approaches, downlink resource schemes enhance the total data rate. The original nonconvex issue is transformed into a convex problem by the semidefinite relaxation technique and an objective function: a reformulation with first order approximation in each algorithm iteration.

In [Ramezani-Kebrya et al., 2017], the authors jointly enhance power of a C_U and a D_U to maximize the sum rate in underlay D2D communication. They take into account combining power control for the C_U and D2D transmitters and suggest a control of power algorithm to improve the total rate. They assume that all users have a single antenna, while the BS has multiple antennas. The goal is to jointly optimize the power control on the C_U and D2D transmitters to maximize the sum rate based on beamforming. The formulated joint optimization problem is nonconvex, and they propose a method to obtain a solution. In [Jiang et al., 2018], the author proposes an RA scheme and a dynamic power control method for D2D communication using the fractional frequency reuse (FFR) model. The optimization problem is NP-hard and cannot be solved directly, so the authors solve the total throughput problem by dividing the original problem into two subproblems: RA and the power control method.

Some studies propose channel selection strategies for CR networks. In [Bayhan and Alagöz, 2012], the best fit channel selection (BFC) for channel selection is produced in the CR network and considered the activity that occurs on both the primary channel and the CR in channel selection. CR nodes can estimate the activities of P_U traffic, specify the state of channel, and expect the time that the channel remains in idle state. As a result, the channels are selected that have a longer idle time. In [Yang et al., 2008, Salem et al., 2017], the longest idle time channel selection (LITC) is and simple Segregation methods are proposed, and CR users select the channel with the longest expected idle time, ignoring its transmission needs. Hence, LITC is considered, and each secondary

user (SU) improves its own gain and wastes resources that are employed by additional network nodes. The two abovementioned studies neglect the impact of sensing errors on channel selection performance, and the channel search method takes a long time to select the available channel. The hopping rate of a CR to switch from channel to channel is increased, which disturbs P_{Us}. This minimizes throughput and channel utilization. By contrast, a distributed channel selection strategy (SURF) for reliable data dissemination in multi-hop CR ad hoc networks is presented in [Rehmani et al., 2013]. In this strategy, a recovery method for poor channel decisions is proposed by changing the currently used P_U activity model to contain the sensing errors probability. SURF adapts the sensing errors probability in its prediction model for upcoming channel choice-making when there is a contradiction between the present prediction model and the current state of the sensing. Hence, the SURF prediction model is adapted for each mismatch case if the result is inaccurate prediction or channel sensing errors. In [Abdelhafez et al., 2019], the authors propose a channel selection scheme (IMIC) to prevent sensing errors to mitigate the interference in cognitive D2D communication. This is occurred using K-Means learning technique to help DUs clusters the channels and utilize the best channels.

The above works considers the single band and cognitive D2D communication to solve the interference issue in different applications. The proposed framework IDCSF considers different bands with different services in 5G networks with two modes of D2D communication. It mitigates the effect of sensing errors using SOM learning technique and the activity of PU is adjusted to let the DU recover from bad channel selection. Moreover, FL and channel selection algorithm are proposed to let the DUs select the best available channel for transmission. This leads to minimize the selection time required for a channel and reduce the hopping rate of a DU to switch from channel to another. Consequently, throughput and channel utilization are improved, and the delay is minimized.

3 System Model and Assumptions

The system model and basic assumptions about the proposed D2D communication system in 5G networks are explained in this section.

3.1 Network Model

In the proposed 5G scenario, we consider a heterogeneous network with different types of services or networks, such as a vehicle network, cellular network, and TV band network, each with a BS with licensed bands as well as a Wi-Fi network or smart home with a licensed or unlicensed band. The network is supposed to contain two types of users, namely primary users, or P_{Us}, and device users, or D_{Us}, and the P_U is the owner of the spectrum. The D_{Us} in the network can communicate directly with each other through or without the control of the BS, depending on a given threshold value ϵ. In this paper two types of D2D communication are utilized: the first type is D2D with the control of BS (underlay mode) and the other type is D2D with the devices control themselves (cognitive D2D) as shown in Figure 1. When the distance (D) which can be measured by received signal strength between two devices is less than or equal to a threshold value, the underlay D2D communication mode will be utilized, where the primary and device users share the same spectrum. This occurs if the bandwidth is sufficient. Otherwise, when the distance between D_{Us} is greater than the threshold value ϵ then the devices operate with cognitive D2D communication mode to obtain either a licensed or unlicensed band among different bands (our focus in this paper) as shown in Figure 2. The devices

themselves perform spectrum sensing, and the D_{Us} can communicate directly with each other without the BS. Therefore, in the proposed work, the mode selected depends on the application used. For the latter, the D2D pair cannot communicate directly in the cellular or vehicle network due to the high distance restriction, which will likely cause interference and high-power consumption. Hence, in this mode, the cognitive radio in D2D communication without the control of the BS is proposed to select the vacant channel from other bands (licensed or unlicensed), such as a Wi-Fi or TV band for communication. We also assume that the device users (D_{Us}) are equipped with a single transceiver and do not have accurate knowledge of the network thus, the transmission and sensing occurred sequentially. In addition, the data channel (CH) is dedicated to the P_{Us}, which have more spectrum privileges than D_{Us}; therefore, the D_U senses the presence of P_U transmissions dynamically and then use the opportunity of common control channel (CCC) to switch to the idle channel of the p_U transmissions.

Since the arrival of the P_U to the channel prevents D_{Us} from using the current CH, the D_{Us} utilize a CCC dedicated to negotiating the use of the potential CH for transmission between them such that the D_{Us} are aware of their neighbors when using the current channel. Note that the proposed is not a routing algorithm. Therefore, the D_{Us} use a single hop and does not maintain end-to-end path or routing tables. A carrier sense multiple access (CSMA) based medium access control (MAC) protocol which uses CCC is utilized for device users' negotiation.

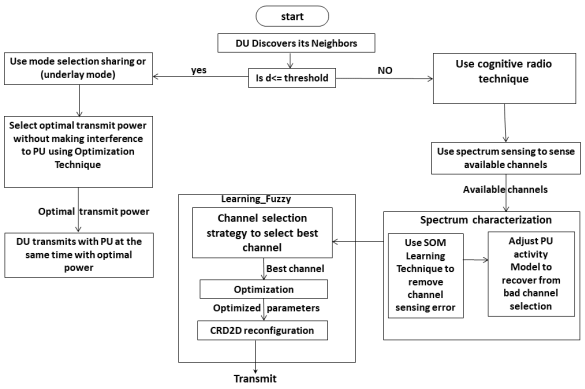


Figure 1: The proposed framework with hybrid D2D communication Modes.

4 The Proposed Intelligent Channel Selection Framework in Cognitive D2D Communication of 5G Networks

The proposed framework utilizes a hybrid of D2D communication categories: one is the underlay mode, where the distance between D_{Us} sender and receiver less than a threshold value, and the other for D_{Us} where the distance greater than a threshold value. In the former mode, the D_U transmits at the same time on the same channel that the P_U uses whereas for the latter the cognitive radio (our focus) is utilized.

4.1 Underlay D2D Communication Mode

In this mode, D2D communication with link establishment using BS is utilized where the P_U and D_U transmit at the same time on the channel only if the interference created by device transmitters at primary receivers below an acceptable threshold. In this mode the transmit power is optimized using GA with the objective function for power minimization discussed in subsection using the objective function of power consumption minimization with equation (6) and the D_U node transmits using the optimized power value on the same channel without disrupting P_{Us}.

4.2 Cognitive D2D Communication Mode

D2D communication with link establishment with control of device link establishment where the cognitive radio is utilized in this mode. In the proposed framework, when the distance between the D_U transmitter and receiver exceeds a threshold value, the D_U searches for another band for communication based on CR capability. The cognitive D2D communication in the proposed channel selection framework in 5G networks is composed of four units as shown in Figure 2. The first unit is the spectrum sensing model, wherein each D_U node senses available channels based on the algorithm for spectrum sensing, which is performed in the physical layer. These sensed available channels are transferred to spectrum characterization, which is the second unit, performed in the MAC layer. In the spectrum characterization unit, the SOM unsupervised learning technique is utilized to classify the available channels into four clusters: Idle, Busy, FalsA, and MissD. Using this technique helps the CR device user to intelligently select the appropriate idle channels and prevents the use of channels that have sensing problems, which are MissD and Busy. This reduces the spectrum sensing errors in the upper layer, which consequently improves spectrum utilization and minimizes interference with P_{Us}. In this unit, the P_U activity model has been adjusted to allow the device user to be more intelligent and handle sensing errors. The third unit is channel selection which is carried out in network layer and includes fuzzy inference system (FIS) and channel selection algorithm. In this unit, the only available channels with Idle and FalsA states resulting from the SOM learning technique are transferred to an FIS in this unit to yields the reliable channels which are channels with higher availability (high probability of channels in idle states). Fuzzy logic (FL) classify channels with Idle and FalsA into different classes, and the class with a high probability of channels in idle states (reliable channels) is passed to channel selector algorithm. This network layer supports multiple channels and maintains the P_U activity model and interference. The channel selection algorithm is also employed in this unit, to which the class of high probability channels in idle states is passed. In this phase some calculations for channel weight values is used to finds the channel with the highest weight value which will be chosen by D_U to transmit the packet as a best channel among different channels in an acceptable amount of time. Upon completion of the channel selection algorithm, the optimization process for quality of service (QoS) parameters begins in the fourth unit which is CRDU reconfiguration unit. Here, the best channel resulted from the channel selection unit is passed to the optimization phase in this unit, and the transmission parameters are optimized. The optimization process is used to determine the QoS parameter values, such as modulation type and transmission power, for the channel selected to achieve different network objectives (e.g., power minimization and throughput maximization). Finally, the device nodes transmit using this best channel and the optimized transmission parameter values resulted from optimization phase. The spectrum characterization, spectrum selection

and CRD2D reconfiguration units are the main topics of this paper's contributions. In proposed framework, we propose a cross-layer framework where each layer has a different role. This framework maximizes spectrum utilization and throughput; reduce sensing errors, false alarms, and miss-detection; and consequently, reduce the hopping rate from channel to channel. Each unit will discuss in detail below.

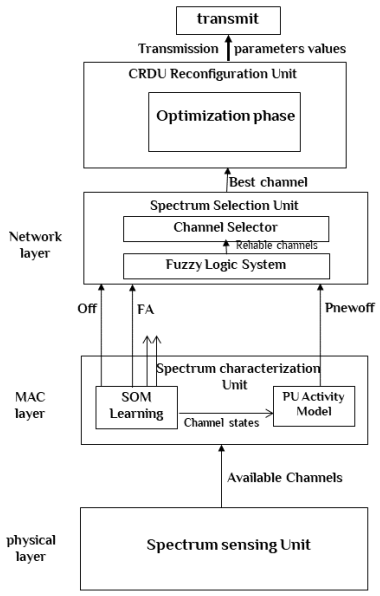


Figure 2: Cognitive D2D Communication Mode in the Proposed Framework.

4.2.1 Spectrum Sensing Model

We consider the D2D communication network environment in 5G, where network operations such as spectrum sensing, spectrum selection, and others are performed by the D_U nodes themselves. This network works in a distributed manner and makes decisions based on locally inferred information. Hence, each D_U node should periodically run a spectrum sensing algorithm at each specific period, called sensing period to detect the presence or absence of a signal from P_U. Spectrum sensing occurs when each D_U node obtains information about the use of the spectrum and the presence of P_U nodes in each area.

In this paper, the common spectrum sensing technique is assumed which is the energy detection spectrum sensing approach [Pandit and Singh, 2017]. In this technique, the energy of the observed signal is compared with a threshold and then decided for the absence or presence of a P_U signal. If the energy of the detected signal is greater than a predetermined threshold value, then the channel is considered busy.

D_U can detect its own signal from a P_U transmitter based on the hypothesis model of presence or absence of a P_U signal, as shown below, to differentiate between unused and

used spectrum bands [Bhowmick et al., 2017]:

$$D_U(t) = \begin{cases} (n(t) + P_U(t)H1 & \text{if } \mathrm{P_U} \text{ is present} \\ n(t)H0 & \text{if } \mathrm{P_U} \text{ is absent} \end{cases} \quad (1)$$

where $n(t)$ is a zero mean additive white Gaussian noise (AWGN), and H0 and H1 are the hypotheses of signal absence and signal presence, respectively. The output of the received signal process which is a test statistic for evaluating the two hypotheses H0 and H1, and it is later compared with the decision threshold for deciding whether a $\mathrm{P_U}$ exists or not. The performance of spectrum sensing is usually determined by the probabilities of false alarm and detection. The probability of detection means the decision is H1 while H1 becomes true, and the probability of false alarm means the decision is H1 while H0 is true. When the probability of detection is high, then the spectrum can be used more [Yucek and Arslan, 2009].

Spectrum sensing model is used to find the available channels that are selected by the networks depending on the application requirements. Therefore, the proposed framework utilizes these lists of available channels that are sensed as a result of spectrum sensing model [Lee and Akyldiz, 2010].

4.2.2 PU Activity Model

$\mathrm{D_{Us}}$ can use the spectrum only when it is not utilized by or is idle for the $\mathrm{P_{Us}}$, and the available channel will not be ready all the time according to the nature of a wireless D2D communication network. In addition, $\mathrm{P_{Us}}$ can arrive at any time; thus, $\mathrm{D_{Us}}$ should leave the channel. Hence, modeling the $\mathrm{P_{Us}}$' activity helps $\mathrm{D_{Us}}$ to access the channels in the absence of the $\mathrm{P_{Us}}$' signal to decrease the sensing errors of the channels to mitigate interference. Thus, it is important to specify the probability of Idle periods for $\mathrm{P_{Us}}$ on the available channels. The absence or presence of the $\mathrm{P_{Us}}$' signal on each channel is modeled using different techniques. In the proposed framework, one of the most important modeling techniques, namely the continuous time alternating Busy/Idle Markov Renewal Process (MRP) [Lee and Akyildiz, 2008] is utilized to determine the $\mathrm{P_U}$ activity model in D2D communication networks. The most important feature of this Busy/Idle $\mathrm{P_U}$ activity model is that it accurately determines when a $\mathrm{P_U}$ is in a Busy or Idle state. The Idle state indicates that the channel is not utilized by the $\mathrm{P_U}$ node, and $\mathrm{D_{Us}}$ can consequently use it, whereas the Busy state indicates that the channel is utilized by the $\mathrm{P_U}$, and $\mathrm{D_{Us}}$ thus cannot use it.

The busy and idle periods are considered to exist independently, and each $\mathrm{P_{Us}}$' arrival is independent. Thus, the Poisson arrival process is followed by each transition, and the channel's Busy and Idle periods are both exponentially distributed.

From the primary user activity model, the probabilities of busy and idle periods are calculated as follows [Rehmani et al., 2013], [Kim and Shin, 2008]:

$$P_{Busy}(t) = \frac{\lambda_y}{\lambda_x + \lambda_y} - \frac{\lambda_y}{\lambda_x + \lambda_y} e^{-(\lambda_x + \lambda_y)t} \quad (2)$$

$$P_{\mathrm{Idle}}(t) = \frac{\lambda_x}{\lambda_x + \lambda_y} - \frac{\lambda_x}{\lambda_x + \lambda_y} e^{-(\lambda_x + \lambda_y)t}, \quad (3)$$

where P_{Busy} is the probability of the channel in Busy state at time t and the probability of the channel in Idle state at time t is $\mathrm{P_{Idle}}$; hence, $\mathrm{P_{Idle}} = 1 - \mathrm{P_{Busy}}$. λ_{x} and λ_{y} are

the distribution rate parameters and can be measured by CRDU nodes via collecting historical samples of channel state transition as used in [Rehmani et al., 2012].

The presence of P_U is missing when the probability of detection P_{dt} is low, and the interference with P_U consequently increases. Therefore, if the probability of false alarm P_{FalsA} is high, then the number of missed opportunities increases. This leads to a reduction in spectrum utilization. The probability of detection P_{dt} indicates the probability that the sensed channel is busy but actually is busy, whereas the probability of P_{FalsA} determines the probability that the channel is detected as busy but actually is idle.

The sensing errors FalsA and MissD have impact on each D_U which will be reflected on the P_U activity model. This leads to a maximization of interference and a reduction in network performance. Therefore, the effect of sensing errors is considered in the P_U activity model to calculate the duration for which the channel can be used by D_{Us} and their values which will be registered in a history table for future prediction. Channel decision procedure might also be incorrect and will disrupt the interference to P_{Us}. Therefore, in the proposed framework, the P_U activity model is adjusted to let the node be more intelligent and consider the sensing errors for future prediction using the equation 6. This can aid in recovering from bad channel selection decisions.

4.2.3 Unsupervised Learning Self-Organizing Map (SOM) Technique

Since 5G networks have numerous bands with more available channels, these channels should be classified to determine channels with sensing errors with FalsA and MissD. This process can be achieved quickly using an intelligent learning technique instead of the conventional method. Thus, to achieve the best channel selection of D2D communication in 5G networks, in this paper a type of unsupervised learning technique called SOM is proposed in the spectrum characterization unit to reduce the probability of FalsA and MissD sensing errors in available channels and to help the D_U node minimize the impact of the probability of such errors.

The SOM learning technique is a popular unsupervised learning technique in neural networks that reduces large data sets by clustering and grouping them into an array of two-dimensional arrays based on competitive learning. The SOM is an excellent tool to explore data in the field of artificial neural networks. It can map high-dimensional patterns into low-dimensional topologies. This map is composed of a one- or two-dimensional grid of nodes, and these nodes are called neurons. It allows the D_U to be aware of the available channel history. [Chaudhary et al., 2014].

The SOM learning technique contains an input vector and an output vector of nodes, with each input node connected to all output neurons. SOM is considered a competition network that searches for similar distances between the input vector and the neuron with the weight vector Wi. It operates in two steps: the first step is to learn the technique to group input data vectors into clusters using a competitive process; the second step is to assign a location for and then classify new data (vectors). It also performs clustering and does not need a predetermined number of clusters, but it utilizes a function of neighborhood to maintain the properties of the topology of the input space [Natita et al., 2016].

The proposed SOM learning technique comprises two inputs and four outputs. The inputs are (1) the sensing state and (2) the prediction state, which are sensed from the spectrum sensing of the D_U node for the channel and the prediction sensing state of neighbors. The four outputs are the resulting clusters depending on the channel state: Busy, Idle, MissD, and FalsA. The architecture of input vector x (the sensing and prediction states) and output vector y (clusters) in SOM learning is depicted in Figure 3.

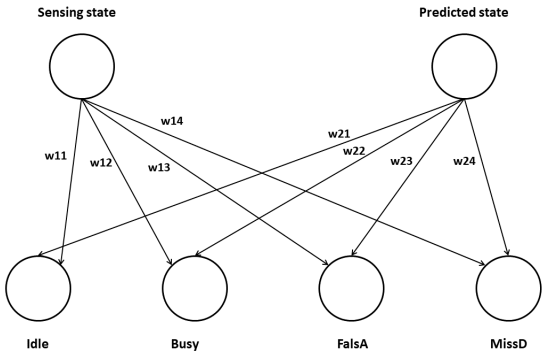


Figure 3: The Architecture of input and output vectors in SOM learning.

At the beginning of learning, all the weights are initialized to small random numbers. Next, the SOM algorithm will try to find the winning neuron based on the minimum distance using Euclidean distance d. The proposed technique finds the distance from the input to the output nodes, and the node with the minimum distance to the input is the winner node. The output nodes specify the distance to the winner node. The output node is influenced by something like the winning node, but at a different rate, if the distance to the neighborhood width is shorter. After the winner neuron is obtained, the weight vector of the neuron is altered to increase similarity to the input vector using the neighborhood function and learning rate. The learning rate α(t) is a training parameter that manages the weight vector size in SOM learning, while the neighborhood function σ(t) determines the change rate of neighborhood around the winner neuron and is defined as follows [Natita et al., 2016].

$$\alpha(t) = \alpha(0)\left(\frac{\alpha(T)}{\alpha(0)}\right)^{1/T} \tag{4}$$

$$\sigma(t) = \sigma(0)\left(\frac{\sigma(T)}{\sigma(0)}\right)^{1/T} \tag{5}$$

where T is the training length.

Grouping the available spectrum channels enables D_{Us} to choose the best channel for transmission. After the available channels are specified, the SOM learning technique runs and after several iterations of learning, all data samples converge to four clusters (Busy, Idle, FalsA, and MissD) based on input states as shown in Figure 4. Each state of the channel is represented by a vector [Arnous et al., 2018]. The first cluster includes all samples with Busy sensing and represented by vector (11); Idle cluster includes all samples with Idle sensing and represented by vector (00); and FalsA includes all samples of channels where the channel in Busy state but already in Idle state and represented by vector (10). The MissD cluster includes all samples with channels in the Idle state, but the channel is already in the Busy state and represented by vector (01). Furthermore, the SOM learning technique affords CRDU the capability to distinguish between the right channels, either Busy or Idle, with false alarms and miss-detection. The resulting outputs of the SOM learning phase are four clusters (Idle, Busy, MissD, and FalsA), but

only two clusters of channels (Idle and FalsA) are passed to the FIS in channel selection unit. These two clusters passed from SOM are classified using the FIS to yield the most reliable channels which is the channels that have higher probability in Idle state.

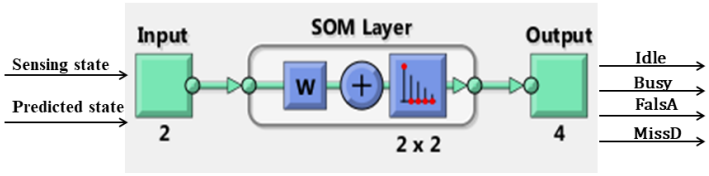


Figure 4: The SOM Learning Technique Process.

After the SOM learning technique is finished, and the result is four clusters, P_U activity model is adjusted using the equation (6) to let the D_U to be more intelligent and handle the sensing errors. Each D_U node calculates the Pnewoff (t), which takes into account the inaccurate channel state estimations, D_U Nodes keep track of both the history of FalsA and MissD of the channels in order to accomplish this. The incorrect estimations are subsequently identified by D_U nodes, who additionally store them in history after calculating the probability P_{FalsA} and P_{MissD} as follows [Rehmani et al., 2013]:

$$P_{\text{newoff}}^{(i)} = P_{\text{Idle}}^{(i)}(1 - P_{\text{FalsA}}^{(i)}) + P_{\text{MissD}}^{(i)}(1 - P_{\text{Idle}}^{(i)}) \tag{6}$$

In case of ideal channel estimation (i.e., $P_{FalsA} = 0$ and $P_{MissD} = 0$). If the FalsA occurs, the D_U node increases the P_{FalsA} counter; otherwise, if the MissD occurs, the D_U node increases the P_{MissD} counter. Each D_U node preserves the P_{FalsA} and P_{MissD} histories in this way.

More specifically, the sensing errors of the channel affect the accuracy of the proposed recovery process. P_{FalsA} refers to the probability of a false alarm, which happens when the measured channel state is Busy, and the predicted channel state is Idle. The unoccupied channel is identified as busy by D_U node and is calculated as:

$$P_{\text{FalsA}}(t) = \frac{X_{Fa}}{NF} \tag{7}$$

where X_{Fa} is the channel's number of false alarm times and NF is the total number of sensing times that occur for the channel. As a result, the D_U node will stop transmitting and missing out on a spectrum opportunity. On the other hand, the probability P_{MissD}, happens when the measured channel state is Busy while the predicted channel state is Idle. The busy channel has been identified as unoccupied by D_U node and calculated as follows:

$$P_{\text{MissD}}(t) = \frac{X_{MD}}{NM} \tag{8}$$

where X_{MD} is the channel's number of miss detection times and NM is the total number of sensing times that occur for the channel. This will cause D_U nodes to experience undesirable interference. P_{FalsA} and P_{MissD} are measured by each D_U node for each channel.

After the P_U activity model is adjusted the probability of channel in OFF state is passed to the fuzzy logic to be utilized for classification.

4.2.4 Channel Selection in Cognitive Radio D2D Communication

To enhance the performance of D2D communication in 5G networks, the most important issue relates to how to reduce the interference caused to P_{Us} and among D_{Us}. This reduction leads to enhanced network performance accordingly. Thus, the best channels should be selected properly. Moreover, in 5G network environments, the spectrum search method may take a long time to choose the best channel and the solution is needed to tackle the searching process and reduce the delay in selecting the best among the available channels.

The phases in this unit start after the SOM learning technique is completed and the output channels without sensing errors (FalsA and Idle) are only passed to the FL phase in this unit. This unit composed of two phases: first, the FIS and second, the channel selector algorithm. It takes data from spectrum sensing and spectrum characterization. In this paper an artificial intelligence (AI) FL technique is proposed to help D_{Us} select the best channel. FL is also adopted to handle uncertainties concerning the best channels among a massive number of spectrum channels, and the result is reliable channels that will be passed to the channel selection algorithm phase thereby reducing the delay resulting from searching only in a specific group of channels rather than all the resulting channels from SOM learning technique. The second phase is channel selector algorithm and is run to calculate the weight values for the resulted reliable channels, and the best channel is then selected among them. These two phases are explained in detail below.

Proposed Fuzzy-Based Channel Selection Phase

In this subsection, a brief overview of FL and its parameters which used to classify the resulted available channels from SOM learning technique is presented to aid in channel selection. after the available channels are classified from learning technique, it is important for D_U to find the best channel. However, in 5G environments the number of channels will be large, thus search method for the channels may takes long time for channel selection, therefore, fuzzy logic system is employed to overcome this problem by speeding the search process time through classifying the channels into different classes based on higher availability. FL is a simple mathematical tool that is suitable for decision-making to provide accurate solutions when the available input values are unclear and noisy. Furthermore, FL is considered an AI method that is used in different fields requiring advanced technologies. FL is a useful method for solving problems that are considered difficult to solve using traditional mathematical methods. The mathematical calculation complexity is also minimized using this concept [Safdar et al., 2022], [Salem et al., 2017].

Once the available channels without sensing errors are determined from the SOM learning technique, the FIS is proposed to classify these channels into reliable channels (channels with high availability) to assist D_U in selecting the best channel. Thus, the channels are accurately ensured, and the time is consequently minimized. In the proposed framework, FL is used not only to assist D_{Us} in selecting the best channels among a massive number of channels but also to address the problems efficiently and achieve more accurate decision-making through different fuzzy processing and minimize the searching time process and reduce the delay.

The proposed FIS is utilized to classify two types of channels (FalsA and Idle) resulting from the learning technique based on three parameters: the probability of a channel being in the Idle state (Pnewoff), the SINR, and the bit rate of the channel. These parameters are fed into the FIS to classify the channels, and the result is the most reliable channels. After the FL phase ends, only the output reliable channels are passed to the channel selection algorithm phase which calculates the channel weight value for each

channel to find the best channel. The channel with the highest weight value is chosen as the best channel among the list of channels to transmit the packets and this best channel is passed to the optimization phase.

A general FIS is composed of four main components [Alozie et al., 2022]: the fuzzifier unit, fuzzy rules, the fuzzifier unit, fuzzy rules, the inference engine, and the defuzzifier unit. The FIS uses the concept of FL to perform decision-making. Figure 5 below depicts the FIS's block diagram. This process requires the following four steps:

- Fuzzification: In this process, inputs are converted from crisp values to fuzzy sets, with each input crisp value determined by a linguistic term such as "low," "medium," and "high.".
- Fuzzy Rules: The rule-based decision unit is the core of the FIS since it maintains the set of IF-THEN rules that are used in the decision-making process to determine the attributes of the input variables.
- Fuzzy Inference Engine: This engine simulates the reasoning by providing a fuzzy inference using both the input values and IF-THEN rules.
- Defuzzification: After making a decision, the defuzzifier unit transforms the fuzzy output values into crisp values.

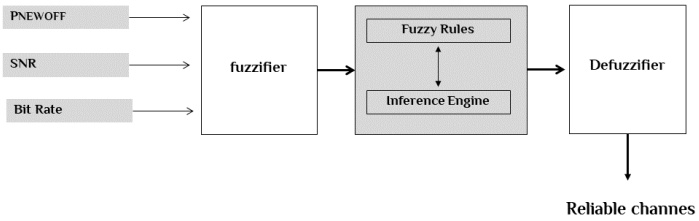


Figure 5: The Fuzzy Inference System Architecture.

When the FL process starts, the fuzzifier unit converts all the inputs into suitable fuzzy values. As a result, each input will yield its own membership value. The relationship between the input and output variables is defined by the fuzzy rule. Furthermore, the rules define the input and output variables of the FIS. Thereafter, the fuzzy values utilized by the inference engine trigger the fuzzy rule to make decisions. The outputs from each rule are combined to produce a result. The obtained fuzzy value is then defuzzified to produce a final crisp value.

The most widely used fuzzy controller is Mamdani's [Mamdani and Assilian, 1975] fuzzy inference system, which is also utilized in the proposed FIS with three inputs and one output. The input and output variables in an FIS should be represented as membership functions [Nayak and Devulapalli, 2015]. These membership functions can be described by different shapes, for example Gaussian, triangular, trapezoidal, and generalized bell shaped. The degree of membership is represented by a number between 0 and 1. We have taken three input variables to select reliable channels (High Pnewoff). All these input variables have three membership functions. Figure 6 illustrates three triangular membership functions for the proposed fuzzy logic labeled with linguistic terms ("low," "medium," and "high") for three input variables. The fuzzy set that indicates the first input variable, or probability of channel in Idle state Pnewoff as shown in Figure 7(a). The fuzzy set's linguistic variables are (low, medium, and high). The second fuzzy input variable is the SINR as shown in Figure 7(b). The third fuzzy input variable is bit rate as shown in Figure 7(c). The output (Reliable channels) is composed of five membership functions: very low, low, medium, high, and very high and the fuzzy set for the output is illustrated in Figure 8. In addition, 27 IF-THEN-based rules are considered, and the AND operator is the fuzzy operator that we used. The most reliable channel in our case of fuzzy rules is IF Pnewoff is high, and the SNR is high and bit rate is high THEN Reliable channel is high. This indicates that the channels are highly reliable. Then, this resulting value is defuzzified to arrive at a final crisp value, and the defuzzification method used is the center of gravity.

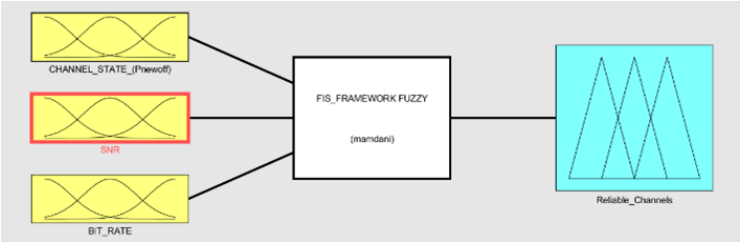
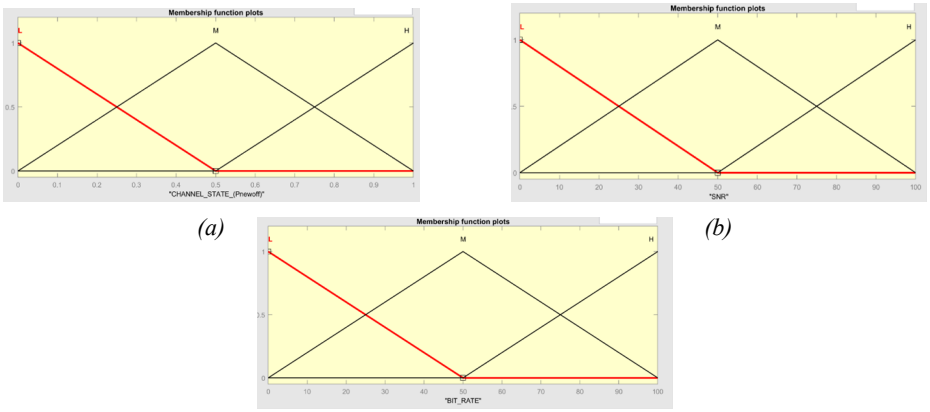


Figure 6: The Fuzzy System for the Proposed Framework.



(a) *(b)*

(c)

Figure 7: Membership Function Plots: (a) Pnewoff. (b) SINR. (c) Bit rate.

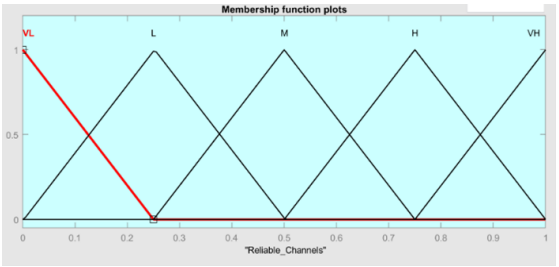


Figure 8: Membership Function for Output Variable (Reliable channels).

After the FL is finished and the result is different classes of channels then the class which contains higher availability is passed to the channel selector algorithm phase to calculate the weight for each channel as discussed in next subsection.

Channel Selector Algorithm Phase in Channel Selection for Cognitive D2D

After the FL phase is finished, the resulting output is the reliable channels and the class with higher availability of channels is passed to the channel selector algorithm phase. In this phase the calculation of channel weight values is applied to obtain the best channel among the list of channels. Each D_U run channel selector algorithm to calculate the weights of channels for each available channel. Algorithm 1 outlines the steps to calculate the weight values of the channels resulting from the FL phase. Some of the reliable channels produced by FL may have the same values as others, such as Pnewoff and SINR values, and we should choose among them. The suggested framework prioritizes selecting a channel with higher availability, smaller number of D_{Us} using the channel, and a larger bandwidth; consequently, we used these factors to calculate the weight values for each channel and selected the best channel among them.

Algorithm 1 Channel Selector Algorithm

1: Initialize: Each D_U node senses the available channels.
2: **for** each node D_{Ui}, **do**
3: **for** each channel, i **do**
4: Each D_U, calculates the probability of channel in Idle state at specific time ($P^{(i)}_{NEWoff}$).
5: Each D_U, calculates the bit rate for each channel.
6: Each D_U estimates the number of D_U exploited by each channel ($DU^{(i)}_{exploited}$).
7: The weight value for each channel is estimated by $\forall_{(i)} \in CH : w^{(i)}_{DU} = \frac{Bi*SINR*Pnewoff}{DU^{(i)}_{exploited}}$ Where i is number of channels, CH is a set of available channels and w is weight.
8: Sort ($w^{(i)}_{DU}$)
9: Best CH= max($w^{(i)}_{DU}$).
10: If two channels are equal in weight value, take higher Pnewoff then higher bit rate.
11: If the channels are the same value take random.
12: Repeat for each CH
13: **end for**
14: **end for**

In this case, the selection algorithm orders the available channels based on channel weight; the best channel has the maximum channel weight. Therefore, when two or more channels have the same weight value, the framework select the best channel as the one with the highest $P^{(i)}_{newoff}$ and then the highest bandwidth. based on the probability of channels in Idle state and then the maximum channel bandwidth. If both equal values, the best channel is selected randomly as illustrated in Table **??**. After the learning technique is run to select the best available channel among the list of channels based on the weight values, the weight values will be 0.2, 0.67, 0.8, and 0.85 for channels 1, 2, 3, and 5, respectively.

DU node	Available channel	P_{newoff}	$DU_{exploit}$	B_i	Weight values
Node 1	1	0.2	2	2	0.2
	2	0.5	3	4	0.67
	3	0.8	8	8	0.8
	5	0.85	2	2	0.85

Table 1: List of available channels at Node 1.

When the list of channels is arranged as shown in Table **??**, node 1 selects channel number 5 for transmission since it has the highest weight value, and this best channel is transferred to the optimization phase.

DU node	Channel List
Node 1	5
	3
	2
	1

Table 2: The ordered channels' list at Node 1.

4.2.5 Optimization Phase to Optimize Transmission Parameters in Cognitive D2D Communication

This optimization phase starts after the channel is selected in the channel selection unit, and the result is the best channel. Even if D_{Us} select the channel properly, other parameters should be optimized to achieve quality of service. Hence, optimization is proposed in the framework to optimize transmission parameters for the selected best channel to achieve high QoS parameters.

When the optimization phase ends, the resulting optimized QoS parameter values are passed to the CR in the D2D communication device unit in order to transmit through the channel that has been selected with the best QoS parameters.

5 Performance Analysis and Simulation Results of Cognitive D2D Communication

The performance metrics of the proposed framework (IDCSF) is simulated and regenerated through extensive experiments using MATLAB and NS2 and then evaluated and compared with the LITC, BFC, SURF, and IMIC selection methods in terms of the following metrics at various parameters for example the number of D_{Us} in the network and the number of available channels at each node.

- Spectrum opportunity utilization: It represents how much of the spectrum opportunities are utilized by the D_{Us}.
- Average throughput: It is the ratio of successfully received bits by each D_U node over time needed to transport the bits.
- Packet delivery ratio: It is the ratio of packets delivered to the D_{Us} to the total number of packets sent in the network.
- Average interference ratio: the ratio of total number of times the channel is occupied by primary user (P_U) device over total number of times the channel selection decision occurs.
- End-to-end delay: it is the time for packet to arrive the destination after leaving the source.

5.1 Results and Discussion

The simulation parameters used for the proposed framework are presented in this subsection. The location of nodes, source and destination pairs, and the availability channel of

each node are randomly deployed within a square area of (700 x 700). The number of D_{Us} is fixed to 150. The communication range of D_U is set to 250 m and packet size is 512 bytes and with a threshold ϵ equal 10 and maximum transmission power for D_U equal to 21dBm. The total number of channels (CHs) in all bands are 400. In this simulation experiments, 600 packets were sent, and each packet is sent by a randomly selected node. The total number of times the channel is occupied by P_U node happens when channel selection framework selects best channel for transmission, however, the P_U is existing on that selected channel. The rate parameters of exponential distribution (λ_x, λ_y) for P_U activity model can be easily measured by CRDU nodes by collecting the historical samples of channel state transitions from the number of transitions as shown in Table **??**.

	CH1	**CH2**	**CH3**	**CH4**	**CH5**	**CH6**	**CH7**	**CH8**	**CH9**	**CH10**
λ_x	1.25	0.4	1	0.4	0.5	2	1	0.18	0.5	0.67
λ_y	0.67	2	1	0.33	1	0.29	0.25	2	1.33	0.5

Table 3: Wireless Channel Parameters used in the Simulation.

5.1.1 Analysis of the impact of Number of Device Nodes on Channel Selection Methods

In this subsection, the proposed framework is evaluated using the effects of the growth of D_U's traffic in terms of average interference, spectrum utilization, throughput, packet delivery, and end-to-end delay ratios. The number of D_{Us} in the network varies from 10 to 250, and number of available channels for each D_U is set to 10. The activity of P_U traffic is also independent and varied for all available channels. Figure 9 shows the simulation results for the interference ratio at various numbers of D_U nodes. It is observed that the average interference ratio for the proposed framework is improved with minimum values compared with IMIC when the number of D_U nodes is 10 whereas maximum improvement in the proposed framework for the interference ratio is achieved in comparison with LITC when number of device nodes is 250.

The improvement in the average interference ratio for the proposed framework IDCSF happens at node 10 and the ratio is minimized by around 6% compared with the IMIC method. The minimum average interference ratio is achieved in proposed framework, as compared with LITC, when the number of D_U nodes is 250, where the ratio is minimized by 65%. Moreover, it is observed that the proposed framework outperforms other methods LITC, BFC, SURF and IMIC, which means it minimizes the average interference ratio at various numbers of D_U nodes by 48%, 38%, 7% and 5% respectively. When the number of D_{Us} increased, the interference ratio also increased in all methods. This is due to the growth in the number of D_{Us} in the network, which maximizes the interference among D_{Us}.

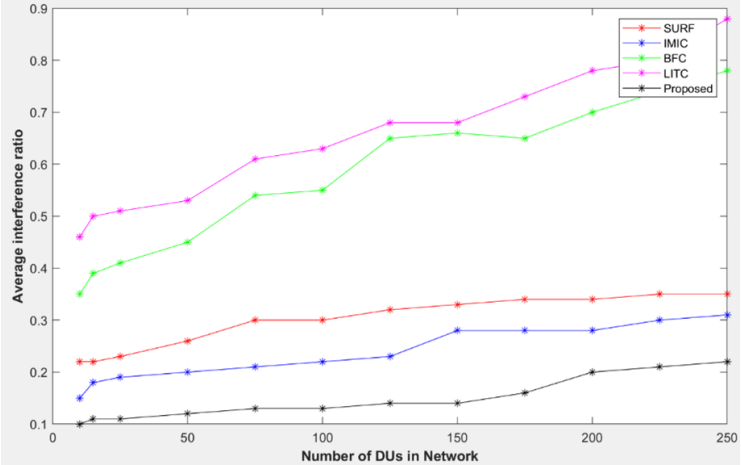


Figure 9: Average interference ratio at different number of DU.

Figure 10 illustrates the average throughput experimental results at various numbers of device user (D_U) nodes for all methods. The proposed framework IDCSF provides the maximum improvement in comparison with LITC when the number of D_U nodes is 250, as the ratio is maximized by 52%. By contrast, it offers minimum enhancement when the number of device nodes is 125 in comparison with IMIC, where the ratio is increased by 8%. The average throughput is highly affected by the total received packets and the interference ratios in the network. This means when the transmission of $8D_{Us}$ is completed successfully, the total number of successfully received packets increases. As a result, the average throughput increases. The proposed framework IDCSF outperforms all other methods LITC, BFC, SURF and IMIC in terms of average throughput at different numbers of device nodes, which is maximized by 48%, 32%, 15%, and 6% respectively.

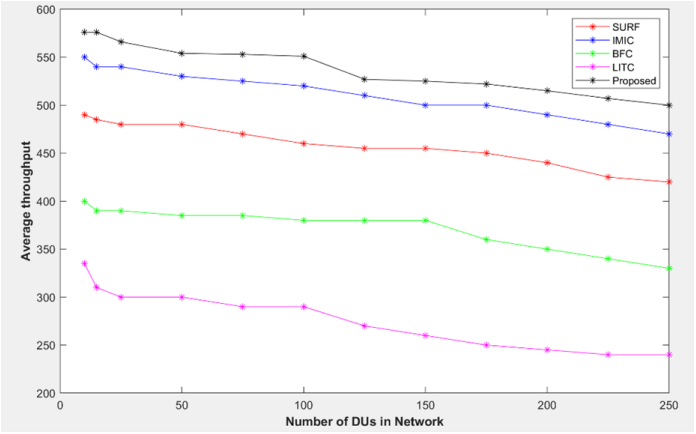


Figure 10: Average throughput ratio at different number of DU.

Figure 11 presents the simulation results of the average packet delivery ratio at various network densities for all methods LITC, BFC, SURF and IMIC. It is observed that the packet delivery ratio decreased when the number of D_{Us} increased. This is because increasing the number of D_{Us} in the network will increase the contention among them, and the interference will increase accordingly, but with different ratios. Moreover, the proposed framework IDRAF outperforms other methods in terms of packet delivery ratio; this is due to the lower interference ratio. Therefore, the packet delivery ratio increases, leading to an increase in the average throughput in the network in a reasonable time. The proposed framework also produces the maximum packet delivery ratio at various numbers of D_U nodes for the LITC, BFC, SURF and IMIC by 54%, 47%,17% and 6% respectively. The packet delivery ratio is highly affected by spectrum utilization and interference ratio. Moreover, selecting the channels with an intelligent way using SOM learning and FL and also considering sensing errors in P_U activity model decreases the interference among D_{Us} and between P_{Us} and D_{Us}. Hence, the packets sent over the network is successfully received.

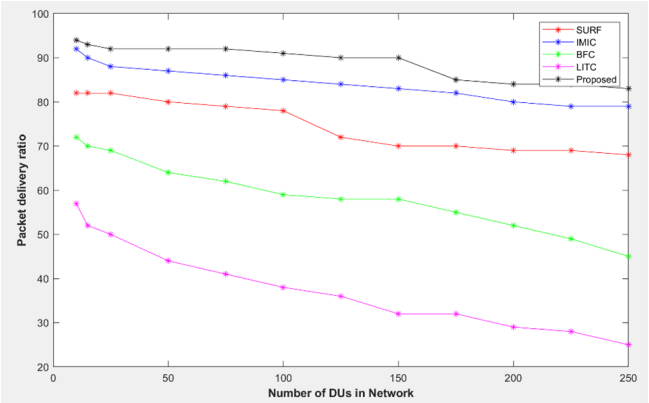


Figure 11: Average packet delivery ratio at different number of DU.

Figure 12 displays the results of evaluating the spectrum utilization at various numbers of DU nodes for all methods LITC, BFC, SURF and IMIC. The proposed framework IDCSF performed the maximum improvement in spectrum opportunity utilization in comparison with LITC when the number of D_U nodes is 10 and 15 where the ratio is 73%, whereas the minimum improvement occurs in spectrum utilization in comparisons with IMIC when the number of D_U nodes is 125 where the ratio increased by 3%. It is observed that the proposed outperforms other mentioned methods in spectrum utilization which increased at different numbers of D_U nodes by 66%, 56%, 42% and 8% respectively. The proposed framework IDRAF outperformed all other methods. This is due to selection of channels with a method that ensures they are not utilized by P_{Us} using the SOM learning technique; hence, the interference will be minimized, and depending on this, spectrum utilization will increase. Spectrum utilization is most related to interference and packet delivery ratios; thus, when the interference ratio decreases and the packet delivery ratio increases, spectrum utilization will increase accordingly, and vice versa. In addition, when the number of D_{Us} increases, the number of received packets increases, and spectrum utilization consequently increases accordingly.

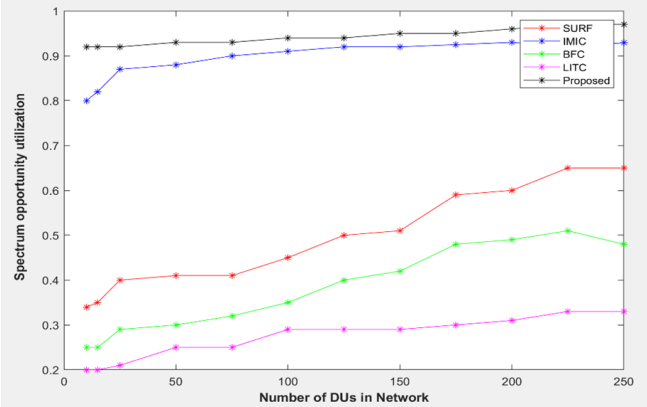


Figure 12: Average spectrum utilization ratio at different number of DU.

Figure 13 shows the results of calculating the end-to-end delay for all methods LITC, BFC, SURF and IMIC at different numbers of DU nodes. It is observed that the proposed framework IDCSF outperforms all other mentioned methods where is decreases by a ratio 62%, 38%, 18% and 6% respectively.

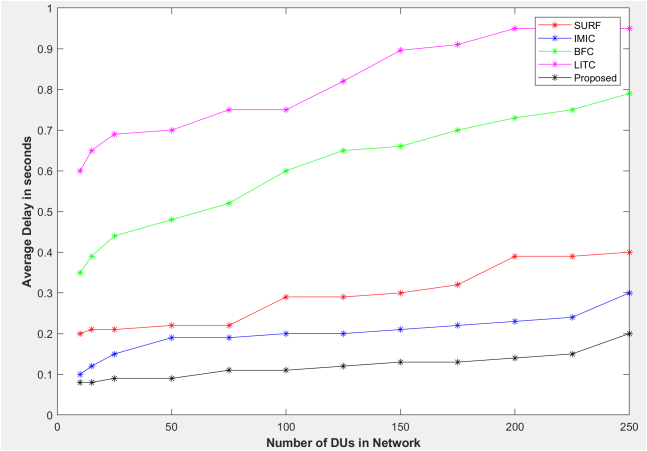


Figure 13: Average end to end delay ratio at different number of DU.

5.1.2 Analysis of Impact of the number of Channels on Channel Selection Methods

In this subsection, the proposed framework is analyzed using simulation to demonstrate the effect of each method: LITC, BFC, SURF and IMIC at various numbers of available channels, and the number of D_{Us} is fixed at 100 nodes and the behavior of P_U activity is independent and different for all available channels for each D_U. Figure 14 presents

result of estimating average interference ratio at various numbers of available channels for all methods. It is observed that the proposed IDCSF minimizes the interference ratio by 63%, 56%, 15% and 10% compared with methods mentioned above.

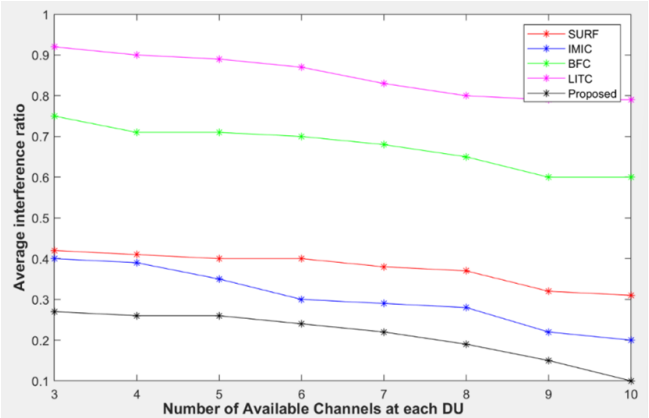


Figure 14: Average interference ratio at different number of available channels.

Figure 15 illustrates the effect of varying the number of available channels on average throughput for the proposed framework and other methods (LITC, BFC, SURF and IMIC). It is observed that the proposed framework can enhance the average throughput by % in comparison with mentioned methods by a ratio 60%, 47%, 28% and 14%, respectively.

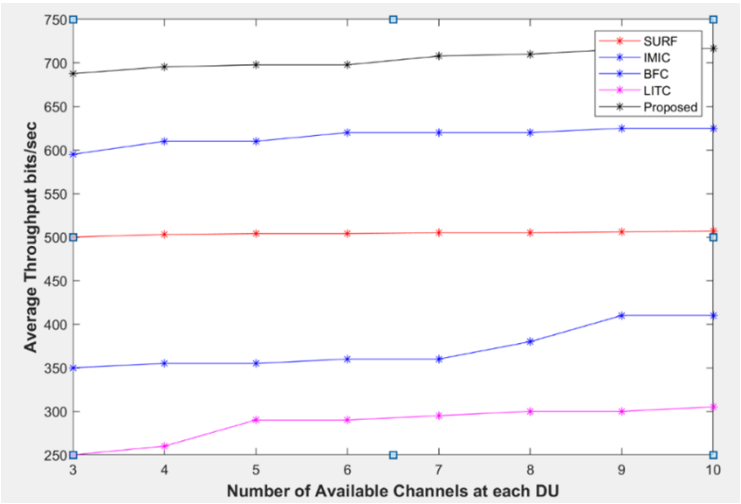


Figure 15: Average throughput ratio at different number of available channels.

Figure 16 illustrates the result of simulations for evaluating the average packet delivery ratio at various numbers of available channels for all methods LITC, BFC, SURF and IMIC. It is noticed that the proposed framework IDCSF can improve the packet delivery ratio in comparison with mentioned methods by 47%, 32%, 14%, and 8%, respectively.

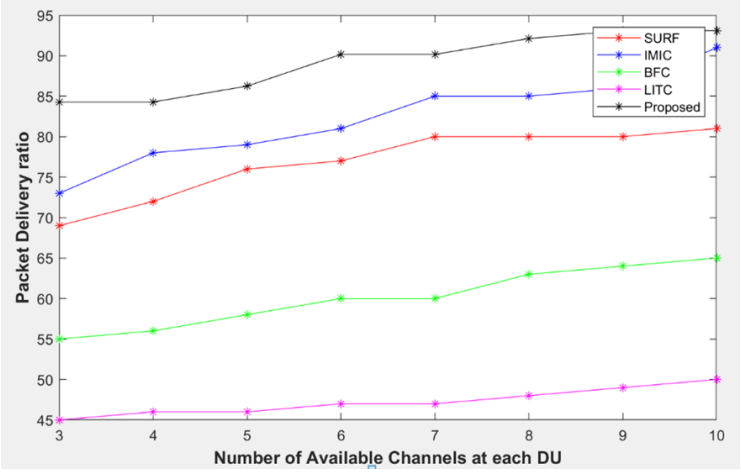


Figure 16: Average packet delivery ratio at different number of available channels.

The performance of average spectrum opportunity utilization is analyzed through simulations at various numbers of available channels for all methods LITC, BFC, SURF and IMIC, as illustrated in Figure 17. It is noticed that the proposed framework IDCSF can improve spectrum utilization in comparison with LITC, BFC, SURF and IMIC by 57%, 37%, 13%, and 4%, respectively and it outperforms these methods.

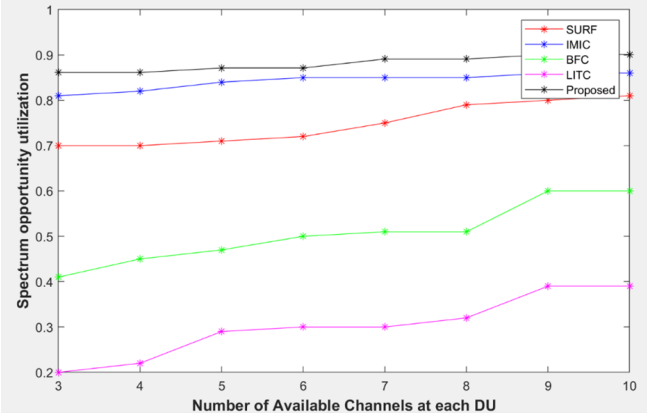


Figure 17: Average spectrum utilization at different number of available channels.

Figure 18 shows the results of simulations of average end-to-end delay at various numbers of available channels for LITC, BFC, SURF, IMIC and IDCSF methods. The proposed framework IDCSF minimizes the average end-to-end delay by 56%, 48%, 25%, and 14% in comparison with other mentioned methods.

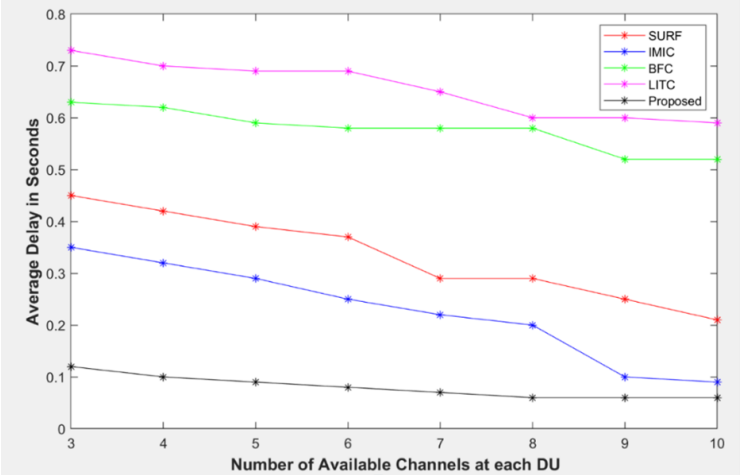


Figure 18: Average end to end at different number of available channels.

6 Conclusion and Future Work

In this paper, D2D communication in 5G networks is improved by the proposed an intelligent distributed channel selection framework to select the best available channel for transmission that fulfills the D_{Us}' transmission requirements. The proposed method is not a routing algorithm.As a result, the DUs use a single hop and do not keep end-to-end paths or routing tables. The main contribution of the proposed framework is the minimization of channel sensing errors for both false alarm and miss-detection metrics. This is achieved using the SOM learning technique in the proposed framework which will exclude channels with Busy and MissD states to reduce the effect of sensing errors, thus selecting the best available channel with an intelligent process. The D_{Us} consequently transmit their packets without disturbing PUs or moving from channel to channel. This minimizes the average delay on the network. The performance of the proposed framework is analyzed to test the effect of varying the number of nodes and the number of available channels. Simulation results confirm that the proposed framework outperforms IMIC, LITC, BFC, SURF, and IDCSF in terms of the following performance metrics: average throughput, spectrum opportunity utilization, average interference, packet delivery, and average end-to-end delay ratios. For future work, further performance metrics should be analyzed, and additional optimization methods should be applied for multiobjective functions that are appropriate for different application requirement. Furthermore, the application or comparison with different unsupervised learning techniques can also be used.

Acknowledgements

This work was supported by Research Supporting Project Number (RSPD2024R585), King Saud University, Riyadh, Saudi Arabia.

References

[Abdelhafez et al., 2019] Abdelhafez, A. M., Elattar, H. M., and Aboul-Dahab, M. (2019). Interference mitigation by intelligent channel selection for device-to-device communications. In *2019 IEEE 10th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON)*, pages 1103–1109. IEEE.

[Alozie et al., 2022] Alozie, E., Nasir, F., Oloyede, A., Sowande, O., Imoize, A., Abdulkarim, A., and Garba, S. (2022). Intelligent process of spectrum handoff in cognitive radio network. *SLU Journal of Science and Technology*, 4(1&2):205–218.

[Araújo et al., 2016] Araújo, D. C., Maksymyuk, T., de Almeida, A. L., Maciel, T., Mota, J. C., and Jo, M. (2016). Massive mimo: survey and future research topics. *Iet Communications*, 10(15):1938–1946.

[Arnous et al., 2018] Arnous, R., El-Desouky, A. I., Sarhan, A., and Badawy, M. (2018). Ilfcs: an intelligent learning fuzzy-based channel selection framework for cognitive radio networks. *EURASIP Journal on Wireless Communications and Networking*, 2018(1):1–18.

[Bayhan and Alagöz, 2012] Bayhan, S. and Alagöz, F. (2012). Distributed channel selection in crahns: A non-selfish scheme for mitigating spectrum fragmentation. *Ad Hoc Networks*, 10(5):774–788.

[Bhowmick et al., 2017] Bhowmick, A., Yadav, K., Roy, S. D., and Kundu, S. (2017). Throughput of an energy harvesting cognitive radio network based on prediction of primary user. *IEEE Transactions on Vehicular Technology*, 66(9):8119–8128.

[Chaudhary et al., 2014] Chaudhary, V., Bhatia, R., and Ahlawat, A. K. (2014). A novel self-organizing map (som) learning algorithm with nearest and farthest neurons. *Alexandria Engineering Journal*, 53(4):827–831.

[Della Penda et al., 2016] Della Penda, D., Fu, L., and Johansson, M. (2016). Energy efficient d2d communications in dynamic tdd systems. *IEEE Transactions on Communications*, 65(3):1260–1273.

[Duong and Shin, 2013] Duong, Q. and Shin, O.-S. (2013). Distance-based interference coordination for device-to-device communications in cellular networks. In *2013 fifth international conference on ubiquitous and future networks (ICUFN)*, pages 776–779. IEEE.

[ElSawy et al., 2014] ElSawy, H., Hossain, E., and Alouini, M.-S. (2014). Analytical modeling of mode selection and power control for underlay d2d communication in cellular networks. *IEEE Transactions on Communications*, 62(11):4147–4161.

[Gismalla et al., 2022] Gismalla, M. S. M., Azmi, A. I., Salim, M. R. B., Abdullah, M. F. L., Iqbal, F., Mabrouk, W. A., Othman, M. B., Ashyap, A. Y., and Supa'at, A. S. M. (2022). Survey on device to device (d2d) communication for 5gb/6g networks: concept, applications, challenges, and future directions. *IEEE Access*, 10:30792–30821.

[Gu et al., 2011] Gu, J., Bae, S. J., Choi, B.-G., and Chung, M. Y. (2011). Dynamic power control mechanism for interference coordination of device-to-device communication in cellular networks. In *2011 Third international conference on ubiquitous and future networks (ICUFN)*, pages 71–75. IEEE.

[Han et al., 2014] Han, J., Cui, Q., Yang, C., and Tao, X. (2014). Bipartite matching approach to optimal resource allocation in device to device underlaying cellular network. *Electronics Letters*, 50(3):212–214.

[Hashima et al., 2021] Hashima, S., ElHalawany, B. M., Hatano, K., Wu, K., and Mohamed, E. M. (2021). Leveraging machine-learning for d2d communications in 5g/beyond 5g networks. *Electronics*, 10(2):169.

[Huang et al., 2016] Huang, Y., Nasir, A. A., Durrani, S., and Zhou, X. (2016). Mode selection, resource allocation, and power control for d2d-enabled two-tier cellular network. *IEEE Transactions on communications*, 64(8):3534–3547.

[Jiang et al., 2018] Jiang, F., Wang, B.-c., Sun, C.-y., Liu, Y., and Wang, X. (2018). Resource allocation and dynamic power control for d2d communication underlaying uplink multi-cell networks. *Wireless Networks*, 24:549–563.

[Kamruzzaman et al., 2022] Kamruzzaman, M., Sarkar, N. I., and Gutierrez, J. (2022). A dynamic algorithm for interference management in d2d-enabled heterogeneous cellular networks: Modeling and analysis. *Sensors*, 22(3):1063.

[Khoueiry and Soleymani, 2015] Khoueiry, B. W. and Soleymani, M. R. (2015). A novel coding strategy for device-to-device communications. In *2015 12th Annual IEEE Consumer Communications and Networking Conference (CCNC)*, pages 200–205. IEEE.

[Kim and Shin, 2008] Kim, H. and Shin, K. G. (2008). Efficient discovery of spectrum opportunities with mac-layer sensing in cognitive radio networks. *IEEE transactions on mobile computing*, 7(5):533–545.

[Lee et al., 2017] Lee, C.-H., Chang, R. Y., Lin, C.-T., and Cheng, S.-M. (2017). Sum-rate maximization for energy harvesting-aided d2d communications underlaid cellular networks. In *2017 IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*, pages 1–6. IEEE.

[Lee and Akyildiz, 2008] Lee, W.-Y. and Akyildiz, I. F. (2008). Optimal spectrum sensing framework for cognitive radio networks. *IEEE Transactions on wireless communications*, 7(10):3845–3857.

[Lee and Akyldiz, 2010] Lee, W.-Y. and Akyldiz, I. F. (2010). A spectrum decision framework for cognitive radio networks. *IEEE transactions on mobile computing*, 10(2):161–174.

[Li et al., 2018] Li, J., Feng, R., Sun, W., Chen, L., Xu, X., and Li, Q. (2018). Joint mode selection and resource allocation for scalable video multicast in hybrid cellular and d2d network. *IEEE Access*, 6:64350–64358.

[Li et al., 2017] Li, Y., Gursoy, M. C., Velipasalar, S., and Tang, J. (2017). Joint mode selection and resource allocation for d2d communications via vertex coloring. In *GLOBECOM 2017-2017 IEEE Global Communications Conference*, pages 1–6. IEEE.

[Mamdani and Assilian, 1975] Mamdani, E. H. and Assilian, S. (1975). An experiment in linguistic synthesis with a fuzzy logic controller. *International journal of man-machine studies*, 7(1):1–13.

[Nagapuri et al., 2022] Nagapuri, L., Prabu, A., Penchala, S., Salah, B., Saleem, W., Kumar, G. S., and Aziz, A. S. A. (2022). Energy efficient underlaid d2d communication for 5g applications. *Electronics*, 11(16):2587.

[Natita et al., 2016] Natita, W., Wiboonsak, W., and Dusadee, S. (2016). Appropriate learning rate and neighborhood function of self-organizing map (som) for specific humidity pattern classification over southern thailand. *International Journal of Modeling and Optimization*, 6(1):61.

[Nayak and Devulapalli, 2015] Nayak, P. and Devulapalli, A. (2015). A fuzzy logic-based clustering algorithm for wsn to extend the network lifetime. *IEEE sensors journal*, 16(1):137–144.

[Pandit and Singh, 2017] Pandit, S. and Singh, G. (2017). *Spectrum sharing in cognitive radio networks*. Springer.

[Ramezani-Kebrya et al., 2017] Ramezani-Kebrya, A., Dong, M., Liang, B., Boudreau, G., and Seyedmehdi, S. H. (2017). Joint power optimization for device-to-device communication in

cellular networks with interference control. *IEEE Transactions on Wireless Communications*, 16(8):5131–5146.

[Rehmani et al., 2012] Rehmani, M. H., Viana, A. C., Khalife, H., and Fdida, S. (2012). Improving data dissemination in multi-hop cognitive radio ad-hoc networks. In *Ad Hoc Networks: Third International ICST Conference, ADHOCNETS 2011, Paris, France, September 21-23, 2011, Revised Selected Papers 3*, pages 117–130. Springer.

[Rehmani et al., 2013] Rehmani, M. H., Viana, A. C., Khalife, H., and Fdida, S. (2013). Surf: A distributed channel selection strategy for data dissemination in multi-hop cognitive radio networks. *Computer Communications*, 36(10-11):1172–1185.

[Safdar et al., 2022] Safdar, G. A., Syed, T. S., and Ur-Rehman, M. (2022). Fuzzy logic-based cluster head election-led energy efficiency in history-assisted cognitive radio networks. *IEEE Sensors Journal*, 22(22):22117–22126.

[Salem et al., 2017] Salem, T. M., Abdel-Mageid, S., Abdel-Kader, S. M., and Zaki, M. (2017). Icssss: An intelligent channel selection scheme for cognitive radio ad hoc networks using a self organized map followed by simple segregation. *Pervasive and Mobile Computing*, 39:195–213.

[Shalmashi et al., 2013] Shalmashi, S., Miao, G., and Slimane, S. B. (2013). Interference management for multiple device-to-device communications underlaying cellular networks. In *2013 IEEE 24th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*, pages 223–227. IEEE.

[Song et al., 2015] Song, L., Niyato, D., Han, Z., and Hossain, E. (2015). *Wireless device-to-device communications and networks*. Cambridge University Press.

[Song et al., 2019] Song, X., Han, X., Ni, Y., Dong, L., and Qin, L. (2019). Joint uplink and downlink resource allocation for d2d communications system. *Future Internet*, 11(1):12.

[Su et al., 2013] Su, L., Ji, Y., Wang, P., and Liu, F. (2013). Resource allocation using particle swarm optimization for d2d communication underlay of cellular networks. In *2013 IEEE wireless communications and networking conference (WCNC)*, pages 129–133. IEEE.

[Tang and Ding, 2015] Tang, H. and Ding, Z. (2015). Mixed mode transmission and resource allocation for d2d communication. *IEEE Transactions on Wireless Communications*, 15(1):162–175.

[Wang et al., 2014] Wang, F., Xu, C., Song, L., and Han, Z. (2014). Energy-efficient resource allocation for device-to-device underlay communication. *IEEE Transactions on Wireless Communications*, 14(4):2082–2092.

[Yang et al., 2008] Yang, L., Cao, L., and Zheng, H. (2008). Proactive channel access in dynamic spectrum networks. *Physical communication*, 1(2):103–111.

[Ye et al., 2014] Ye, Q., Al-Shalash, M., Caramanis, C., and Andrews, J. G. (2014). Resource optimization in device-to-device cellular systems using time-frequency hopping. *IEEE Transactions on Wireless Communications*, 13(10):5467–5480.

[Yu et al., 2014] Yu, G., Xu, L., Feng, D., Yin, R., Li, G. Y., and Jiang, Y. (2014). Joint mode selection and resource allocation for device-to-device communications. *IEEE transactions on communications*, 62(11):3814–3824.

[Yucek and Arslan, 2009] Yucek, T. and Arslan, H. (2009). A survey of spectrum sensing algorithms for cognitive radio applications. *IEEE communications surveys & tutorials*, 11(1):116–130.

[Zhong et al., 2014] Zhong, W., Fang, Y., Jin, S., Wong, K.-K., Zhong, S., and Qian, Z. (2014). Joint resource allocation for device-to-device communications underlaying uplink mimo cellular networks. *IEEE Journal on Selected Areas in Communications*, 33(1):41–54.