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Intelligent Allocation of Channel Resources in 5G Network

Abrar Bashar[1], Dr. Zenon Chaczko[2]

[1,2] Department of ICT and Telecommunication Engineering, University of Technology Sydney, Sydney, Australia
[1]Email: abrar.bashar@student.uts.edu.au
[1]Email: 12793345@student.uts.edu.au

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Abstract- Fifth Generation (5G) network is a sort of the network that is being discoursed about, in recent times. This is something that has being embraced by China in recent times. However, while there is major demand in this, the network needed to maintain this is quite complicated. In order for this network to be under control, cognitive radio (CR) technology requires basic level of intelligence otherwise it won't happen. This article emphasizes about the distribution of cognitive cellular network in order to have a smooth real-time process. Such method connects artificial intelligence as well as this technology into an innovating multi-agent system (MAS). It's a holistic pattern for 5G communication networks. It is of utmost importance to allocate all the resource efficiently, to primary and secondary users and the base stations to ensure optimum utilization, of implementing this resource in cellular network. For that to happen we proposed four-layered framework for layer distribution and creating a benchmark MAS model. In addition, we proffer the ideal methods, technologies and process and come to a conclusion regarding the effectiveness via numerical simulations. Lastly this report discusses about the challenges and open issues.

Index Terms- 5G, Base Station, Channel Allocation, MAS Model, MARL.

I. Introduction

Fifth Generation (5G) cellular networks has evolved since its invention in late 2018. Within the span of less than two years it has become a key tool in the world of Information and Communication Technology (ICT) industry [1] [2]. This network is nimble and is capable of assisting supremely high data rates, for enhancing provisioning of service and meeting the necessities of diversification. Consequently, it results in the users having superior internet service and experience, by the users where they can download gigabytes of data in seconds [3]. While offering such sounds fancy the groundwork for providing it is a lot. The wireless technology needs to be adaptive and support multiple functional networks. These include cognitive radio (CR), technologies that are device to device (D2D) and many more. One may think the emergence of newer technologies will help the process to create an efficient 5G network, but this will make it very challenging to implement. Such potential challenges that may hinder the effective implementation of this network are astronomical growth regarding mobile internet service and its traffic, and a high level of spectrum scarcity [4]. Cognitive Radio is one of the most encouraging technologies of 5G networks, where it garnered significant industrial and academic attention. It is believed a bit of research is needed to solve the above challenges. Also, unlike its predecessors 3G and 4G, 5G scores more in a lot of aspect such as access to the device, data volumes, and different communication scenarios [5] [6]. The configuration problems are immense, and the service requirements are tedious, and for that to neutralize the enhancement of autonomy and intelligence is highly critical. Basically, CR is termed as a smart technology capable to sense, analyse and make decision regarding allocating resources dynamically, and managing spectrum. Despite equipped with such features it's not immune to its complexity such as global optimization constraints, taking more time to compute, and having a complex nature [7]. The good news is such complexities can be compensated. As the era of artificial intelligence (AI) is approaching it can complement CR's benefit of learning smart and making better decisions when approaching with the environment, will implement faster [8]. In the world of AI, machines have the human-like perceptive and learning abilities when they are exposed to the similar environment. AI and humans will complement each other courtesy of the superior intelligence level of the former [9]. Consequently, the robotic human will offer communicative networks, and Internet of Vehicle (IoV) software to enhance individual's cognitive benefits. Some of the AI technologies already started optimizing networks to connect themselves in the human world. As AI requires superior data to function effectively, combining with CR will be super advantageous, something that a 5G network has the power to implement, because such combination will give the robots the similar level of human intelligence and autonomy. The learning techniques will be introduced by AI and its role can be shown in CR. Reinforcement Learning (RL) is applied in a lot of cognitive radio network (CRNs) schemes as a method of unsupervised learning. Some of the examples include channel routing, and sensing, followed by dynamic channel selection. Both the primary and secondary users of CRNs, can allocate their dynamic resources intelligently through online learning patterns, and with that can take the maximum actions needed in their respective environment, for enhancing the utilization of spectrum resource [10] [11] [12]. RL algorithm do generate favourable performance of CRNs, however there is one key factor dependent on its effectiveness: the characteristics of the networks' system. This involves single to multi agent as well those of centralized and decentralized. As a lot of genuine communication moments are multi agent system (MASs) as well systems that are observable, a lot of industrial and academic research has been taking place in recent times, regarding AI technologies' adaptation in multi-agent environments [13]. One of the instances involves applying MARL aka multi-agent reinforcement learning for allocating power cooperatively in CRNs. In addition, the algorithm is used for predicting the detects and the throughput that are found in CRNs' idle channels. Also a multi-agent model of RL base station was proposed alongside the optimization technology for distribution of heterogeneous network of small cells. All the methods are the drivers of solving the problems regarding efficient resource allocation regarding optimizing networks in communication. There is one small limitation however, as there are no framework for hierarchical distribution of networks to operate in multi-agent environments. The AI based technologies are an inspiring technique to solve the problems mentioned above. Therefore I am proposing, a four layered frameworks on the basis of two MARL mechanism

1) A mechanism that categorizes 5G networks on four tiers on the basis of combining AI and CR.
2) Establishing a MAS model of three levels, for primary users, secondary users, and base stations. Then introducing key application technologies in the model and evaluating the performance via numerical analysis and simulations.
3) Having a smart base station control mechanism alongside channel resource allocation, for achieving network optimization in cellular phones
4) Discussing the opportunities and challenges, of the 5G wireless communication.

II. HIERARCHICAL NETWORKING FRAMEWORK AND MAS MODEL

In this research we propose the framework regarding hierarchical network distribution that requires the implementation of AI technologies to primary and secondary users' resource allocation as well the 5G cellular networks' base station resource control for guaranteeing the quality of service requirements, enhancing spectrum resource utilization, and maximizing the BS' resource control strategy of the CR users. The frameworks as well as the MAS model of three levels are elucidated below. As illustrated in Figure. 1, this framework is solely on the basis of 5G cellular networking that has four tiers: Tier 1: Cognitive Radio (CR) users, Tier 2: Cellular Base Stations (BSs) Tier 3: Cloud Processing Tier 4: Application

Tier 1: Cognitive Radio (CR) users: For the layer of CR user, the framework of 5G cellular network regarding cognitive radio scenario, is being taken into consideration. This consists of a lot of cells among many CR users, that tries to transfer data to the base station of the cellular on each cell. Generally the users can be a number of both primary and secondary, with the former having higher priority for the usage of channel resource. For each cell both the AI and CR technologies and put together to distribute CRNs' channel resources. Each of the users are considered as an agent, both primary and secondary, albeit having different characteristics. Each cell have a complex MAS where both the agents coexist. Both of them interacts with CRN's environment and learn behaviours among each other regarding performing dynamic things intelligently. This ultimately improves the efficiency of utilizing its resource. Consequently it boosts the communication network and hence the data gets uploaded to the base station really fast. As both of the agent learns intelligently they adopt MARL algorithm that will be elaborated in the following section

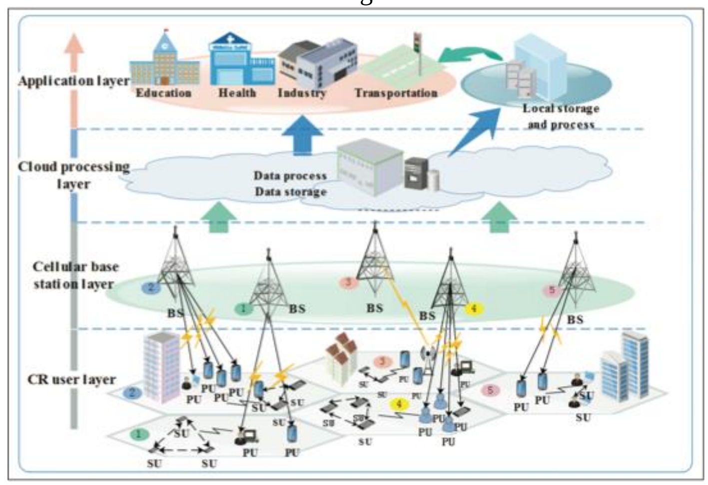

Figure 1: Hierarchical distributed cognitive network architecture.

Tier 2 : Cellular Base Stations (BS): Base station is the infrastructure of the wireless cellular, and thus is an indispensable factor to an effective communication network. Normally 5G networks have smaller and traditional base stations, hence having a two-tier hierarchical cell network. But the framework that we proposed to ease the model only considers one kind of BS, in cell structure. It can be seen in Figure 1, there are many BSs, every single of them covers the cell of CR user cell layers. Such layers helps to connect the layer of CR user as well as cloud processing. Each base station is termed as agents in the layer, and constitutes MAS for the agents that are isomorphic.
Tier 3 : Cloud Processing: It is a common knowledge that there are tons of merits for cloud computing, which involves cheap computing costs, connecting resources and bringing more flexibility. For centralized data processing there is cloud processing centre that has numerous AI algorithms and cloud computing. The base stations send various data to the processing centre of the cloud, where the data is processed and stored centrally. To be more precise, machine and deep learning can be used for data classification and prioritization. Data that are top priority are transmitted as fast as possible to the local users, and those of least priority are temporarily stored on the cloud that helps to expand the storage space, while reducing the data loss and transmission time from the base station to the users.
Tier 4: Application: Lastly the data in the networks are ultimately processed via the processing centre of the cloud and

are finally transmitted to the layer for application to important fields, like transportation, health and education.

III. Three Level MAS Model

The three-level MAS model that we have proposed features the infrastructure of both the distributed as well as hierarchical networks. Tier 1 and 2 of this network has MASs that includes MARL algorithm. The model that we've proposed is made to attain the following objective in CRN's multi-agent scenario. Firstly MARL, an AI technology is implemented to CR users for 5G networks; we propose a new and unique channel resource mechanism that can enable both primary and secondary users to use the channel resources efficiently, and having impeccable quality of service. Secondly in this report we propose a smart three-level MAS model for BS control mechanism for understanding the perceptual performance of them and adjusts the requirement for each resource.

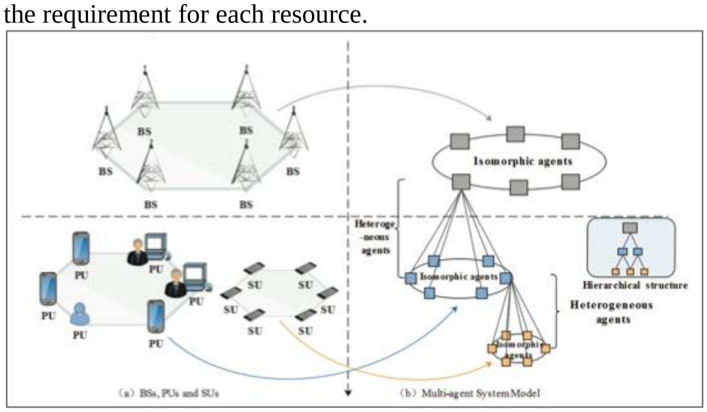

Figure 2: Multi-Agent Scenario In Crns

Figure 2 shows the three-level MAS model where two things are displayed. Firstly it shows the scenario of actual communication in CRN, secondly in an abstract model. Basically the agents can understand the environments. The MAS has a high number of single agents that interact internally via communication and are independent. This model was based on two factors: competition and collaboration. In figure 2(b) the phenomenon among the agents are layered based on isomorphic agent's behaviour. Both the primary users (PUs) and (SUs) are among. Despite being isomorphic agents they are heterogeneous. Therefore the proposed model indicates they have competitive relationship among them and their layer have cooperative relationship. Basically both isomorphic and heterogenous agents are combined to create a sophisticated MAS. Most real-life scenarios consists of highly complex MAS. So after taking these into consideration, we developed two smart algorithm mechanisms to tackle the allocation of resources and problems associated with smart channel through our proposal.

IV. Channel Resource Allocation Mechanism

The technologies that were used in the proposal were smart base station and channel resource allocation mechanism. For this mechanism, the scenario is MAS that has a number of PUs and SUs. Each of the cognitive users are termed as agents, while the other ones and 5G network are considered as environment. All of the agents learn from the environment and make decisions through interaction and spectrum resource allocation, for optimizing each agent's benefit. Through that, MARL algorithm will be implemented to solve problems found in MAS. In addition analysing the agent's behaviour is crucial as we need to find an appropriate MARL method. So from this aspect we believe we need three components that needs treatments. Below are the details of the components.

In our proposed model we conclude agents are pretty basic and will involve both PUs and SUs as agents. All of them are individuals that have the power to perceive, learn, observe and make decisions. All of them interact in the CRN's environment via properly guided rules. Figure 3 illustrated an abstract MAS model, involving channel resource allocation as well as the smart BS control model. For the former there are numerous PUs and SUs and the former has the power to communicate each other. Every agent gets a perceptive state that comes from environment.

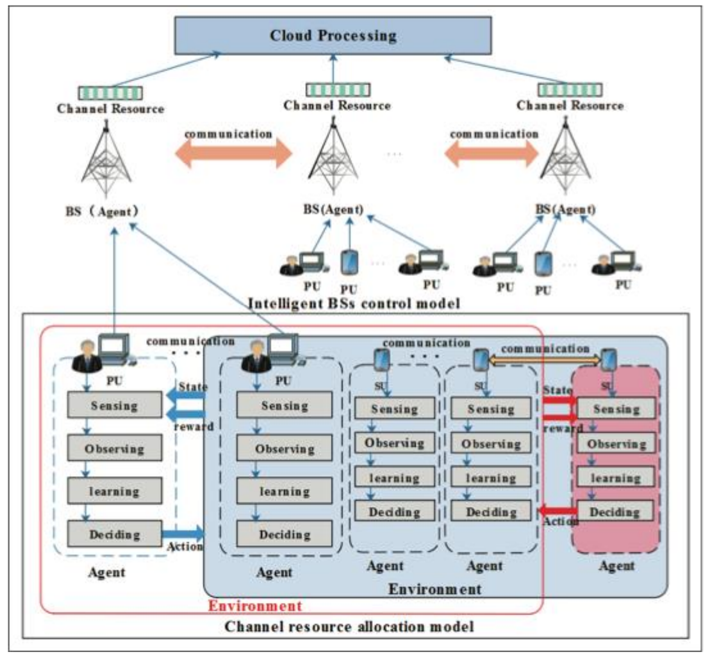

Figure 3: Channel resource allocation model and Intelligent BS control model

Through that they decide what will be the best course of action after observing and learning online.

Environment is termed as POMDP meaning 'Partially Observable Markov Decision Process (POMDP). But in this MAS model when an agent makes a decision, the rest of them are fixed where MDP aka Markov's Decision Process acts as an environment. When single PU agent communicates in the environment, the remaining are a part of it in CRN's that includes all the primary and secondary users.

Rules are very crucial in MARL. There are two of them that should be considered: one is isomorphic agent and another one is heterogeneous agent. For the former the agents are from one PU to another and one SU to the next. For heterogeneous the agents are from PU to SU. The rewards alongside policies between these two are proposed below.

There are competitions amongst PUs in the MAS. Firstly PUs obtains the channel resources that Base Stations (BS) allocated.

After that the PUs utilizes the partial resources then offer the rest to SUs. SUs then have to fight for spare channel resources; therefore PUs would be given a resource allocation mechanism, so that the benefits are optimized.

The secondary unit agents firstly store the channel resource's state of usage that consist of current channels' numbers, and the total PUs and SUs. Competition and neutrality are the two relationships between the CR users. Numerically, we can state that C is equal to the number of channel resources whereas PUs and SUs, are termed as M and N. The relationship of SUs are neutral when C-M ≥ N. Also the various spare channel resources can be obtained when SUs negotiate among themselves. The relationship among SUs become competitive when C-M < N, where C-M is the subchannel. These are then competing for spectrum resources in the subchannel of C-M. So we can conclude SU can make a fairly reasonable policy.

In CRN both of these agents can be able to learn as well as interact. In the interaction process, PUs prefers to use the spectrum resources that BSs allocates. Then spare resources are distributed to SUs. The data demands of SUs are defined as S = {s1, s2, ... sn}. For multi-agent environments both of these agents have an objective to optimize resource utilization. PUs can understands SU's data demands and characteristics to achieve the task. For each PU's strategy the allocation, wait for request are termed as π. When PU's spare resources are sufficient to allocate for SUs, each of them prefers waiting whereas when they don't have adequate resources they can opt to get requests from other PUs. The last case is getting a request from a different PU, whereas the current one can choose to accept or decline the request. The terminology of PUs rewards are defined by R = {r1, r2, ... rm}. The reward for long run is RL = min{1/MSR,1}. When RL=1 it shows that PUs resources are capable to meet SUs' demands. However if RL <1, PUs have to take request from their own counterparts that has RL=1, only then they can successfully undertake online learning via interaction with SUs for maximum allocation of resources strategy for the dynamic environment. Like PUs the SUs' goal has changed dynamically. To select PU's resources there are MN-1 ways to achieve that. So the policies are designed for both the agents to collaborate their actions for achieving efficiency and common objective of enhancing utilization of resources.

V. Intelligent BS Control Mechanism

Figure 3 also illustrates MARL model about a smart base station control system. Being a basic infrastructure of the network, BSs offers standard signal coverage alongside the resource of channels about existing cells for ensuring users will have a wide range of channel resources available with the least data transmission rate. Hence we projected a prototype BS control mechanism in both BS and CS layer, classifying as MAS. The biggest purpose of the control mechanism is to have a better utilization of channel resource and rate of transmission.

Agent: The model of the BS was a single agent in cellular network. In its layer every agent's acts as isomorphic and all of them perform as the most interactive communication.

Environment:- It consists of MAS and external environment of every agent in particular, which is the remaining agents in BS layer and the primary users of the network

Rule: Rules define a set of rewards and policies for agents. As shown in Fig. 3, a two-tier system is considered in the intelligent channel control model, including cellular BSs and PUs.

Basically BS has the coverage of the cellular area, where the quality of communication of the whole system is based on the total resources own by each BS, alongside BSs' quantity and many more. Higher coverage in channel spectrum resource is expected by switching among each BS.

They can attain maximum accurate estimation of channel resource's probability distribution smartly via trial and error learning method online. Then we have discussed agents' policies as well as rewards. As they are the agents in MAS and N Bs B = {b1, b2, ... bn}) are the drivers that manages N cells, the resources are distributed to all the primary users via each BS as probabilities (P). P = {p1, p2, ... pn}, (pi ∈ [0, 1], Σ pi = 1). At the start the channel spectrum resources regarding every BS are allocated randomly, and PU's probability distribution resource is termed as A={a1,a2,...an},(ai ∈ [0,1],∑i ai = 1). In mathematics it can be decoded

$$I = \frac{P}{A} = \left(\frac{p1}{a1}, \frac{p2}{a2}, \dots, \frac{pn}{an}\right)$$

followed by

$$\left(\frac{P}{A}, 1\right)$$

All the elements of D show BS channel resource's value of probability distribution. R is denoted as the agents' reward aka channels resource utilization. This is formulated by $R' = \sum D / M$

R= The reward value of every agents after implementation of normalization; M= BSs' total channel resources.

The strategy of BS depends on R. Based on its value we can decide and strategize whether BS should stick to this or opt for another BS channel. If the value of D ≥ 1 the channels can be changed to BS that has the probability distribution of less than 1, and then the spare resources will be used by others.

The BS attains the CR user layer's resource utilization through interaction with environment and learning online. In addition they learn the best actions and achieve their utmost rewards to better their channel resource utilization during interaction. By using MARL method, BS learns about the strategy to distribute optimal channel dynamically, and it reaches at its peak when R=1.

VI. Result Analysis

Under this section we measure the performances of two smart algorithm mechanisms in three-level MAS. The experiment is done on the basis of Windows 10 OS (Intel® CoreTM i7-6700 CPU @ 3.40 GHz). In this smart base control mechanism, it is derived from the Figure 4a. In the figure there are three bars: Red signifies PU's data demand, green is the BSs' probability distribution of starting resources and the blue is probability distribution after taking part in online learning. On the basis of bar chart, the resources that are distributed by each BS and PU's demands are virtually identical after online learning. The simulation result shows that the maximum resource allocation's probability distribution can be attained via smart base system control mechanism. To test BS's ability in autonomous resource allocation after interaction with dynamic environment, we have suggested to use KL divergence for the calculation whether there are similar probability distribution of such resource prior to and after completion of online learning. Figure 4b shows that KL divergence occurs at 0.45 at the start. From there onwards, it takes a steep decline to 0.04. There has been a minute growth in the curve value but it declined further and the results are between 0 to 0.05.

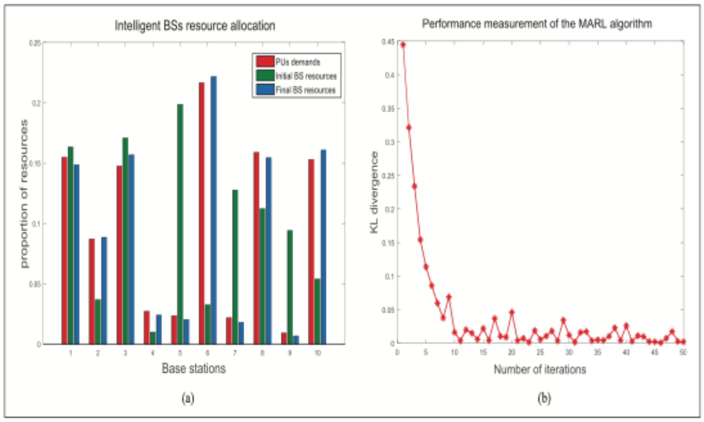

Figure 4: The performance evaluation of the intelligent BS control mechanism.

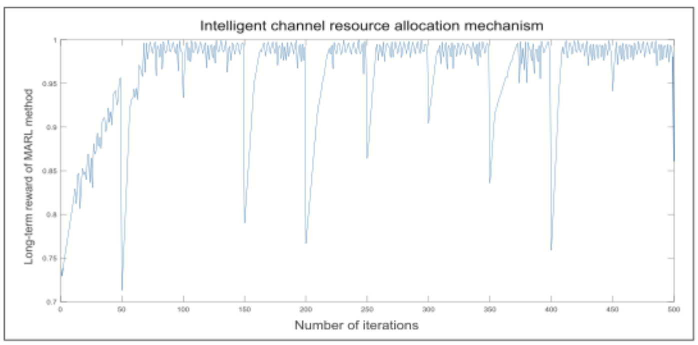

Figure 5: The performance evaluation of the intelligent channel resource allocation mechanism.

The curve meets at comparatively low level. Hence it can be indicated that the smart mechanism of BS resource allocation offers the strategy to learn for BSs' agent and attains its maximum probability distribution by using the MARL method. Also in this mechanism a reward for long-term is displayed, on the basis of assuming that there is a dynamic environment during the process of learning. Figure 5 shows a fluctuating figure in each iteration, as strategy causes to diverse and dynamic environment of the secondary users (SUs). The long-term result eventually goes to 0. Then the iteration level surges to 0.50, eventually reaches at zenith of 0.95 on the 50th attempt. The graph makes it clear to comprehend that curve value declines in the change of strategy and the following round of learning. Despite the consistently changing of rewards, the experiment comes into a stable result of 1 in each iteration. The trend rises and reaches to 1 constantly, which is basic, indicating that the resources are designed for optimum use between both the agents aka PUs and SUs. The curve fluctuates due to dynamic changes of strategy of SUs needs to be a matter of notice. After all the analysis of experimental results that shown before via hierarchical MAS, it can be concluded that the MARL method offer better performance in an environment which is dynamic, where the agents can allocate it's resource and maximum communication networks.

VII. CONCLUSION

In this article a four layered framework of distributed network where it breaks down 5G networks by four categories. The problem can be solved for the demands of heavy users allocating resources reasonably and unreasonably, we offered two mechanisms of it, through using MARL in MASs. We did by proposing the channel mechanism to maximize strategies within CR users, with the objective to optimum resource utilization. Then we followed it by proposing smart base system control mechanism which helps BSs and PUs to understand the channel resources available for adjusting the resources' probability distribution intelligently.

REFERENCES

[1] P.K. Agyapong, M. Iwamura, D. Staehle, W. Kiess, A. Benjebbour, "Design considerations for a 5G network architecture", IEEE Communications Magazine, vol. 52, no. 11, pp. 65-75, 2014.

[2] E. Ahmed, A. Gani, S. Abolfazli, L. J. Yao, S.U. Khan, "Channel assignment algorithms in cognitive radio networks: Taxonomy open issues and challenges", IEEE Communications Surveys & Tutorials, vol. 18, no. 1, pp. 795-823, 2014.

[3] J.G. Andrews, "Seven ways that HetNets are a cellular paradigm shift", IEEE Communications Magazine, vol. 51, no. 3, pp. 136-144, 2013.

[4] G. Caso, M.T.P. Le, L. De Nardis, M. Di Benedetto, "Non-Cooperative and Cooperative Spectrum Sensing in 5G Cognitive Networks", Handbook of Cognitive Radio, pp. 1-21, 2017.

[5] "Cisco visual networking index: Forecast and methodology 2016–2021", White Paper C 11-481360-01 09/17, 2017.

[6] "Building a Workforce Ready for the Internet of Everything", White Paper DEC14CS4634 12/14, 2014.

[7] L. Nielsen, The Networked society Commercial in confidence, 2013.

[8] N.U. Hasan, W. Ejaz, N. Ejaz, H.S. Kim, A. Anpalagan, M. Jo, "Network selection and channel allocation for spectrum sharing in 5G heterogeneous networks", IEEE Access, vol. 4, pp. 980-992, 2016.

[9] C. Jiang, Y. Chen, K.R. Liu, Y. Ren, "Optimal pricing strategy for operators in cognitive femtocell networks", IEEE Transactions on Wireless Communications, vol. 13, no. 9, pp. 5288-5301, 2014.

[10] M. Ju, K. Kang, "Cognitive radio networks with secondary network selection", IEEE Trans. Veh. Technol., vol. 65, no. 2, pp. 966-972, 2016.

[11] S. Latif, S. Akraam, M.A. Saleem, "Joint Optimization of Interference and Cost in Cognitive Radio Heterogeneous Network Using Fuzzy Logic Powered Ants", Wireless Communications and Mobile Computing, 2017.

[12] N. Panwar, S. Sharma, A.K. Singh, "A survey on 5G: The next generation of mobile communication", Physical Communication, vol. 18, pp. 64-84, 2016.

[13] L. Wang, G.S.G. Kuo, "Mathematical modeling for network selection in heterogeneous wireless networks - A tutorial", IEEE Communications Surveys & Tutorials, vol. 15, no. 1, pp. 271-292, 2013.