Autonomous Network Optimization and Dynamic Channel Allocation for Cognitive radio-based Consumer IoT

Laraib Abbas, Umar Shoaib, Marwan Omar, and Ali K. Bashir

***Abstract*—The heterogeneous environment of next-generation Consumer Internet of Things (CIoT) demands efficient resource utilization and reliable network services. On the contrary, the proliferation in the diverse nature of smart consumer IoT devices is causing spectrum scarcity and uneven utilization of available resources. Cognitive Radios (CRs) provide the most suitable solution for spectrum scarcity through dynamic spectrum access. To achieve spectral efficiency and provide consumer-centric network services we propose a novel Cognitive Radio based Autonomous Network Management framework called (CR-ANM). The framework combines the benefits of cognitive radios, Network Function Virtualization (NFV), and Software Defined Networking (SDN), to decouple the control plane from the data plane and is divided into two further operations called Dynamic Priority Determination (DPD) and Efficient Channel Allocation (ECA). DPD is responsible for determining the SU's priority using a fuzzy logic-based decision controller. Whereas ECA optimizes the channel allocation process and allocates the best available channel to SU. Which increases the channel availability by 77% and reduces the service drop rate by 81.8%. Both schemes run as Virtual Utility Functions (VUFs) on dedicated virtual machines assigned by the SDN controller. This approach increases energy efficiency for low-power consumer IoT devices and improves network reliability.**

***Index Terms*— Cognitive Radio Network (CRN), efficient channel allocation, Consumer Internet of Things (CIoT), Network Function Virtualization (NFV), Software Defined Networking (SDN)**

I. INTRODUCTION

THE fifth generation industrial revolution including Industry 5.0 and the Consumer Internet of Things (CIoT), has led to the significant growth in number of smart devices and home appliances [1], [2]. The communication paradigm of consumer IoT demands computational intelligence and efficient resource utilization alongside reliable and reconfigurable network elements [3], [4]. The current era of communication encompasses emerging future network technologies such as Artificial Intelligence (AI), Cognitive Radios (CR), Software Defined Networking (SDN), and Network Function Virtualization (NFV). To fulfill the consumer-centric and application specific transmission requirements of consumer IoT devices, the integration of above-mentioned technologies can provide autonomous and sustainable network solutions. Cognitive radios are computationally intelligent wireless devices, that are designed to intelligently use available radio frequency spectrum in a flexible and adaptive manner [5]. They can identify underutilized portions of the spectrum and automatically select the best available frequency band to transmit and receive data. This allows cognitive radios to operate in a more efficient and reliable manner, while also minimizing interference with other wireless communication devices. Cognitive Radio Network (CRN) is the most suitable network technology for achieving efficient resource utilization, Dynamic Spectrum Access (DSA), and Autonomous Network Management (ANM).

Radio spectrum band is a scarce natural resource and should be utilized in an efficient manner. Due to a variety of smart applications in consumer IoT environment, the licensed spectrum band utilization span is not constant with space and time. Whereas unlicensed spectrum is always crowded and faces congestion for data transmission. CRs also known as Secondary Users (SUs) can coexist with any licensed user also known as Primary Users (PUs) and can efficiently sense and detect free available spectrum holes for transmission without interfering with the transmission of PUs. CRs can access the free available spectrum in three modes: Interweave Mode, Underlay Mode, and Overlay [5]. The cognitive abilities of CRs also make them responsible for spectrum sensing, spectrum sharing, spectrum management, and spectrum mobility. These features show the eligibility of cognitive radio devices to form an autonomous, sustainable, and computationally intelligent network. That is why we propose a CR-based autonomous network framework that includes the significant benefits of SDN and NFV technology, to provide dynamic and application specific services to the heterogeneous communication system of consumer IoT.

SDN is a network architecture approach that separates the network control plane and data plane [6]. The controller provides a single point of control for the network, and it can dynamically adjust the network traffic flow based on real-time conditions and traffic patterns. The data plane, which is responsible for forwarding network traffic, remains in the network devices. Whereas, in an NFV architecture, network functions are implemented as software running on virtual machines or containers [7]. It decouples traditional hardware-based network functions with software-based virtualized

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TABLE I
LIST OF ABBREVIATIONS

Notation	Description
Ch_{High}^{A}	Channel availability for SU_{High}
Ch_{Low}^{A}	Channel availability for SU_{Low}
Ch_R	Channel rank
CC_{Req}	SUs required channel capacity
CH_{Idle}	Total number of idle channels
CH_N	Total number of channels
N_{CRL_h}	Number of channels in SU_{High} CRL
N_{CRL_l}	Number of channels in SU_{Low} CRL
N_{High}^{SU}	Number of high priority SUs
N_{Low}^{SU}	Number of low Priority SUs
PU_N	Total number of PUs
SU_N	Total number of SUs
$TP_{SU_{Min}}$	Minimum threshold of TP_{SU}
TP_{SU}	Transmission power of SU
T_{tr}	Transmission time
VM_N	Total number of VMs
VUF_{DPD}	Number of VUFs for dynamic priority determination
VUF_{ECA}	Number of VUFs for efficient channel allocation
VUF_{High}	VUF for high priority transmission
VUF_{Low}	VUF for low priority transmission
δ_i	Maximum data rate on interweave mode
δ_u	Maximum data rate on underlay mode
λ_{PU}	PU arrival rate
λ_{SU}	SU arrival rate
λ_{SDR}	Service drop rate
λ_{SU}^{N}	SU new service request rate
λ_{SU}^{O}	SU ongoing service request rate

network functions that can run on standard hardware. This allows network operators to deploy and manage network functions more easily and flexibly. This approach reduces capital costs and operational expenses, increases service agility, and improves the quality of service. Our proposed network framework CR-ANM includes the significance of both technologies integrated in a way that provides reliable and flexible network services as well as efficient spectrum utilization.

The following section provides the study of the most relevant state-of-the-art works to enhance CRN spectral efficiency as well as the computational intelligence of the core network.

A. Related Work

The heterogeneous nature of the consumer IoT communication system and unpredictable channel states make the channel selection decision more crucial [8]. The author in [9] optimizes the channel assignment process of cognitive radio-based IoT devices and Power Beacons (PBs) using the mixed integer linear program (MILP) technique. IoT devices set their transmission power using a game theory-based iterative approach. On the other hand, a reinforcement learning-based approach is used for multichannel allocation for industrial IoT and cognitive IoT in [10]. A greedy algorithm-based channel allocation scheme called CASGA is proposed in [11] for cognitive radio-based vehicular networks. The algorithm divides the transmission services based on their load and allocates channels to maximize throughput and quality of service. In higher load VANET applications are divided into two categories, safe and unsafe application services, and the acceptance probability of safe application services is increased through SMDP-based channel allocation. The author in [12] proposed an iterative algorithm-based scheme to improve spectral efficiency and network throughput of CR-IoT, where the system intelligently senses and adjusts the threshold of SNR to adjust the throughput tradeoff. On the other hand, an AI-based channel allocation approach called DeepCH for Satellite Internet of Things (SIoT) is proposed in [13]. The deep reinforcement-based algorithm is energy efficient and facilitates the dynamic channel allocation problem optimally. The Author in [14] proposed a guard band-aware channel assignment mechanism that considers the Rayleigh fading time constraint in different time slots to assign multiple channels to SUs. This approach is called batch-based channel assignment and is efficient enough to increase network capacity as well as the number of assigned channels to a particular SU. Similarly, another auction-based multichannel allocation scheme is proposed in [15] where a common channel is assigned to multiple SUs to increase the reusability of a single channel. To accomplish this goal, non-interfering SUs are divided into groups according to their transmission specifications using a bidder group formation scheme. The scheme selects a winner strategy and a pricing strategy to allocate the idle channels. A cooperative Q-learning-based energy-efficient spectrum allocation scheme is proposed in [16] whereas, a multi-agent-based and reinforcement learning-based dynamic spectrum access framework is proposed in [17]. Both approaches are distributed in nature and improve the spectrum access efficiency of the network. Similarly, the SU transmission priority-based channel allocation approach is proposed in [18].

All the above-mentioned approaches are significantly adding value to dynamic spectrum access and channel allocation in cognitive radio networks. But on the other hand, most of the works overlook the importance of channel quality before selection causing an increment in handoff rate and transmission delay. Some of the schemes offer priority-based channel allocation to provide application-specific transmission services but statically categorize the users, overlooking the benefits of reconfigurable and dynamic network services.

The author in [19] proposed an integrated network framework that combines the benefits of NFV, SDN, and software-defined radios (SDR). The optimization scheme is implemented on real-time Orchestration and Reconfiguration Control Architecture (ORCA) and has a very limited scope. The Markov Random Field (MRF) energy optimization scheme is used for Virtual Utility Function (VUF) computation. The framework lacks the benefits of hybrid Interweave/Underlay (IU) channel access modes. It overlooks the significant adjustable parameter settings e.g. channel quality, Signal-to-Interference-Plus-Noise-Ratio (SINR), and TP of SUs to reduce the handoff rate. The author in [20] proposed a cognitive radio network integration with NFV, SDN, and Fog Computing (FC) for coastal smart cities. Multiple cognitive radio virtual networks are launched using Virtual Network Functions (VNFs) and are controlled by SDN controller for vehicular and

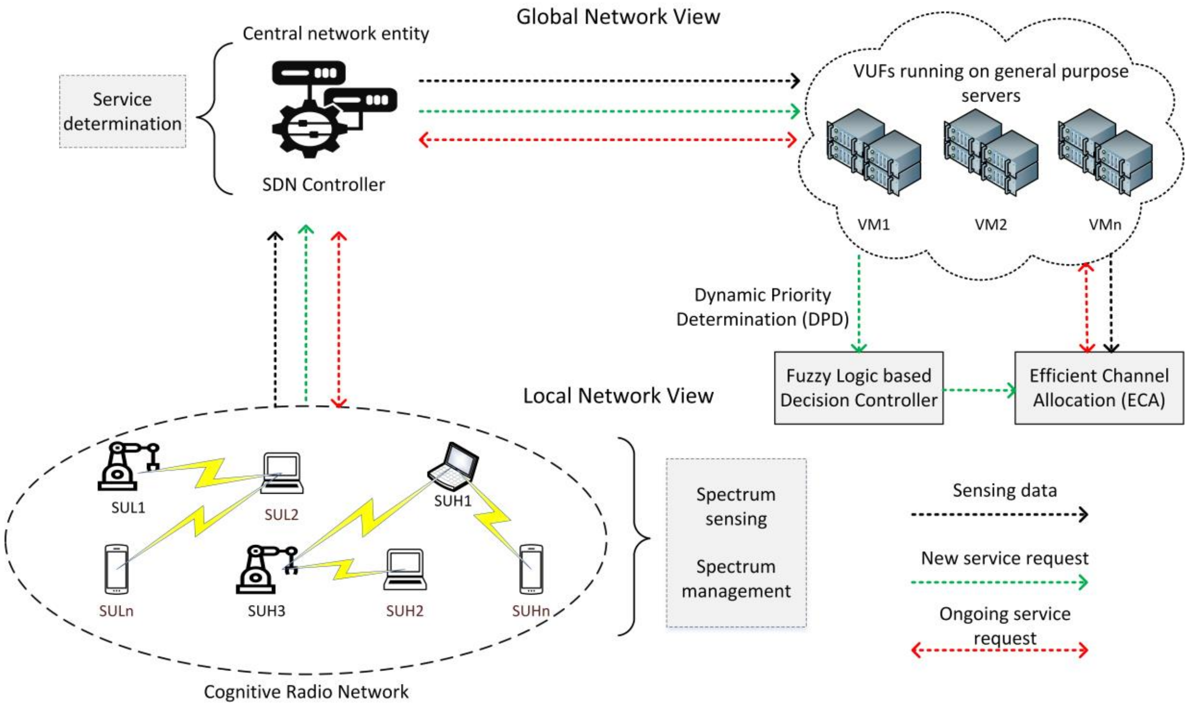

Fig. 1. Working of Cognitive Radio Autonomous Network Management (CR-ANM) framework where spectrum sensing and spectrum management is performed by data plane and DPD and ECA is managed by control plane

maritime end-to-end communication system. On the other hand, a framework based on general configuration and placement of NFV on SDRs is proposed in [21]. The literature shows that the integration of SDN and NFV with next-generation communication networks to achieve dynamic, on-demand, and low-cost services is inevitable now. In addition, To the best of our knowledge, there is no significant work available in the literature that serves autonomous network management and efficient spectrum utilization for CR-based consumer IoT at the same time. The following section provides the research contribution and significance of the proposed framework.

B. Research Contribution and Significance

Cognitive-based Autonomous Network Management framework called CR-ANM addresses the shortcomings of discussed related work and offers an autonomous network framework that consists of two planes: *Data plane* is responsible for spectrum sensing, spectrum management, and spectrum access; *Control Plane* is responsible for SU's priority determination and efficient channel allocation. To achieve spectral efficiency, the proposed framework CR-ANM enables the network to provide application-specific services according to transmission requirements by dividing the SU into two categories SU_{High} and SU_{Low}. The VUFs are responsible for deciding SUs priority allocating high-ranked channels for delay-sensitive or multimedia application transmissions and inducing a hybrid IU mode of channel management for non-delay sensitive application transmissions. Furthermore, the contribution and significance of this paper are summarized as follows:

- *Flexible and Dynamic network framework*: To the best of our knowledge, the proposed framework CR-ANM is one of the pioneers' works that integrates CR, NFV, and SDN in a way that provides dynamic and flexible network services and decouples the channel allocation and decision control from CRN to reduce configuration cost and energy consumption. In addition, the dedicated virtual machine for each SU reduces the computational complexity and service response delay.
- *Priority-based channel allocation scheme*: CR-ANM ranks the available channels according to their properties and allocates them dynamically to SUs considering their transmission requirements. This approach ensures the optimum utilization of available resources.
- *Performance evaluation on significant parameters*: Our proposed framework is evaluated on the five significant parameters; channel availability, Service Drop Rate (λ_{SDR}), Service Response Delay (SRD), transmission delay, and network throughput. Whereas no other related work from literature has considered these parameters altogether for evaluation. The promising results demonstrate a significant reduction in SDR leading to an improvement in network throughput by 51.9%, as compared to the comparative scheme SE-CRN [18].

C. Paper Organization

The rest of the paper is organized as follows. Section II explains the network model of the proposed framework CR-ANM, its components, and CTMC modeling. Section III describes the performance evaluation parameters and simulation results. The research contribution is concluded in section IV. The list of scientific notations used in the paper is given in Table I.

II. Proposed Framework CR-ANM

The proposed framework CR-ANM is a dynamic and intelligent network framework that integrates SDN and NFV with CRN in a way that the channel allocation control is separated from the data plane. The control plane is responsible for SUs Dynamic

TABLE II

INFERENCE RULES AND RESPECTIVE DECISIONS FOR FUZZY LOGIC BASED DECISION CONTROLLER

Rule #	TPs Input Condition			Decision	
	TP_{SU}	$SINR$	CC_{Req}	VUF_{High}	VUF_{Low}
1, 2	H	H	H, M	✓	
3	H	H	L		✓
4, 5	H	M	H, M	✓	
6	H	M	L		✓
7, 8	H	L	H, M	✓	
9	H	L	L		✓
10, 11	M	H	H, M	✓	
12	M	H	L		✓
13, 14	M	M	H, M	✓	
15	M	M	L		✓
16	M	L	H	✓	
17, 18	M	L	M, L		✓
19	L	H	H	✓	
20, 21	L	H	M, L		✓
22	L	M	H	✓	
23, 24	L	M	M, L		✓
25	L	L	H	✓	
26, 27	L	L	M, L		✓

Priority Determination (DPD) and Efficient Channel Allocation (ECA). Both schemes DPD and ECA run as virtual utility functions on VMs to reduce computational complexity and hardware cost. The data plane consisting of the physical network is only responsible for spectrum sensing and spectrum mobility which helps to minimize energy consumption as well. The following section explains the complete working of the proposed framework CR-ANM as shown in Fig. 1.

A. Dynamic Priority Determination (DPD)

Dynamic Priority Determination scheme is designed to calculate SUs priority according to its transmission requirements to provide application-specific services. SUs send new service requests to the SDN controller with sensing data consisting of Transmission Parameters TPs to determine the priority. The controller forwards the request to the dedicated VM to initiate the relevant VUF. The DPD VUF is a fuzzy logic-based decision controller that takes the values of TPs as input parameters to the inference engine, applies the inference rules as shown in Table II, and decides SU's priority as SU_{High}or SU_{Low}. The transmission parameters for priority determination are CC_{Req}, $SINR_{SU}$, and TP_{SU} and can be explained as follows:

- ***Required Channel Capacity*** $(\boldsymbol{CC_{Req}})$ is the minimum value of channel capacity in bits per second, required by SU to transmit its data and can be calculated by the Shannon-Hartley theorem:

$$CC_{Req} = \beta \ log_2(1 + {}^{P_S}/_{P_{NI}}) \qquad (1)$$

Where β is the bandwidth of the channel measured in Hz, P_S is the average power of the signal received measured in watts, and P_{NI} is the average value of the power of noise and interference over the channel measured in watts.

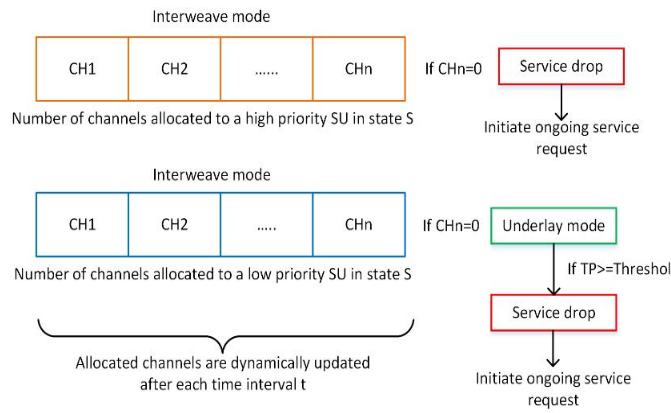

Fig. 2. Working of interweave channel access mode for high priority SUs and hybrid IU channel access mode for low priority SUs

- ***Transmission Power*** $(\boldsymbol{TP_{SU}})$ is the maximum value of transmission power of a SU, required to maintain the transmission without causing any harmful interference to the nearby PU's transmission and is calculated as:

$$TP_{SU} = TP_{CC} - TP_{Rx} - \delta_{GLT} + N_{SU} + SINR_{Req} \qquad (2)$$

Where TP_{CC} is the transmission power received at a common channel, TP_{Rx} is the value of transmission power calculated on the SU receiver, and the value of gain, loss, and tolerance is denoted with δ_{GLT}, N_{SU} is the final calculated noise ratio on the SU antenna, and $SINR_{Req}$ is the required value of $SINR$ to transmit its data. SU can transmit its data at the initially calculated maximum value of its transmission power at interweave mode. In underlay mode, SU must minimize the value of TP_{SU} to continue its transmission parallel to the PU's transmission on the same channel. SU drops the service and initiates an ongoing service request if it hits the minimum threshold of transmission power and cannot continue its transmission on the same channel.

- ***Signal-to-Interference-Plus-Noise Ratio*** $(\boldsymbol{SINR_{SU}})$ on SU's receiving antenna can be calculated as:

$$SINR_{SU} = \frac{TP_{SU}}{\sum_{i=1}^{N_{PU}} TP_{SUi} + \sum_{j=1}^{N_{SU}} TP_{SUj} + \Delta_{SUx}^2} \qquad (3)$$

Where, N_{PU} and N_{SU} are the number of PUs and SUs using the same channel for transmission, TP_{SUi} and TP_{SUj} are the transmission powers at which neighbor SUs are transmitting. Whereas the variance of White Gaussian Noise on the SU receiver is donated by Δ_{SUx}^2.

B. Efficient Channel Allocation (ECA)

After the SU priority determination process is completed, the VUF ECA is initiated which allocates available channels to SUs according to their priorities. For delay-sensitive and multimedia application transmission, ECA for SU_{High} allocates the best available free channels and sorts them according to their rank from high to medium and medium to low based on channel properties. Channel rank Ch_R is calculated as [22]:

TABLE III
CTMC STATE TRANSITION TABLE OF DPD AND ECA

	PU/SU activity	**Destination state and condition**	**Transition rate**
		Dynamic Priority Determination (DPD)	
1	SU arrives and initiates a new service request	$(SU_N + 1, srv_{new} + 1, srv_{on}, VM_N, VUF_{DPD}, VUF_{ECA})$	
2	SDN controller creates a VM and initiates VUF for DPD	$(SU_N, srv_{new}, srv_{on}, VM_N + 1, VUF_{DPD} + 1, VUF_{ECA})$	λ_{SU}
3	Priority is determined and VUF for ECA is initiated	$(SU_N, srv_{new}, srv_{on}, VM_N, VUF_{DPD}, VUF_{ECA} + 1)$	
4	In case of service drop SU initiates an ongoing service request	$(SU_N, srv_{new}, srv_{on} + 1, VM_N + 1, VUF_{DPD}, VUF_{ECA} + 1)$; $N_{CRL} = 0$	λ_{SU}^{O}
5	SU transmission is completed	$(SU_N - 1, srv_{new}, srv_{on}, VM_N - 1, VUF_{DPD}, VUF_{ECA} - 1)$	λ_{SU}
		Efficient Channel Allocation (ECA)	
6	DPD identifies a high priority SU, and free channels are available	$(N_{High}^{SU} + 1, N_{Low}^{SU}, PU_N, CH_N, CH_{idle}, N_{CRL_h}, N_{CRL_l}, t_w)$; $CH_{idle} > 0$	
7	ECA allocates channels to SU_{High}	$(N_{High}^{SU}, N_{Low}^{SU}, PU_N, CH_N, CH_{idle} - N_{CRL_h}, N_{CRL_h}, N_{CRL_l}, t_w)$;	λ_{SU}
8	SU_{High} starts its transmission using one of the allocated channels on interweave mode	$(N_{High}^{SU}, N_{Low}^{SU}, PU_N, CH_N, CH_{idle}, N_{CRL_h} - 1, N_{CRL_l}, t_w)$; $N_{CRL_h} > 0$	
9	SU_{High} senses PU's activity and switches to another allocated channel available in CRL	$(N_{High}^{SU}, N_{Low}^{SU}, PU_N + 1, CH_N, CH_{idle}, N_{CRL_h} - 1, N_{CRL_l}, t_w)$; $N_{CRL_h} > 0$	λ_{PU}
10	PU activity is detected, and no channel is available in CRL	$(N_{High}^{SU}, N_{Low}^{SU}, PU_N + 1, CH_N, CH_{idle}, N_{CRL_h}, N_{CRL_l}, t_w)$; $N_{CRL_h} = 0$	
11	SU_{High} drops the service and initiates an ongoing service request to DPD	$(N_{High}^{SU}, N_{Low}^{SU}, PU_N, CH_N, CH_{idle}, N_{CRL_h}, N_{CRL_l}, t_w + 1)$; $N_{CRL_h} = 0$	
12	DPD identifies a low priority SU, and free channels are available	$(N_{High}^{SU}, N_{Low}^{SU} + 1, PU_N, CH_N, CH_{idle}, N_{CRL_h}, N_{CRL_l}, t_w)$; $CH_{idle} > 0$	λ_{SU}
13	ECA allocates channels to SU_{Low}	$(N_{High}^{SU}, N_{Low}^{SU}, PU_N, CH_N, CH_{idle} - N_{CRL_l}, N_{CRL_h}, N_{CRL_l}, t_w)$;	
14	SU_{Low} starts its transmission using one of the allocated channels on interweave mode	$(N_{High}^{SU}, N_{Low}^{SU}, PU_N, CH_N, CH_{idle}, N_{CRL_h}, N_{CRL_l} - 1, t_w)$; $N_{CRL_l} > 0$	
15	SU_{Low} senses PU's activity and switches to another allocated channel	$(N_{High}^{SU}, N_{Low}^{SU}, PU_N + 1, CH_N, CH_{idle}, N_{CRL_h}, N_{CRL_l} - 1, t_w)$; $N_{CRL_l} > 0$	
16	PU activity is detected, and no channel is available in CRL	$(N_{High}^{SU}, N_{Low}^{SU}, PU_N + 1, CH_N, CH_{idle}, N_{CRL_h}, N_{CRL_l}, t_w)$; $N_{CRL_l} = 0$	λ_{PU}
17	SU_{Low} continues its transmission in underlay mode on the same channel	$(N_{High}^{SU}, N_{Low}^{SU}, PU_N, CH_N, CH_{idle}, N_{CRL_h}, N_{CRL_l}, t_w)$; $N_{CRL_l} = 0$	λ_{SU}
18	PU activity is detected and SU_{Low} cannot operate on underlay mode	$(N_{High}^{SU}, N_{Low}^{SU}, PU_N + 1, CH_N, CH_{idle}, N_{CRL_h}, N_{CRL_l}, t_w)$	λ_{PU}
19	SU_{Low} drops the service and initiates an ongoing service request	$(N_{High}^{SU}, N_{Low}^{SU}, PU_N, CH_N, CH_{idle}, N_{CRL_h}, N_{CRL_l}, t_w + 1)$	λ_{SU}

$$Ch_R = \frac{Ch_{idle}^t}{(Ch_{busy}^t \times \lambda_{PU}^{Ch}) + Ch_{idle}^t} \qquad (4)$$

Where Ch_{idle}^t is the total idle time of a particular channel and Ch_{busy}^t is the total busy time measured over the channel Ch in time t. While the PU arrival rate on a channel Ch on a unit time t is denoted as λ_{PU}^{Ch}. ECA for high-priority applications allocates the channels ranked from high to medium so that SU_{High} could operate in its full TP_{SU} in interweave mode to maintain the required quality of service. In the case of PU activity sensed on the channel SU_{High} can immediately switch to the next available channel on the allocated Channel Rank List (CRL). SUs send sensing data to their assigned VMs continuously which is why CRL is updated periodically after every interval of time t. This dynamic behavior of CRL allocated to a particular SU reduces the chances of hard handoffs and ensures transmission quality and continuity. In case the total number of channels in CRL is denoted by N_{CRL_h}, approaches zero, SU_{High} drops the service and initiates an ongoing service request after a waiting time t_w, which is directed directly to ECA for channel allocation. ECA for SU_{Low} assigns free available channels ranked as medium or low for non-delay sensitive data transmissions. SU_{Low} performs continuous sensing to keep their CRL updated after every time interval t. SU_{Low} can operate at its full power in interweave mode on one of the assigned channels whereas, in the case of PU activity detection it will switch to the next allocated channel within negligible switching time. In case the number of channels in CRL, denoted by N_{CRL_l} approaches to zero, SU_{Low} reduces its transmission power TP_{SU} and continue transmitting on underlay mode coexisting with PU on the same channel as shown in Figure 2. TP_{SU} hitting its lowest threshold will cause channel drop and SU_{Low} will initiate an ongoing service request after the waiting time t_w. The maximum value of data rate on interweave spectrum access that can be achieved by a SU where $SU \epsilon \{SU_{High}, SU_{Low}\}$, can be calculated as:

$$\delta_i = \beta \log_2(1 + {}^{TP_{SU} G_{SU}}\!/_{\Delta_{SUx}^2}) \qquad (5)$$

Where β is the bandwidth of the channel, G_{SU} is the value of channel gain for SU and Δ^2_{SUx} is the power of additive White Gaussian Noise. In underlay spectrum access mode, the SU_{Low} reduces its transmission power causing a decrease in its data rate as well. The minimum data rate of a SU_{Low} on an underlay mode is denoted by δ_u and can be calculated as:

$$\delta_u = \beta \log_2(1 + {}^{TP_{SU_{Low}} G_{SU_{Low}}} \big/ {}_{TP_{PU} G_{PU} \Delta^2_{SU_{Low}}}) \qquad (6)$$

Where β is the bandwidth of the channel, $G_{SU_{Low}}$ and G_{PU} is the value of channel gain for SU_{Low} and PU operating on the same channel, $TP_{SU_{Low}}$ and TP_{PU} is the transmission power of SU_{Low} and PU, whereas, the power of additive White Gaussian Noise is denoted by $\Delta^2_{SU_{Low}}$.

C. System Model and Assumptions

The network model is divided into data plane and control plane. The data plane consists of a distributed cognitive radio network environment with active SU_N number of SUs and a primary network environment with PU_N number of PUs, where SU_N is a positive integer. The network consists of CH_N number of non-overlapping channels with variable channel capacities and are modeled as Idle and Busy states following the Markov 2-State model. The total number of free available channels is denoted by CH_{Idle}. PU arrival rate during SU transmission, SU arrival rate, and SU new service request rate for VUFs observe poison distribution with the rate of λ_{PU}, λ_{SU} and λ^N_{SU}. The service time of SUs is assumed to follow an exponential distribution. We assume that SUs perform perfect spectrum sensing and sensing delay is considered negligible to evaluate the performance of the proposed framework CR-ANM on fairgrounds [18]. In the control plane, an SDN controller module is the central network controller, in charge of service determination and VM provisioning. The controller instantiates the requested service as a VUF on a dedicated VM and one VM can run multiple VUFs. VM_N is the total number of VMs running on a general-purpose set of hardware in a specific state of the network and is equivalent to SU_N [23]. A common and dedicated channel is allocated for control messaging of SUs with SDN controller to initiate a specific service. SU might request to initiate a new service or to continue an ongoing service. To determine the service SDN controller receives Transmission Parameters (TPs) from SUs and forwards them to the concerned VM to initiate the relevant VUF.

D. Continuous Time Markov Chain (CTMC) Modeling

We assume S is the set of all possible states of the network. Whereas, the state of DPD is denoted by $x = (SU_N, srv_{new}, srv_{on}, VM_N, VUF_{DPD}, VUF_{H/L})$, where SU_N is the total number of SUs in the network, srv_{new} and srv_{on} represents the number of new service requests generated by a SU. The total number of virtual machines is denoted by VM_N where number VM_N in any state x is $VM_N(x) = SU_N(x)$. The total number of VUFs for DPD, and ECA running on VMs at a state x is denoted by VUF_{DPD}, and VUF_{ECA}. The list of all possible states of the CTMC model of DPD scheme is presented in Table 2, with consequent transition rate and conditions. The steady-state probability $\eta(x)$ of state x can be measured as:

$$\eta(R) = O; \sum_{x \epsilon S} \eta(x) = 1 \qquad (7)$$

TABLE III

SIMULATION PARAMETERS AND THEIR RESPECTIVE SETTINGS

Simulation Parameters	Settings
Simulation area	1000×1000m
λ_{PU}	$\lambda\epsilon(1, 2, 3, \ldots, 8)$
λ_{SU}	$\lambda\epsilon(4, 6, 8, \ldots, 16)$
TP_{SU} in interweave mode	5 W
TP_{SU} in underlay mode	0.05 W
Threshold in underlay mode	1.16 db
t_w	1.5 sec
PU detection time	1ms
Service response time	0.5 sec
Channel capacity	2-6 Mbps

Where, R is the matrix for transition rate, and the vector containing one row and zero entries is denoted by O. On the other hand, the state of ECA scheme is denoted by y with the initial state of $y = (N^{SU}_{High}, N^{SU}_{Low}, PU_N, CH_N, CH_{idle}, N_{CRL_h}, N_{CRL_l}, t_w)$. N^{SU}_{High}, and N^{SU}_{Low} represents the number of high and low-priority SUs, whereas PU_N denotes the number of PUs in the network in the state y. CH_N and CH_{idle} are the number of available channels and the number of idle channels in the network. Number of allocated channels in SU_{High} and SU_{Low} CRLs are denoted by N_{CRL_h} and N_{CRL_l}. Whereas t_w is the waiting time of a SU after a service drop, before initiating an ongoing service request. The list of all possible states of CTMC model of ECA scheme is presented in Table 2, with consequent transition rate and conditions. The steady-state probability $\eta(y)$ of state y can be measured as:

$$\eta(R) = O; \sum_{y \epsilon S} \eta(y) = 1 \qquad (8)$$

Where R is the matrix for transition rate, and the vector containing one row and zero entries is denoted by O.

III. RESULTS AND DISCUSSION

The following section explains the performance evaluation process and comparative results of the proposed scheme CR-ANM with one of the state-of-the-art works SE-CRN proposed in [18] with simulation settings given in Table III. SE-CRN utilizes a dynamic channel reservation approach to assign optimal channels to high-priority SUs whereas channel quality has not been considered and all channels have the same capacity which is contrary to the heterogeneous nature of the wireless system. In addition, the channels are assigned by a central controller or base station which causes service response delay in case of increase in network load. On the contrary, our proposed framework CR-ANM allocates a dedicated VM to each node for service determination as well as channel allocation which deals with network load in a distributed manner. Moreover, the process of efficient channel allocation is optimized through channel rank calculation. To evaluate the significance and efficiency of the proposed framework CR-ANM as compared to SE-CRN, we study the following QoS evaluation metrics:

Channel Availability for SU_{High} and SU_{Low} in a state y can be defined as:

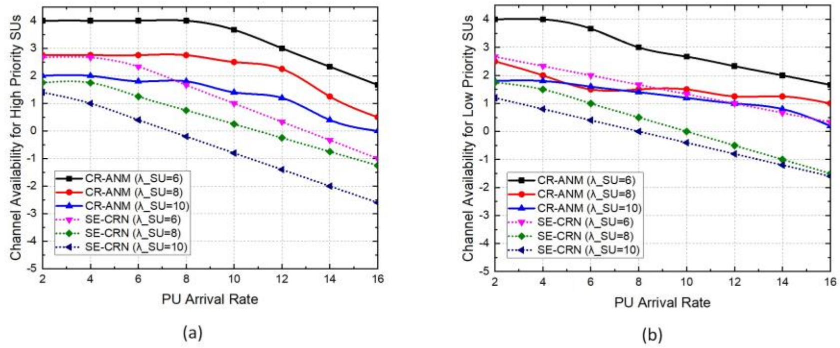

Fig. 3. Comparative results of CR-ANM and SE-CRN channel availability for (a) high priority SUs, (b) low priority SUs with the function of PU arrival rate λ_{PU}

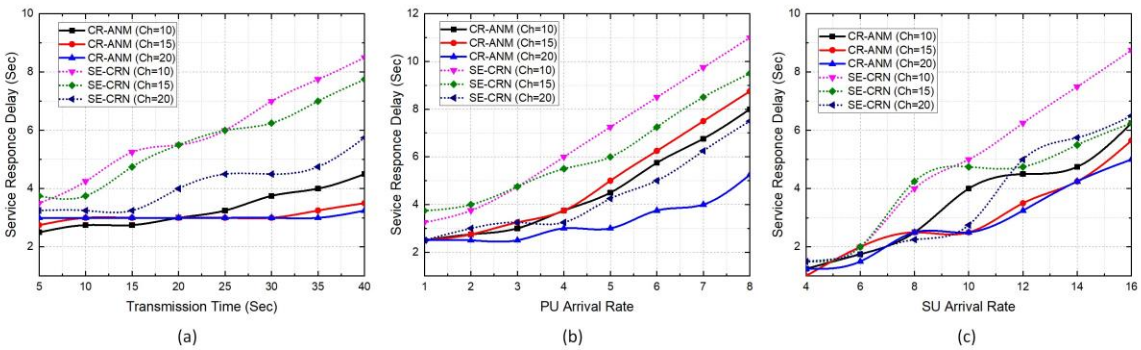

Fig. 4. Comparative results of CR-ANM and SE-CRN service drop rate λ_{SDR} with the function of (a) Transmission time T_{tr}, (b) PU arrival rate λ_{PU} and (c) SU arrival rate λ_{SU}

$$Ch_{High}^{A} = 1 - \sum_{N_{CRL_h}(y)} \eta\,(y);\ (y)\epsilon S \qquad (9)$$

$$Ch_{Low}^{A} = 1 - \sum_{N_{CRL_l}(y)} \eta\,(y);\ (y)\epsilon S \qquad (10)$$

Figure 3 shows the comparative results of the proposed scheme CR-ANM with SE-CRN with respect to channel availability for (a) high-priority SUs and (b) low-priority SUs. Results varied with the function of the PU arrival rate λ_{PU} and SU arrival rate λ_{SU}. Increase in λ_{PU} is inversely proportional to the number of idle channels CH_{idle} available for SU_{High} and SU_{Low} transmission. The promising results show that ECA scheme ensures the best channel allocation to SUs by assigning them channels according to their transmission requirements using channel rank and the hybrid IU mode ensures transmission continuity for SU_{Low} even if PU arrival rate increases.

Service Drop Rate (λ_{SDR}) can be defined as the average number of services dropped by SUs in the network due to the non-availability of channels in CRL during time t in any state y where $y\epsilon S$. Figure 4 shows the comparative results of proposed schemes in terms of service drop rate with the function of; (a) transmission time, where, $\lambda_{PU} = 2$, and $\lambda_{SU} = 10$ (b) PU arrival rate where $T_{tr} = 15$ sec, and $\lambda_{SU} = 10$, and (c) SU arrival rate where, $\lambda_{PU} = 2$, and $T_{tr} = 15$ sec. An increase in transmission time causes more chances for a PU arrival on a particular channel causing the increase in channel handoff and service drop rate. Figure 4(a) shows the definite decrease in SDR as compared to SE-CRN due to efficient channel management and dynamic channel allocation of high-ranked channels. Similarly increasing λ_{PU} and λ_{SU} did increase the value service drop rate but dynamic updates of high-ranked channels in CRL and underlay mode switching caused lesser service drop rate in CR-ANM as compared to the comparative scheme.

Service Response Delay (SRD) is defined as the total time taken by SDN controller to respond to service requests initiated by SUs in time t:

$$SRD = \sum_{SU_{High},SU_{Low}}^{n} \left(\frac{N_{SR}}{t(x)} \times T_{SR}\right) + \lambda_{SDR};(x)\epsilon S \qquad (11)$$

Where, N_{SR} is the total number of service requests made by SUs in time t, and T_{SR} is the time taken by a VM to fulfill one service request. Figure 5 shows the comparative results of proposed schemes in terms of service response delay with the function of; (a) transmission time, where, $\lambda_{PU} = 2$, and $\lambda_{SU} = 10$ (b) PU arrival rate where $T_{tr} = 15$ sec, and $\lambda_{SU} = 10$, and (c) SU arrival rate where, $\lambda_{PU} = 2$, and $T_{tr} = 15$ sec. In CR-ANM the SDN controller allocates dedicated VMs to each SU for dynamic priority determination and efficient channel allocation. Increase in λ_{SU} and λ_{PU} does increase the number of new service requests and number of ongoing service requests but this distributed and dynamic channel allocation nature of the proposed scheme helped to reduce SRD significantly as compared to centralized SE-CRN.

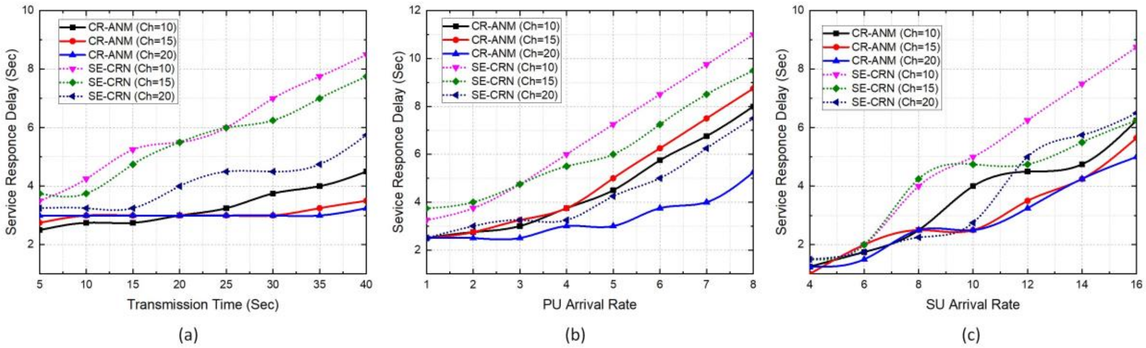

Fig. 5. Comparative results of CR-ANM and SE-CRN service response delay SRD with the function of (a) Transmission time T_{tr}, (b) PU arrival rate λ_{PU} and (c) SU arrival rate λ_{SU}

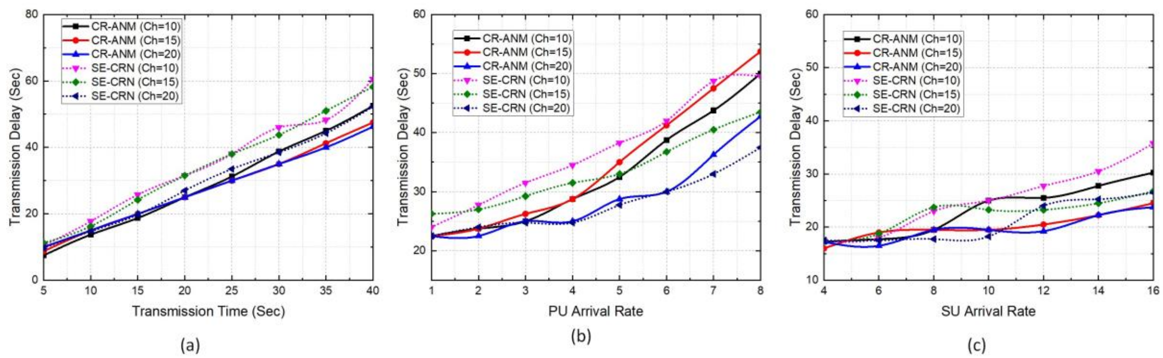

Fig. 6. Comparative results of CR-ANM and SE-CRN transmission delay with the function of (a) Transmission time T_{tr}, (b) PU arrival rate λ_{PU} and (c) SU arrival rate λ_{SU}

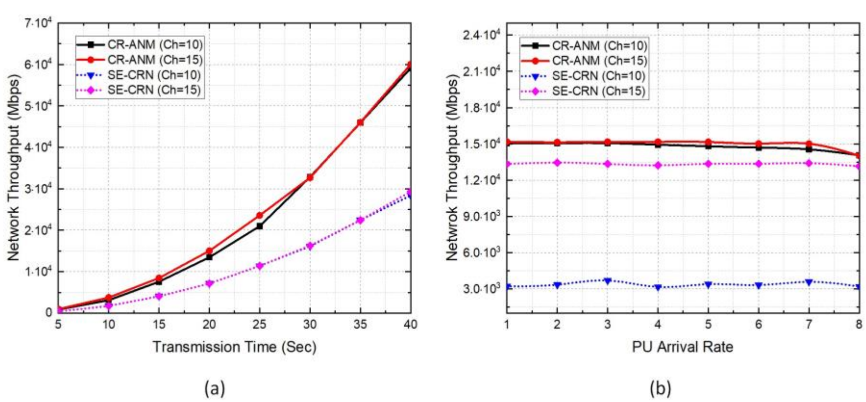

Fig. 7. Comparative results of CR-ANM and SE-CRN network throughput with the function of (a) Transmission time T_{tr}, and (b) PU arrival rate λ_{PU}

Transmission Delay is the average amount of time taken by SUs to transmit data from a source node to a destination node and complete a service within a specific period T_{tr}. Transmission delay is calculated as:

$$Transmission\ Delay = SRD + \frac{\sum_{SU_{High}, SU_{Low}} D}{T_{tr}} \quad (12)$$

Figure 6 shows the comparative results of proposed schemes in terms of transmission delay with the function of; (a) transmission time, where, $\lambda_{PU} = 2$, and $\lambda_{SU} = 10$ (b) PU arrival rate where, $T_{tr} = 15$ sec, and $\lambda_{SU} = 10$, and (c) SU arrival rate where, $\lambda_{PU} = 2$, and $T_{tr} = 15$ sec. Increase in all these above factors except CH_N drastically affect the system performance and increase the transmission delay. DPD and ECA schemes run as VUFs on dedicated virtual machines which is the reason why decoupling the control panel from data panel in such a distributed manner dramatically helps reduce delay as well as the computational complexity of the system. The comparative scheme SE-CRN shows an increase in transmission delay due to its centralized nature because the network load causes control overhead on the central node. On the contrary, CR-ANM outperformed and improved network performance and flexibility providing quality of service.

Network Throughput is defined as the number of packets transferred from the source SU node to the destination SU node within a specific time t and can be calculated as:

$$Network\ Throughput = \left(\lambda_{ptr} \times T_{tr}\right) - \lambda_{SDR} \quad (13)$$

Where, λ_{ptr} denotes the packet transfer rate, and T_{tr} is transmission time. Figure 7 shows the comparative results of proposed schemes in terms of network throughput with the function of; (a) transmission time, where $\lambda_{PU} = 2$, and $\lambda_{SU} = 10$, and (b) PU arrival rate where, $T_{tr} = 15$ sec, and $\lambda_{SU} = 10$. The comparative graphs show that service drop rate, service response delay, and transmission delay are interdependent on each other and have a great impact on network efficiency. The proposed scheme CR-ANM efficiently managed to counter the factors affecting performance evaluation parameters thus significantly improving network throughput as compared to SE-CRN.

IV. Conclusion

In this paper, we proposed a multi-attribute-based network framework called CR-ANM for resource constraint communication of the Consumer Internet of Things. Our system integrates three groundbreaking technologies CR, SDN, and NFV in a way that reduces system complexity as well as equipment cost. CR-ANM deals with the challenge of spectrum scarcity with Efficient Channel Allocation (ECA) and provides dynamic and application-specific priority-based network services by Dynamic Priority Determination Scheme (DPD). To achieve efficient results, it is suggested to place VM servers within the user premises, in case of remote placement it may cause an increase in transmission delay. As N_{SU} is equal to N_V that is why the increase in the number of dedicated VMs may cause an increase in computation load over the server depending upon server specifications. In future work, CR-ANM can be evaluated on different parameters to test its energy efficiency and cost-effectiveness in various application areas.

References

[1] M. A. Saleem *et al.*, “Provably Secure Conditional-Privacy Access Control Protocol for Intelligent Customers-Centric Communication in VANET,” *IEEE Transactions on Consumer Electronics*, vol. 70, no. 1, pp. 1747–1756, 2024, doi: 10.1109/TCE.2023.3324273.

[2] X. Xu, J. Wu, A. K. Bashir, and M. Omar, “Machine Learning and Zero Knowledge Empowered Trustworthy Bitcoin Mixing for Next-G Consumer Electronics Payment,” *IEEE Transactions on Consumer Electronics*, vol. 70, no. 1, pp. 2210–2223, 2024, doi: 10.1109/TCE.2024.3361690.

[3] C. K. Wu, C.-T. Cheng, Y. Uwate, G. Chen, S. Mumtaz, and K. F. Tsang, “State-of-the-Art and Research Opportunities for Next-Generation Consumer Electronics,” *IEEE Transactions on Consumer Electronics*, vol. 69, no. 4, pp. 937–948, 2023, doi: 10.1109/TCE.2022.3232478.

[4] P. Consul, I. Budhiraja, D. Garg, N. Kumar, R. Singh, and A. S. Almogren, “A Hybrid Task Offloading and Resource Allocation Approach for Digital Twin-Empowered UAV-Assisted MEC Network Using Federated Reinforcement Learning for Future Wireless Network,” *IEEE Transactions on Consumer Electronics*, vol. 70, no. 1, pp. 3120–3130, 2024, doi: 10.1109/TCE.2024.3368156.

[5] M. R. Hassan, G. C. Karmakar, J. Kamruzzaman, and B. Srinivasan, “Exclusive Use Spectrum Access Trading Models in Cognitive Radio Networks: A Survey,” *IEEE Communications Surveys & Tutorials*, vol. 19, no. 4, pp. 2192–2231, 2017, doi: 10.1109/COMST.2017.2725960.

[6] A. Akbar, M. Ibrar, M. A. Jan, A. K. Bashir, and L. Wang, “SDN-Enabled Adaptive and Reliable Communication in IoT-Fog Environment Using Machine Learning and Multiobjective Optimization,” *IEEE Internet Things J*, vol. 8, no. 5, pp. 3057–3065, 2021, doi: 10.1109/JIOT.2020.3038768.

[7] B. Han, V. Gopalakrishnan, L. Ji, and S. Lee, “Network function virtualization: Challenges and opportunities for innovations,” *IEEE Communications Magazine*, vol. 53, no. 2, pp. 90–97, 2015, doi: 10.1109/MCOM.2015.7045396.

[8] A. Taneja and S. Rani, “Robust Resource Control Mechanism for Connected Support to IoT-Based Sustainable Consumer Electronics for Industry 5.0,” *IEEE Transactions on Consumer Electronics*, vol. 70, no. 1, pp. 1463–1470, 2024, doi: 10.1109/TCE.2023.3325914.

[9] T. He, K.-W. Chin, S. Soh, and Z. Zhang, “A Novel Distributed Resource Allocation Scheme for Wireless-Powered Cognitive Radio Internet of Things Networks,” *IEEE Internet Things J*, vol. 8, no. 20, pp. 15486–15499, 2021, doi: 10.1109/JIOT.2021.3071396.

[10] C. Sun, H. Ding, and X. Liu, “Multichannel spectrum access based on reinforcement learning in cognitive internet of things,” *Ad Hoc Networks*, vol. 106, p. 102200, 2020, doi: https://doi.org/10.1016/j.adhoc.2020.102200.

[11] R. Li and P. Zhu, “Spectrum Allocation Strategies Based on QoS in Cognitive Vehicle Networks,” *IEEE Access*, vol. 8, pp. 99922–99933, 2020, doi: 10.1109/ACCESS.2020.2997936.

[12] I. Bala, A. Sharma, A. Tselykh, and B.-G. Kim, “Throughput optimization of interference limited cognitive radio-based Internet of Things (CR-IoT) network,” *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 7, pp. 4233–4243, 2022, doi: https://doi.org/10.1016/j.jksuci.2022.05.019.

[13] B. Zhao, J. Liu, Z. Wei, and I. You, “A Deep Reinforcement Learning Based Approach for Energy-Efficient Channel Allocation in Satellite Internet of Things,” *IEEE Access*, vol. 8, pp. 62197–62206, 2020, doi: 10.1109/ACCESS.2020.2983437.

[14] H. Bany Salameh, N. Al-Nusair, S. H. Alnabelsi, and K. A. Darabkh, “Channel assignment mechanism for cognitive radio network with rate adaptation and guard band awareness: batching perspective,” *Wireless Networks*, vol. 26, no. 6, pp. 4477–4489, 2020, doi: 10.1007/s11276-020-02344-w.

[15] M. Devi, N. Sarma, and S. K. Deka, “A Double Auction Framework for Multi-Channel Multi-Winner Heterogeneous Spectrum Allocation in Cognitive Radio Networks,” *IEEE Access*, vol. 9, pp. 72239–72258, 2021, doi: 10.1109/ACCESS.2021.3079260.

[16] A. Kaur and K. Kumar, “Energy-Efficient Resource Allocation in Cognitive Radio Networks Under Cooperative Multi-Agent Model-Free Reinforcement Learning Schemes,” *IEEE Transactions on Network and Service Management*, vol. 17, no. 3, pp. 1337–1348, 2020, doi: 10.1109/TNSM.2020.3000274.

[17] X. Tan *et al.*, “Cooperative Multi-Agent Reinforcement-Learning-Based Distributed Dynamic Spectrum Access in Cognitive Radio Networks,” *IEEE Internet Things J*, vol. 9, no. 19, pp. 19477–19488, 2022, doi: 10.1109/JIOT.2022.3168296.

[18] A. U. Khan, G. Abbas, Z. H. Abbas, M. Waqas, and A. K. Hassan, “Spectrum utilization efficiency in the cognitive radio enabled 5G-based IoT,” *Journal of Network and Computer Applications*, vol. 164, p. 102686, 2020, doi: https://doi.org/10.1016/j.jnca.2020.102686.

[19] S. Adamantia, K. Grigorios, T. Konstantinos, K. Vasileios, and P. Symeon, “Autonomic Network Management and Cross-Layer Optimization in Software Defined Radio Environments,” *Future Internet*, vol. 11, no. 2, Feb. 2019.

[20] H. Ghafoor and I. Koo, “An Integrated Cognitive Radio Network for Coastal Smart Cities,” *Appl. Sci.*, vol. 9, no. 17, Aug. 2019.

[21] W. Liu *et al.*, “Enabling Virtual Radio Functions on Software Defined Radio for Future Wireless Networks,” *Wirel Pers Commun*, vol. 113, no. 3, pp. 1579–1595, 2020, doi: 10.1007/s11277-020-07245-x.

[22] L. Abbas, U. Shoaib, and A. K. Bashir, “Priority based dynamic spectrum management using Virtual Utility Functions in Cognitive Radio enabled Internet of Things,” *Comput Commun*, vol. 196, pp. 239–248, 2022, doi: https://doi.org/10.1016/j.comcom.2022.10.002.

[23] M. Liaqat *et al.*, “Federated cloud resource management: Review and discussion,” *Journal of Network and Computer Applications*, vol. 77, pp. 87–105, 2017, doi: https://doi.org/10.1016/j.jnca.2016.10.008.