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Deep Learning-Based Spectrum Sharing in Next Generation Multi-Operator Cellular Networks

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Summary

Owing to the exponential increase in wireless network services and bandwidth re-quirements, sharing the radio spectrum among multiple network operators seems inevitable. In wireless networks, enabling efficient spectrum sharing for resource allocation is quite challenging due to several random factors, especially in multi-operator spectrum sharing. While spectrum sensing can be useful in spectrum-sharing networks, the chance of collision exists due to the inherent unreliability of wireless networks, making operators reluctant to use sensing-based mechanisms for spectrum sharing. To circumvent these issues, we utilize an alternative approach, whereby we propose an efficient spectrum-sharing mechanism leveraging a spec-trum coordinator (SC) in a multi-operator spectrum-sharing scenario assisted by deep learning (DL). In our proposed scheme, before the beginning of each timeslot, the base station of each operator transmits the number of required resources based on the number of packets in the base station's queue to SC. In addition, base stations also transmit the list of available channels to SC. After gathering information from all base stations, SC distributes this collected information to all the base stations. Each base station then utilizes the DL-based spectrum-sharing algorithm and computes the number of resources it can use based on the number of packets in its queue and the number of packets in the queues of other operators. Furthermore, by leveraging DL, each operator also computes the cost it must pay to other operators for using their resources. We evaluate the performance of the proposed network through extensive simulations. It is shown that the proposed DL-based spectrum-sharing mechanism outperforms the conventional spectrum allocation scheme, thus paving the way for more dynamic and efficient multi-operator spectrum sharing.

KEYWORDS:

Shared spectrum, machine learning, deep neural network, cellular networks, resource allocation.

1 | INTRODUCTION

The growing number of high-end consumer devices such as mobile phones and tablets running bandwidth-hungry applica-tions has massively increased the demand for mobile data. It is expected that the mobile data transmission will be around 4.8

zettabytes[1]. The existing wireless cellular networks should expand their aggregated network capacity. To meet the requirements of next-generation wireless networks, more efficient radio resource management, and allocation schemes are required. Conventionally, a licensed spectrum band is allocated to a mobile network operator (MNO) and each MNO serves its users through the licensed spectrum only. The licensed spectrum is sporadically used by the operator and spectrum utilization varies geographically, ranging from 15% to 85%, on average, with a high variance in time[2]. This means an operator may have idle resources due to low demand from its users at any given time instant. These resources can be shared with another operator that does not have sufficient resources to serve its users.

Since the licensed spectrum is a limited and expensive resource, efficiently sharing the idle spectrum resources with other wireless networks is highly desirable[3]. In this context, several research works, such as dynamic spectrum access (DSA)[4], cognitive radio (CR)[5], and multi-operator spectrum sharing[6] have been proposed. In DSA and CR, unlicensed secondary users can use the idle resources from the licensed spectrum of a primary network operator. To this end, several sensing-based mechanisms have been developed to utilize unused resources of the primary network opportunistically[7,8], however, collision-free communication can not be guaranteed. On the other hand, in multi-operator spectrum sharing, multiple MNOs agree to share their spectrum band, with mutual consent and full or minimal exchange of operator's information[9]. Two general schemes are usually used in multi-operator spectrum sharing i.e. spectrum pooling and mutual renting. In the prior case, an operator selects resources from a dedicated spectrum pool for information transmission. In the latter case, an MNO (lender) can rent the unused spectrum to another operator (buyer) and gather additional revenue and enhanced spectrum utilization benefits.

Conventionally, the licensed spectrum resources of an MNO guarantee its wireless access and technological compatibility requirements while avoiding interference caused by other MNOs. This can give full control to an MNO for utilizing the spectrum band. However, the exclusive licensed spectrum environment often faces low spectrum utilization[10] especially outside of densely populated areas and peak hours. In this regard, regulatory authorities are globally seeking new solutions for efficient spectrum utilization leveraging spectrum sharing[11] which can allow spectrum sharing among multiple MNOs and can enable MNOs to access the unused spectrum resources of other MNOs dynamically. However, a dynamic and efficient spectrum-sharing process in a multi-operator network while maintaining the regulations and performance constraints is a challenging task[12]. To this end, in[14], the authors proposed a spectrum-sharing mechanism in cellular networks for opportunistic resource allocation based on the fluctuations of the incoming traffic. Multi-operator spectrum sharing schemes have gained research interest in both academia and industry[13]. Table 1 summarizes some of the major related works in multi-operator spectrum sharing networks.

In a multi-operator spectrum sharing architecture, a large number of cellular users, variations in channel quality, and dynamic spectrum utilization of multiple MNOs can cause adverse effects on the network performance[22]. Due to the dynamic nature of spectrum utilization, next-generation networks will require radio access networks for efficient spectrum sharing. To this end, an open-RAN framework[23] for next-generation networks is highly desirable, allowing seamless reconfiguration and optimization of wireless network entities[24]. Owing to its high efficiency in dealing with complex calculations and dynamic environments, deep learning (DL) is regarded as an effective candidate for wireless communication systems[25]. A DL model can be trained according to the wireless network environment to enable different services such as power control[26], resource allocation[27], spectrum management[28] etc. In this context, DL can be used for efficient spectrum sharing and resource allocation. Motivated by this, we have proposed a DL-based spectrum sharing and resource utilization for a multi-operator spectrum sharing network. Authors in[29] and[30] have briefly surveyed the application of DL in wireless networks. Authors in[31] proposed an ML-based inter-operator spectrum sharing in millimeter-wave communication bands to reduce the signaling overhead for information exchange among multiple operators.

Owing to the increase in demand and the high cost of spectrum resources, spectrum sharing among multiple operators can be a viable solution. Motivated by the discussions in the previous few paragraphs, we aim to study a multi-operator spectrum-sharing network, consisting of N MNOs. Leveraging the fact that through multi-operator spectrum sharing, MNOs can enhance their spectrum utilization by lending unused spectrum resources to other operators and vice versa, MNOs agree to share the licensed spectrum. The proposed spectrum sharing enables dynamic and efficient communication considering the currently available resources among the participating MNOs. Each MNO has a base station deployed in a coverage area under observation. At the base station, when the number of radio resources is less than the minimum required radio resources to transmit a certain number of data packets, the base station then maintains a packet queue where the leftover packets are stored. To enable communication between multiple MNOs, a *spectrum coordinator* (SC) is deployed within the coverage area of base stations[21]. We assume that each MNO has installed a DL module at the base station which receives the information about the number of packets in the queue of each base station and then estimates the resource utilization of the MNO for the next timeslot. Based on the estimated output of the DL module, an MNO selects the resources. Hence, if an MNO requires some extra resources from the spectrum

Table 1 Summary of Existing Literature in Performance Analysis of a multi-operator spectrum sharing network

Ref.	System Model	Performance Metrics	Main Results/Findings	Limitations
Ref[15]	Spectrum sharing among two licensed operators	Spectrum sharing gain and capacity	Enhanced spectrum sharing gain from 10% to 100%	Primarily for two operators
Ref[16]	Multiple operators sharing common pool of resources	Throughut	Amount of resources to share increase throughput	Strrong coordination among operators is required
Ref[17]	Multi-operator primary and secondary network	Blocking probability and cost of secondary operator	Improved utilization of spectrum while ensuring grade of service	Beneficial for temporary spectrum shortage
Ref[18]	Operators have dedicated bands and are sharing a common pool of resources	Throughput and Fairness	Fairness among operators is ensured with an improved throughput	Impact of wirless channel is not considered
Ref[19]	Operators share common pool and one operator use spectrum at a time	Cell sum capacity and fairness	Operators can share the spectrum improving capacity and fairness	Strong coordination is required
Ref[20]	Operators share common pool with a strong centralized coordination	Spectrum efficiency and user rate	Fair spectrum sharing improves performance by 60%	Requires strong coordination among operators and impact of wireless channel is not considered
Ref[21]	Non-orthogonal spectrum sharing leveraging game theory	Social welfare (bps/Hz)	Spectrum allocation improve sum rate (social welfare)	Incentive of sharing spectrum is not considered
This work	Dedicated spectrum bands are opportunistically used by other operators when required	Cost paid by buyer, delay, and throughput	Improved throughput and reduced delay	

of other MNOs, the DL module estimates the number of resources it can use, and the cost it has to pay other MNOs for using their spectrum resource.

To this end, our goal is to provide an efficient mechanism for spectrum sharing while maintaining fairness among operators. While most of the works did not consider the impact of channel quality while lending the spectrum to other operators, we also considered channel quality to ensure maximum throughput for the primary network. The performance of the proposed scheme is analyzed through simulations and compared with the conventional resource allocation scheme whereby spectrum resources are not shared and only a dedicated spectrum band is used for communication. The results show that the proposed scheme outperforms the conventional scheme in terms of improved throughput and reduced delay. The major contributions of this work are summarized as follows:

1. A DL-based spectrum-sharing mechanism leveraging SC in a multi-operator spectrum-sharing network is proposed whereby only the information about the number of packets in the queue and channel quality sequence are shared.

2. To provide a wireless communication link between the base stations of multiple operators, SC is deployed which acts as a relay. The base station of each operator shares the information with SC, which is then relayed to all base stations in the cell.

3. For efficient spectrum sharing with minimal data exchange, a DL module is used at each base station for efficient resource allocation. DL module estimates the resource utilization and cost estimation of an MNO.

4. Extensive simulations have been conducted and the proposed scheme has been evaluated under different network conditions. Moreover, we have also compared the performance of the proposed scheme with the conventional non-spectrum sharing scheme.

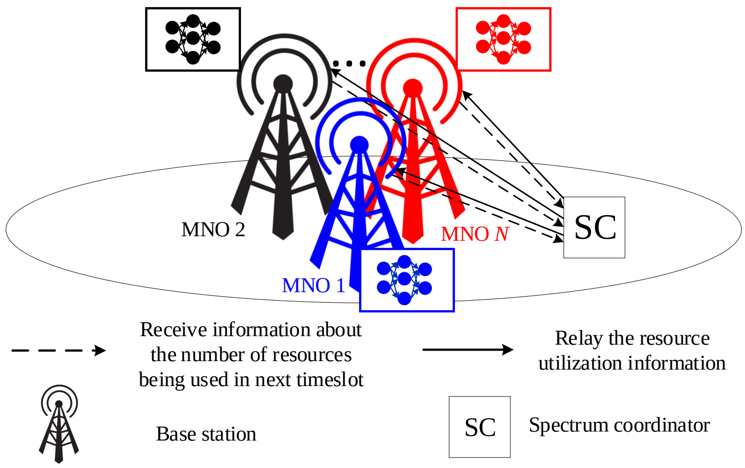

Figure 1 System model for the proposed multi-operator spectrum sharing network leveraging spectrum coordinator.

The rest of the paper is organized as follows. In Section 2 we explain the considered network model and explained the proposed DL-based spectrum sharing scheme. The performance of the proposed scheme is evaluated and compared with the conventional scheme in Section 3. Lastly, we conclude the paper in Section 4.

2 | PROPOSED SCHEME

In this section, we explain the proposed scheme where we consider N number of MNOs, and each MNO has its own dedicated spectrum band. As shown in Fig. 1, base stations of N MNOs have been deployed and it is assumed that these MNOs agree to share their unused spectrum resources. To enable communication among multiple base stations, we introduced a new device, namely, spectrum coordinator (SC), which is deployed within the vicinity of multiple base stations. SC can be deployed by any third-party manufacturer that works as a relay among the base stations of multiple MNOs. The third-party manufacturer and a regulator can enforce policies that protect each operator's business interests while promoting efficient spectrum utilization. Moreover, trust can be developed among multiple operators for the sharing of data and operational details for efficient collaboration. All MNOs agree to share their information about their spectrum utilization with the SC. Instead of sensing the spectrum for opportunistic utilization, each base station transmits its spectrum utilization information to SC which then relays this information to all other MNOs in the networks. Furthermore, to ensure synchronization among base stations, SC periodically transmits the synchronization signals to all the base stations in the network. Unlike previous works, such as[21], whereby wired links were utilized, we consider that base stations and SC exchange information through separate channels termed as *SC communication channels*, to avoid the delay in communication between base stations and SC. The motivation behind this wireless link is primarily the versatility, flexibility, easy accessibility, and lower maintenance cost.

In the considered network, time is slotted into equal-length intervals and we assume that the transmission of each packet lasts for one timeslot. Also, the frequency band of each operator is divided into K_{CH} number of channels. These K_{CH} channels are licensed to the primary MNO and the MNO communicates with its users according to a synchronous slot structure. In this paper, each time-frequency block is termed a cellular resource block (CRB). At the beginning of each timeslot, the base station acquires the channel state information regarding the channels it will utilize from its spectrum band. It, then, arranges channels in sequence based on channel quality indicator values. The channel sequence here means that the channel numbers are arranged in descending order based on the channel quality. This method is adopted to ensure the highest quality of service provisioning for the users of the MNO that is sharing its band with other MNO's base stations. The packets arrive at each base station following an independent Poisson arrival process with rate λ. We consider that each base station is equipped with a queue of size, L_Q, and newly arrived packets will stay in the queue if they arrive within a timeslot. It is assumed that each packet occupies one unit of queue size. In other words, there can be a maximum of L_Q number of packets in the queue. Each packet is being served at the beginning of the timeslot, following the first-in-first-out principle. Furthermore, a newly arrived packet will be dropped if the queue is already full.

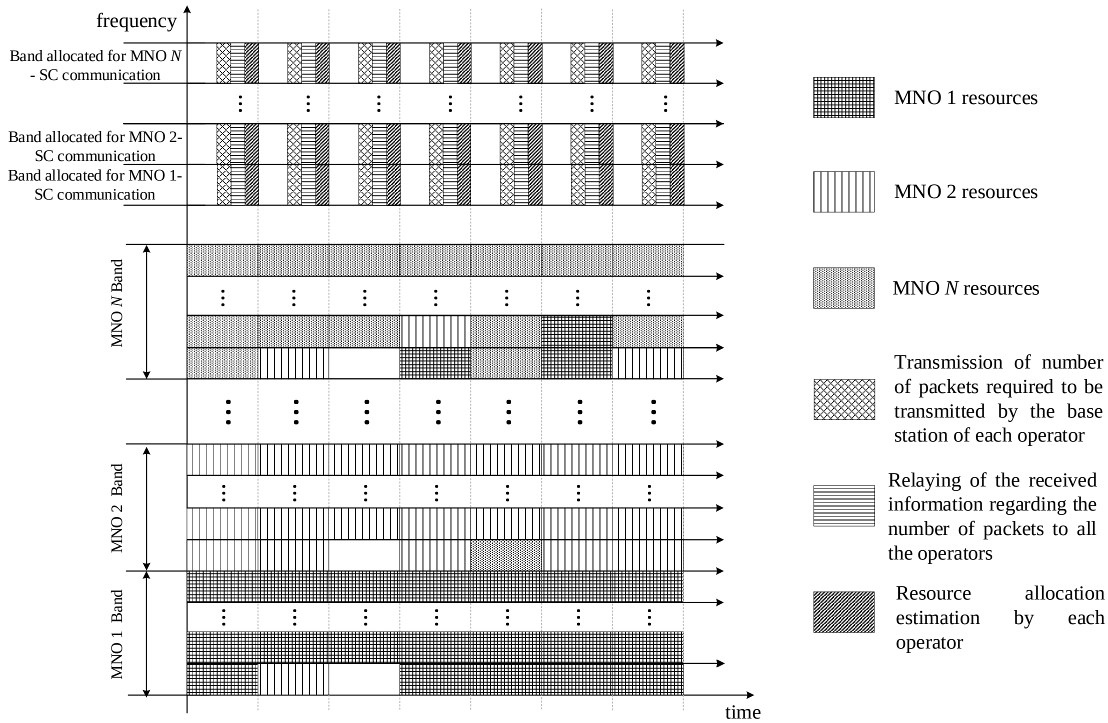

Figure 2 An example of resource allocation procedure for spectrum sharing among N number of mobile operators.

Each timeslot of the *SC communication channel* is further divided into three mini-slots. During the first mini-slot, each base station transmits information about the number of packets in its queue and the channel sequence to the SC through *SC communication channels*. Moreover, each base station also shares the channel sequence with the SC. During the second mini-slot, SC relays the gathered information to all base stations, as shown in Fig. 2. During the third mini-slot, each base station then estimates its CRB utilization and then schedules users for transmission depending on its number of packets and the number of packets in its own queue, and the number of packets in the queue of other MNOs.

Despite the conceptual simplicity of the proposed idea, the resulting analysis can become complex, owing to the multiple operators and wireless channels. Thus, we leverage a DL-based spectrum-sharing algorithm to compute the CRB utilization and cost to be paid to other operators. DL is used to optimally allocate the resources among multiple MNOs with minimum communication among MNOs. Base stations share information about the number of packets in the queue and the sequence of channels, and all MNOs estimate the utilization of resources accordingly.

2.1 | Deep learning for resource allocation in multi-operator spectrum sharing scheme

An example of the DL module specifically for the base station of MNO 1 is shown in Fig. 3. All base stations in the considered network are embedded with a similar DL module. All MNOs use their respective DL modules to make spectrum-sharing decisions, concurrently. The input layer of the DL module consists of N neurons. There are three fully connected hidden layers and one output layer. The input of the DL module consists of a 1D array of N elements, X_{pkt_n} where $n \in \{1, 2, \cdots, N\}$ and N is the total number of MNOs. Each element, X_{pkt_i}, is the normalized value of the number of packets in the queue of an MNO and it is normalized using $(X_{pkt_i} - \mu)/\sigma$, where μ and σ are the mean and variance values, respectively.

The output, O_{uti_n}, is a 1D array of $2N - 1$ elements. Here, $O_{uti_n} = \{Y_{uti_1}, Y_{uti_2}, \cdots, Y_{uti_N}, C_{uti_i}, \cdots, C_{uti_N}\}$ for $n \in \{1, 2, \cdots, N\}$ and $i \in \{1, 2, \cdots, N\}$ and $i \neq n$. Also, Y_{uti_i} is the normalized value of the number of CRBs used by an MNO from its own and other MNOs' spectrum. As an example, Y_{uti_1} for MNO1 means the number of packets used by MNO 1 from its band. Also, C_{uti_i} is the normalized value of the cost paid to other MNOs for using their CRBs. Hereby, C_{uti_1} is not considered since we considered the DL module of MNO 1, and the cost of renting is to be paid to other operators only.

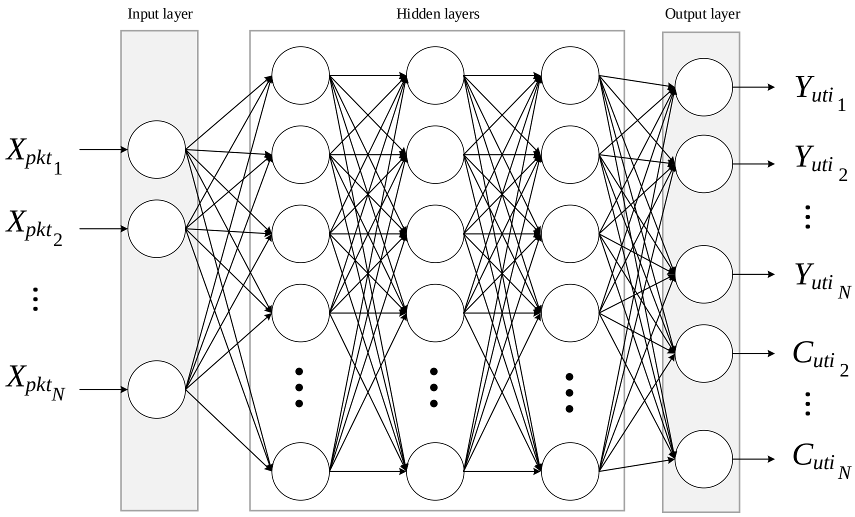

Figure 3 An MLP model of MNO 1 for spectrum sharing in a multi-operator network consisting of N mobile network operators.

Table 2 An example of training data generated for MNO 1 considering that 3 MNOs in the networks.

MLP input (X_{uti})			MLP Output (O_{uti})				
X_{pkt_1}	X_{pkt_2}	X_{pkt_3}	Y_{uti_1}	Y_{uti_2}	Y_{uti_3}	C_{uti_2}	C_{uti_3}
13	9	7	10	0	3	0	24
12	6	14	10	2	0	14	0
2	9	6	2	0	0	0	0
12	13	12	10	0	0	0	0
14	12	7	10	0	1	0	8
17	4	5	10	6	1	30	6

2.1.1 | Resource allocation and pricing strategy for data generation

Owing to the usage of supervised DL, data generation is one of the main things for training of DL modules. The data was generated using a custom-built network simulator, whereby we employed a discrete-event simulator specifically designed for spectrum-sharing scenarios. To generate this data, we have considered that there are three MNOs in the network willing to share their spectrum with each other. The main focus of the proposed scheme is to ensure cost-effective resource utilization in a multi-operator spectrum-sharing scenario based on pre-defined policies. The data is generated based on the discrete-event simulation results to train the DL module for given values of X_{pkt_i} for $i \in \{1, 2, 3\}$. For a given input of X_{pkt_i}, the output is generated in terms of utilization and cost. Hereby, utilization means the number of resources to be used by another operator, and cost refers to the amount paid to another operator for utilizing its resources. To this end, we employ certain strategies for efficient spectrum sharing which each MNO follows:

1. **Strategy 1:** Enhanced spectrum utilization of an underutilized spectrum of an MNO
    - When the number of packets to be transmitted by an MNO is greater than K_{CH}, then that MNO checks which other MNOs have some CRBs available based on their number of packets. If other MNOs have some unused CRBs, then the MNO, under observation, has to select the CRBs of that MNO with more unused CRBs available.
2. **Strategy 2:** Meeting the minimum resource requirement criteria

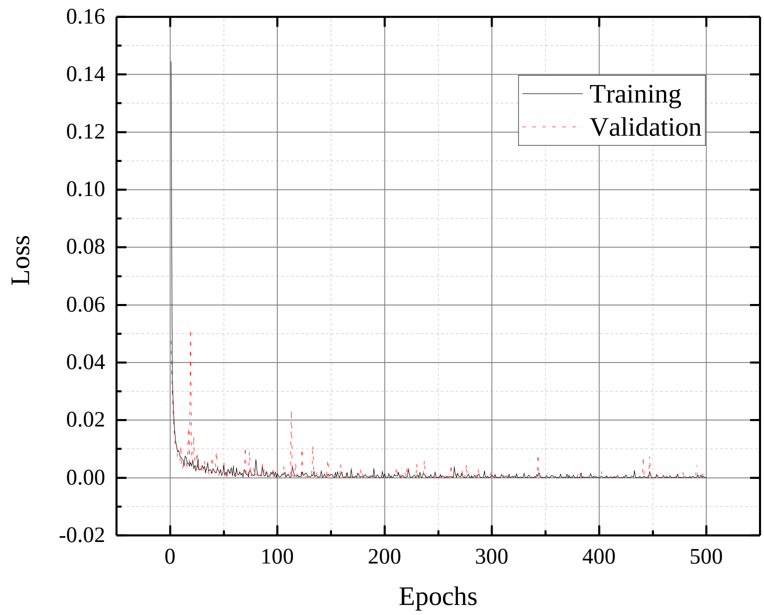

Figure 4 Training loss and validation of the neural network of MNO 1.

- When two MNOs have the number of packets greater than their K_{CH} channels and one MNO has some unused resources, then the MNO (under observation) will utilize those CRBs only if its resource sharing requirement[1] is less than or equal to the resource-sharing requirement of the other MNO.

Following these two strategies, we have generated the data. An example of input and output data pairs before and after applying normalization and denormalization, respectively, from the training data set of MNO 1 is shown in Table 2. For simplicity, the number of channels available for each MNO (K_{CH}) is set to 10. First, we generated the number of packets following the Poisson arrival process and labeled the outputs. These inputs and outputs are then normalized and used for the training of the DL module. From Table 2, it can be observed that when the number of packets to be transmitted in MNO 1's queue (i.e., $X_{pkt_1} = 13$) is greater than K_{CH} and other MNOs have unused CRBs (i.e., $X_{pkt_2} = 9$ and $X_{pkt_3} = 7$, as in first row), then MNO 1 first utilizes the unused CRBs of MNO 3 for the transmission of its packets owing to the higher number of available resources of MNO 3 (following the strategy 1).

For each resource utilization of another MNO, an MNO has to pay the cost. The cost is computed as the number of CRBs utilized by the borrower MNO multiplied by the number of channels used by the lender MNO plus one[2]. Following the previous example, if MNO 1 has 13 packets in its queue and K_{CH} is 10, then it requires 3 CRBs from the unused resources of other MNOs. Furthermore, assuming that MNO 3 has 7 packets in its queue, operator A can use the remaining 3 unused resources of MNO 3 and pay the price of $3 \cdot (7 + 1) = 24$. This simple pricing strategy is adopted to reduce the complexity and to ensure the dynamic dependence of the pricing on the number of unused CRBs of other operators. In the case when MNO 1 has to utilize the unused resources of the rest of the operators (MNO2 and MNO 3) as in the last row of the Table 2, it first utilizes the resources of that operator which has the least number of packets in the queue to enhance the spectrum utilization of that operator and added revenue generation. The rest of the packets are transmitted via the resources of MNO 2. Moreover, in the case when two MNOs have a number of packets higher than K_{CH} and the other MNO has idle CRBs, then the MNO that has the least number of packets among the two, will utilize those idle CRBS (following strategy 2) as in second last row. Hereby MNO 2 has fewer packets as compared to MNO 1 i.e. 12. Thus first MNO 2 utilizes the two CRBs and the remaining one CRB is used by MNO 1. Lastly, when all MNOs have the number of packets greater than K_{CH}, spectrum sharing is not possible. Similar data is generated for MNO 2 and MNO 3 and used to train the DL module for each MNO.

[1] Resource sharing requirement here is the number of packets remaining in the queue of MNO 1 after MNO 1 has transmitted some packets using the CRBs of its own spectrum band.

[2] Here one is added to avoid the utilization cost of 0.

2.2 | Training of the MLP Model

We have used supervised learning to train the MLP model. The task of supervised learning is to learn a function that maps an input to an output based on example input-output pairs. To train the MLP model, training data is required. In this paper, we generate the training data using simulation. For this, we assume that the base station of each MNO has a database generator module. This module takes the number of packets in the queue of all base stations in the network as input and generates the output containing information on predicted spectrum utilization and cost based on the predefined spectrum-sharing policies between MNOs. This data is stored in a local database at the base station. Following the strategies mentioned in the previous subsection 2.1.1, we generate a dataset of a size of 100,000 samples. The data is labeled and later used for training, validation, and testing. To this end, 49%, 21%, and 30% of these are randomly selected for training, validation, and testing, respectively.

3 | PERFORMANCE EVALUATION

To evaluate the performance of the proposed scheme, we assume that the packets are arriving at each operator following the Poisson arrival process. In the simulation, the average delay is computed as the difference between the time when a packet arrives in the queue and when it is transmitted to the user. For performance evaluation, we consider that the base stations of all MNOs are co-located. It is worth mentioning here that the assumption of co-located base stations is mainly taken into account to compute the signal-to-noise ratio (SNR) performance. Hereby the impact of interference is not considered as we consider that if a collision occurs during the concurrent transmissions of multiple operators using the same CRB, packets have to be retransmitted again. Since the primary focus of this paper is to study the performance of the spectrum-sharing algorithm, the assumption is that these co-located base stations have minimal effects on this performance metric. Moreover, owing to the massive deployment of femtocell base stations by different MNOs, the likelihood of their deployment in close vicinity is substantial. Furthermore, another practical assumption of such a network is to consider SC as a macro base station acting as a relay for the co-located femto base stations of multiple operators.

Sum throughput (T) is calculated using the classical Shannon capacity formula. It is assumed that the channel fading between the base station and the user follows Rayleigh fading. We have considered a block fading channel model, i.e., channel fading varies for each timeslot. However, during one timeslot, channel fading remains constant. Each operator knows the channel quality of the channels to be used for transmission from its spectrum band. In the case of spectrum sharing, where a base station is utilizing the idle CRBs of other operators, the channel fading between the base station and the user is random. The signal-to-noise ratio (SNR) (γ) between i^{th} serving base station and j^{th} user can be computed as

$$\gamma = \frac{P_{TX}|h_{i,j}|^2}{d_{i,j}^{\alpha}\upsilon^2}, \tag{1}$$

where P_{TX} is the transmit power of base station, $h_{i,j}$ and $d_{i,j}$ are the Rayleigh fading channel with mean 1 and distance between i^{th} base station and j^{th} user. α is the path loss exponent, and υ^2 is the AWGN variance at the receiving antenna. Assuming that the base stations of multiple operators are co-located and users are uniformly distributed around the base stations with the coverage area of R, the distribution of the distance between the base station and a user can be computed as given by[32] as

$$f_R(d) = \frac{2d}{R^2}. \tag{2}$$

Thus, the average distance ($\bar{d}$) between the base station and user is given as

$$\bar{d} = \frac{2R}{3}. \tag{3}$$

The SNR averaged over the distance (d) will be given as

$$\gamma_{\bar{d}} = \frac{P_{TX}|h_{i,j}|^2}{\bar{d}^{\alpha}\upsilon^2}, \tag{4}$$

and the sum throughput (T) of an operator can be computed as

$$T = \sum_{n=1}^{K_{CH}^*} B \cdot \log_2(1 + \gamma_{\bar{d}}), \tag{5}$$

Table 3 Values of parameters used to obtain simulation results.

Symbol	Description	Value
K_{CH}	Number of channels	10
L_Q	Length of the queue	20
P_{TX}	Transmit power of base station	15W [33]
v^2	Noise variance	0.01
R	Radius of coverage area of base station	30m
α	Path loss exponent	2.7
B	Bandwidth of a channel	2.0MHz

Table 4 MLP model architectures for $N = 3$ MNOs

Model	**Layer (type)**	**No. of nodes**	**Activation function**	**Parameters**
MLP	Input (dense)	3	-	-
	Hidden (dense)	50	RELU [36]	200
	Hidden (dense)	50	RELU	2550
	Hidden (dense)	50	RELU	2550
	Output (dense)	5	-	255
Total parameters				**5,555**

where K^*_{CH} is the total number of channels used by the base station of an MNO during a timeslot[3] and B is the bandwidth of each channel. Unless otherwise specified, the values of parameters used to obtain simulation results are given in Table 3.

The considered DL module for the proposed scheme is implemented using Keras [34] version 2.2.4, neural network library, with Tensorflow [35] version 1.15 on a desktop computer having 76T RTX–OPS Turing architecture GPU with a memory speed of 14 Gbps. The architecture of the considered DL module is given in Table 4. Adam optimizer is used to train the MLP algorithm with a learning rate of $\eta = 10^{-4}$. The number of epochs is set to 500, with a batch size (M) of 64. Moreover, loss is calculated using *mean-squared-error*(MSE), given as

$$MSE = \frac{1}{M} \cdot \sum_{i=1}^{M} (O_{uti_i} - \hat{O}_{uti_i})^2, \tag{6}$$

where O_{uti_i} is the actual output and $\hat{O}_{uti_i}$ is the predicted output for a given i^{th} input sample. Also, M is the batch size. As shown in Fig. 4, the DL module learns the data patterns efficiently, and the training and validation losses, converge at approximately 25 epochs. The training time of the proposed MLP module is approximately 963μsec per sample and the testing time is 1msec.

Fig. 5 plots the cost that an MNO has to pay to other MNOs for using their unused CRBs. The cost to be paid is a function of the number of packets in the queue of an operator. As the value of λ increases during a timeslot, the cost to be paid to other operators also increases. However, after reaching the maximum value, cost decreases because the number of unused CRBs is reduced. Since the value of λ is the same for all operators, the cost to be paid by all MNOs is nearly the same. In real-world scenarios, the assumption of the same values of λ usually occurs in normal situations owing to the normal consumer behavior. Moreover, this result shows the fairness in the spectrum among MNOs when they have the same priority to buy the unused spectrum of other operators and the arrival process and λ are the same.

In Fig. 6, the sum throughput and average delay of MNO 1 for proposed and conventional schemes are plotted versus varying values of arrival rate (λ). It can be seen from the figure that as the value of λ increases, the sum throughput increases. This is because, for lower λ values, CRBs are not fully utilized as fewer packets are transmitted. As the value of λ increases, throughput also increases. However, more packets have to wait in the queue which increases the average delay. In case of higher λ values, operators can share the unused CRBs with each other resulting in an improved sum throughput. This results in improved delay

[3]The value of K^*_{CH} is the number of channels used by the base station from its own band (K_{CH}) plus the number of channels used from the band of other MNOs.

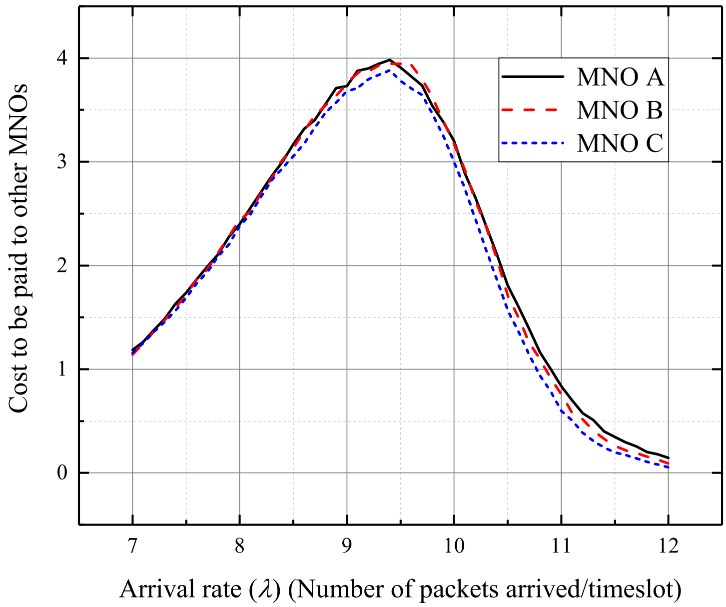

Figure 5 Price to be paid by an MNO to other MNOs for using their resources.

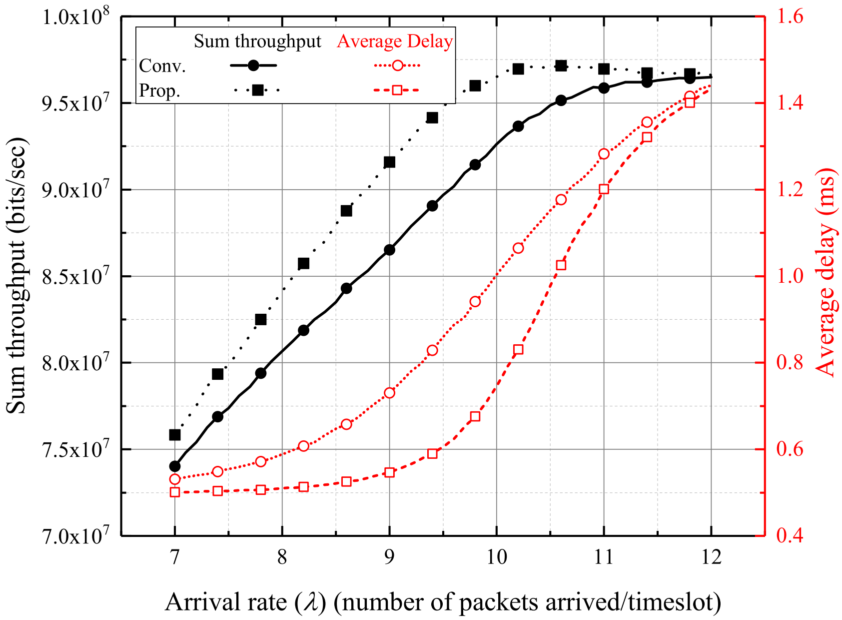

Figure 6 Sum throughput and average delay of MNO 1 under the condition that all MNOs have the same λ values.

performance since operators can serve their users using the idle resources of other operators. It is noted, the same value of λ for all operators yields approximately similar performance in terms of sum throughput and average delay. Therefore, only the results for MNO 1 are presented in Fig. 6.

Fig. 7 plots the sum throughput of MNO 1 for conventional and proposed schemes with different values of λ against simulation time. It can be observed that the proposed scheme outperforms the conventional scheme. Since more packets are transmitted by an MNO, by using the idle CRBs of other operators, the sum throughput of the MNO 1 increases considerably. However, as the value of λ increases, the number of unused CRBs reduces and sharing of the spectrum band also reduces. Thus, the throughput performance of the proposed scheme and the conventional scheme becomes comparable.

In Fig. 8, the average packet transmission delay MNO 1 is plotted versus timeslots for different values of λ. For $\lambda = 10$, since other MNOs have some idle CRBs available, MNO 1 can effectively utilize their idle CRBs when it requires, and thus the packet transmission of MNO 1 observes less delay. However, as the value of λ is increased, the difference in the performance

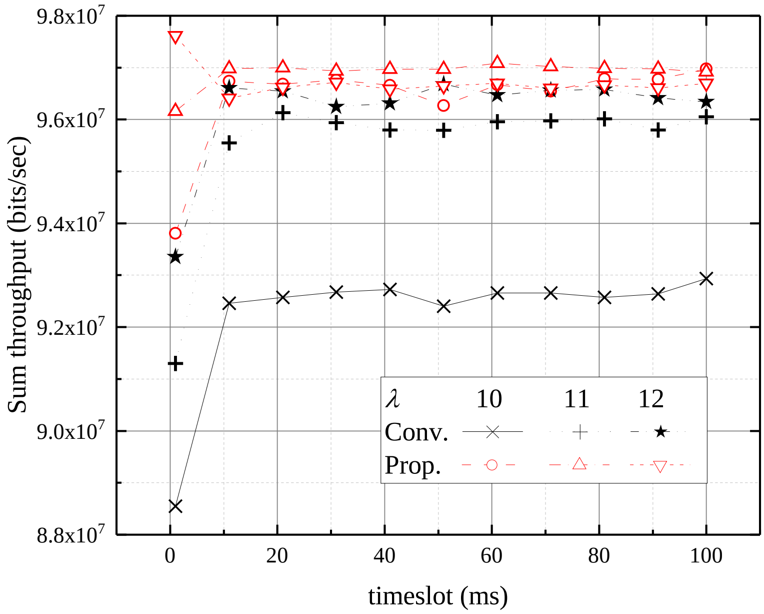

Figure 7 Sum throughput of MNO 1 under the condition that all MNOs have the same λ value.

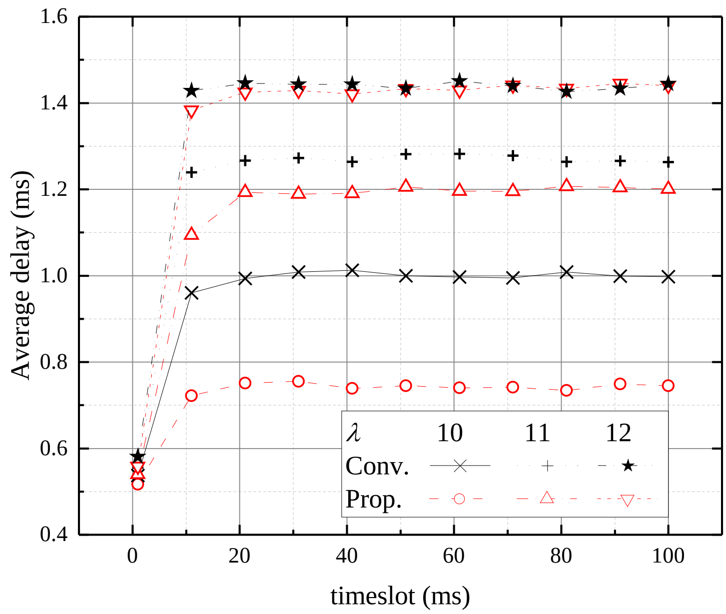

Figure 8 Average delay of MNO 1 under the condition that all MNOs have the same λ value.

of proposed and conventional schemes reduces. This is because no MNO has idle CRBs to be shared with MNO 1 and hence resource sharing is limited among multiple MNOs.

To simulate the results for changing values of λ during simulation for the MNOs, we have assumed that initially, the arrival rate of all MNOs is the same i.e. $\lambda = 10$. At 50^{th} timeslot, λ is changed to 10, 5, and 15 for MNO 1, 2, and 3, respectively. The sum throughput performance of the proposed scheme is shown in Fig. 9. It can be observed that even when all MNOs have the same λ value, the performance of the proposed scheme is slightly better than the conventional scheme. However, as the values of λ differ for each MNO, the sum throughput performance of the proposed scheme outperforms the conventional scheme considerably. Especially for MNO 3, as the number of packets arrived increases, the proposed scheme can efficiently utilize the unused CRBs of other MNOs for packet transmission of MNO 3. This results in increased sum throughput of MNO 3.

The delay performance of the proposed and conventional scheme, when λ values change during the simulation time, is plotted in Fig. 10. It is observed, for the same value of λ of each MNO, the proposed scheme performs better as compared to the

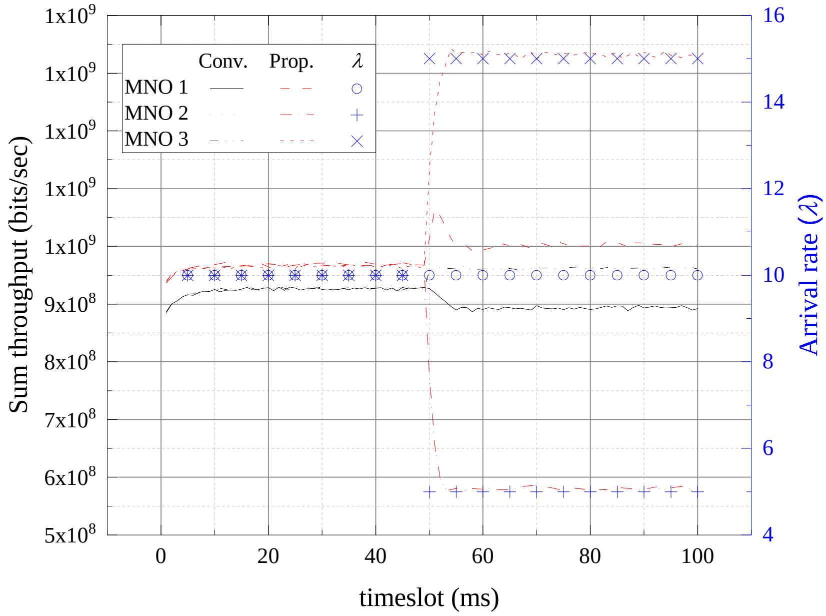

Figure 9 Sum throughput of different MNOs having same arrival rate i.e., $\lambda = 10$ initially and changed to different values of arrival rates ($\lambda_1 = 10$, $\lambda_2 = 5$, $\lambda_3 = 15$) at 50^{th} timeslot.

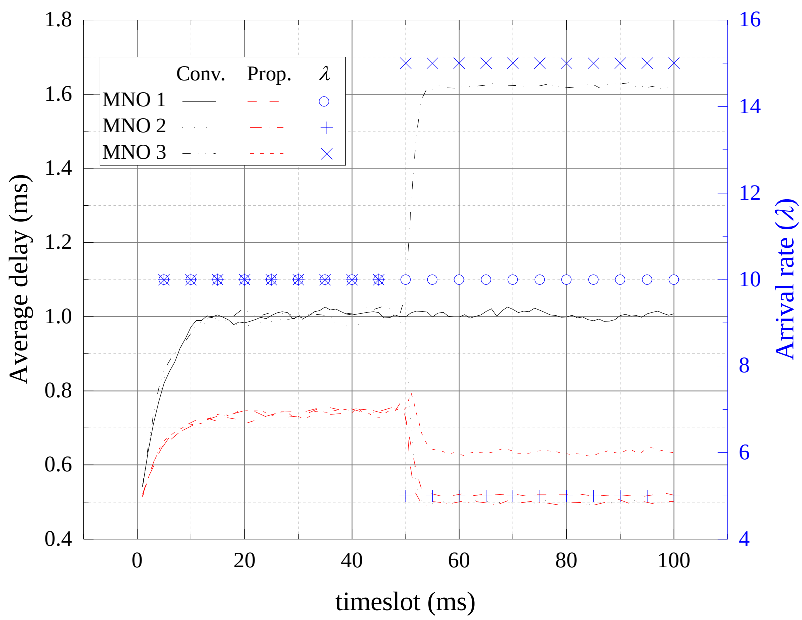

Figure 10 Average delay of different MNOs having same arrival rate i.e., $\lambda = 10$ initially and changed to different values of arrival rates ($\lambda_1 = 10$, $\lambda_2 = 5$, $\lambda_3 = 15$) at 50^{th} timeslot.

conventional scheme in terms of transmission delay. However, as the value of λ for each MNO changes, the proposed scheme outperforms the conventional scheme considerably. As the value of the arrival rate of MNO 3, i.e. λ_3, increases, the delay of MNO 3 using the conventional resource allocation scheme also increases considerably. However, compared to the conventional scheme, the delay performance of MNO 3 in the proposed scheme reduces considerably. This is because, MNO 3 in the proposed scheme utilizes the unused CRBs of MNO 1 and MNO 2, efficiently. Similarly, the delay of MNO 1 also reduces because it uses unused CRBs of MNO 2. It can be seen that, initially, the average delay of MNO 3 increases, but then reduces quickly. At timeslot 50, MNO 1 has fewer packets in the queue as compared to MNO 3, hence, MNO 1 utilizes the resources of MNO 2 first. After that, MNO 3 utilizes the resources of MNO 2 and its performance improves.

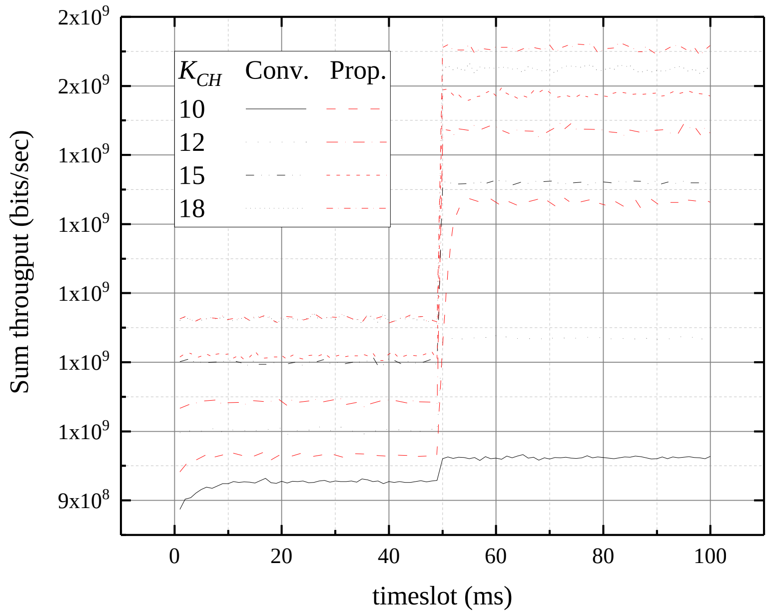

Figure 11 Sum throughput of MNO 1 plotted for different values of K_{CH} where each MNO has the same arrival rate, i.e., $\lambda = 10$, initially and changed to different values of arrival rates (i.e., $\lambda_1 = 10$, $\lambda_2 = 5$, $\lambda_3 = 15$) at 50^{th} timeslot.

In Fig. 11, we have studied the effects of varying values of K_{CH} on the performance of MNO 1. For this, we performed simulations for 10, 12, 15, and 18 channels. Intuitively, as the value of K_{CH} increases, the sum throughput of MNO 1 also increases. This is because more packets can be transmitted during a timeslot. When the value of K_{CH} is 10, the throughput performance of MNO 1 for the proposed scheme is better than the conventional scheme as MNO 1 can utilize the idle resources of other operators efficiently. As the value of K_{CH} increases, the difference in the throughput performance of proposed and conventional schemes is reduced. This is because MNO 3 can serve its users using its own spectrum resources and require fewer resources from other MNOs.

4 | CONCLUSION

With the massive increase in high bandwidth requirements, efficient spectrum allocation schemes are required. Spectrum sharing among multiple MNOs can provide an effective solution for spectrum allocation where multiple MNOs can share the spectrum band with each other to provide services to their users. In this paper, we proposed an efficient spectrum-sharing scheme for resource allocation among multiple MNOs. The base station of each MNO transmits the number of packets in its queue to the spectrum coordinator (SC) along with the channel sequence based on the channel quality indicator value. SC then relays the received information to all the base stations in the network. Each base station is equipped with a deep learning (DL) module based on a multilayer perceptron algorithm. This DL module takes the information about the number of packets as an input and estimates the resource allocation information and cost to be paid to other MNOs as an output. The performance of the proposed scheme has been evaluated using simulations. The results showed that the proposed scheme outperforms the conventional spectrum allocation scheme in terms of improved sum throughput and reduced delay.

In the future, we aim to consider other real scenarios, where the distribution of users and wireless channel characteristics can vary over time. Moreover, the traffic arrival patterns for each operator can vary over time. In addition, base stations of different MNOs in proximity may cause interference with other MNOs in a shared spectrum scheme. Consequently, for an effective allocation of spectrum resources, operators may need to deploy further enhanced deep learning strategies, such as online learning or transfer learning.

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CONFLICT OF INTEREST

There exists no conflict of interest to disclose from all authors on the submission of this manuscript.

References

1. Cisco Annual Internet Report (2018-2023), Cisco, White Paper, 2018. https://www.cisco.com/c/en/us/solutions/collateral/executive-perspectives/annual-internet-report/white-paper-c11-741490.html

2. Akyildiz IF, Lee WY, Vuran MC, Mohanty S. NeXt generation/dynamic spectrum access/cognitive radio wireless networks: A survey, Computer Networks Journal (Elsevier) 2006; 50 (13): 2127–2159.

3. Liang L, Ye H, and Li GY. Spectrum Sharing in Vehicular Networks Based on Multi-Agent Reinforcement Learning. IEEE Journal on Selected Areas in Communications 2019; 37 (10): 2282–2292.

4. Chang HH, Song H, Yi Y, J. Zhang, He H, Liu L. Distributive Dynamic Spectrum Access Through Deep Reinforcement Learning: A Reservoir Computing-Based Approach. IEEE Internet of Things Journal 2019; 6 (2): 1938–1948.

5. Zhang W, Wang CX, Ge X, Chen Y. Enhanced 5G Cognitive Radio Networks Based on Spectrum Sharing and Spectrum Aggregation. IEEE Transactions on Communications 2018; 66 (12): 6304–6316.

6. Xiao Y, Krunz M, Shu T. Multi-Operator Network Sharing for Massive IoT. IEEE Communications Magazine 2019; 57 (4): 96-101.

7. Cichoń K, Kliks A, Bogucka H. Energy-Efficient Cooperative Spectrum Sensing: A Survey. IEEE Communications Surveys & Tutorials, 2016; 18 (3): 1861-1886.

8. Awin F., Abdel-Raheem E., Tepe K. Blind Spectrum Sensing Approaches for Interweaved Cognitive Radio System: A Tutorial and Short Course. IEEE Communications Surveys & Tutorials, vol. 21, no. 1, pp. 238-259, Firstquarter 2019.

9. Shin M, Mughal DM, Park S, Kim S-H, Chung MY. Cellular Licensed Band Sharing Technology Among Mobile Operators: A Reinforcement Learning Perspective, 2021; 120 (1): 27-47.

10. Valenta V, Maršálek R, Baudoin G, Villegas M, Suarez M, Robert F. Survey on spectrum utilization in Europe: Measurements, analyses and observations. 2010 Proceedings of the Fifth International Conference on Cognitive Radio Oriented Wireless Networks and Communications 2010; 1–5.

11. Mustonen M, Matinmikko M, Holland O, Roberson D. Process model for recent spectrum sharing concepts in policy making. Telecommunications Policy 2017; 41 (5-6), 391-404.

12. Bhattarai S, Park JJ, Gao B, Bian K, Lehr W. An overview of dynamic spectrum sharing: Ongoing initiatives, challenges, and a roadmap for future research. IEEE Transactions on Cognitive Communications and Networking. 2016; 2 (2): 110–128.

13. Rahman M, Yuksel M, Quint T. A Game-Theoretic Framework to Regulate Freeriding in Inter-Provider Spectrum Sharing. IEEE Transactions on Wireless Communications 2021; 20 (6): 3941–3957.

14. Aazhang B, Lilleberg J, Middleton G. Spectrum sharing in a cellular system. Eighth IEEE International Symposium on Spread Spectrum Techniques and Applications - Programme and Book of Abstracts (IEEE Cat. No.04TH8738), Sydney, NSW, Australia 2004; 355–358.

15. Jorswieck EA, Badia L, Fahidieck T, Karipidis E, Luo J. Spectrum Sharing Improves the Network Efficiency for Cellular Operators. IEEE Communications Magazine 2014; 52 (3): 129-136.

16. Luoto P, Pirinen P, Bennis M, Samarakoon S, Scott S, Latva-aho M. Co-Primary Multi-Operator Resource Sharing for Small Cell Networks. IEEE Transactions on Wireless Communications 2015; 14 (6): 3120-3130.

17. Asaduzzaman M, Abozariba R, Patwary M. Dynamic Spectrum Sharing Optimization and Post-Optimization Analysis With Multiple Operators in Cellular Networks. IEEE Transactions on Wireless Communications 2018; 17 (3): 1589-1603.

18. Luoto P, Bennis M, Pirinen P, Samarakoon S, Latva-Aho M. Enhanced Co-Primary Spectrum Sharing Method for Multi-Operator Networks. IEEE Transactions on Mobile Computing 2017; 16(12): 3347-3360.

19. Anchora L, Mezzavilla M, Badia L, Zorzi M. A performance evaluation tool for spectrum sharing in multi-operator LTE networks. Computer Communications 2012; 35: 2218–2226.

20. Wang T and Adve R. Fair Licensed Spectrum Sharing Between Two MNOs Using Resource Optimization in Multi-Cell Multi-User MIMO Networks. IEEE Transactions on Wireless Communications 2022; 21 (8): 6714-6730.

21. Sanguanpuak T, Guruacharya S, Rajatheva N, Bennis M, Latva-Aho M. Multi-Operator Spectrum Sharing for Small Cell Networks: A Matching Game Perspective. IEEE Transactions on Wireless Communications 2017; 16 (6): 3761–3774.

22. Tehrani RH, Vahid S, Triantafyllopoulou D, Lee H, Moessner K. Licensed spectrum sharing schemes for mobile operators: A survey and outlook. IEEE Communications Surveys & Tutorials 2016; 18 (4): 2591–2623.

23. O-RAN Alliance, “White Paper: O-RAN: Towards an Open and Smart RAN,” Tech. Rep., 2018.

24. Bonati L, Polese M, D’Oro S, Basagni S, Melodia T. Open, Programmable, and Virtualized 5G Networks: State-of-the-art and the Road Ahead. Computer Networks 2020; 182.

25. Wang T, Wen C, Wang H, Gao F, Jiang T, Jin S. Deep learning for wireless physical layer: Opportunities and challenges. China Communications 2017; 14 (11): 92–111.

26. Jang HS, Lee H, Quek TQS. Deep Learning-Based Power Control for Non-Orthogonal Random Access. IEEE Communication Letters 2019; 23 (11): 2004–2007.

27. Liang L, Ye H, Yu G, Li GY. Deep-Learning-Based Wireless Resource Allocation With Application to Vehicular Networks. Proceedings of the IEEE 2020; 108 (2): 341-356.

28. Liu R, Ma Y, Zhang X, Gao Y. Deep Learning-Based Spectrum Sensing in Space-Air-Ground Integrated Networks. Journal of Communications and Information Networks 2021; 6 (1): 82-90.

29. Chen M, Challita U, Saad W, Yin C, Debbah M. Artificial Neural Networks-Based Machine Learning for Wireless Networks: A Tutorial, IEEE Communications Surveys & Tutorials 2019; 21 (4): 3039–3071.

30. Zappone A, Renzo MD, Debbah M. Wireless Networks Design in the Era of Deep Learning: Model-Based, AI-Based, or Both?, IEEE Transactions on Communications 2019; 67 (10): 7331–7376.

31. Ghadikolaei HS, Ghauch H, Fodor G, Skoglund M, Fischione C. A Hybrid Model-Based and Data-Driven Approach to Spectrum Sharing in mmWave Cellular Networks. IEEE Transactions on Cognitive Communications and Networking 2020; 6 (4): 1269–1282.

32. Tabassum H, Siddique U, Hossain E, Hossain MJ. Downlink Performance of Cellular Systems With Base Station Sleeping, User Association, and Scheduling. IEEE Transactions on Wireless Communications 2014; 13 (10): 5752–5767.

33. TB3hp mini TETRA base station, Online: https://www.securelandcommunications.com/tb3hp-mini-tetra-base-station. Accessed on: May 31, 2024.

34. Gulli A, Pal S. Deep learning with Keras, Packt Publishing Ltd. 2017.

35. M. Abadi, P. Barham, J. Chen, Z. Chen, A. Davis, J. Dean, M. Kudlur, Tensorflow: A system for large–scale machine learning, in: Proc. 12th USENIX Symposium on Operating Systems Design and Implementation (OSDI), 2016, 265–283.

36. Nair V, Hinton GE. Rectified linear units improve restricted boltzmann machines. Haifa 2010: 807–814.