Artificial Intelligence as an Enabler for Cognitive Self-Organizing Future Networks

Siddique Latif¹, Farrukh Pervez¹, Muhammad Usama², Junaid Qadir²

¹National University of Science and Technology, Islamabad, ²Information Technology University (ITU), Lahore

The explosive increase in number of smart devices hosting sophisticated applications is rapidly affecting the landscape of information communication technology industry. Mobile subscriptions, expected to reach 8.9 billion by 2022 [1], would drastically increase the demand of extra capacity with aggregate throughput anticipated to be enhanced by a factor of 1000 [2]. In an already crowded radio spectrum, it becomes increasingly difficult to meet ever growing application demands of wireless bandwidth. It has been shown that the allocated spectrum is seldom utilized by the primary users and hence contains spectrum holes that may be exploited by the unlicensed users for their communication. As we enter the Internet Of Things (IoT) era in which appliances of common use will become smart digital devices with rigid performance requirements (such as low latency, energy efficiency, etc.), current networks face the vexing problem of how to create sufficient capacity for such applications. The fifth generation of cellular networks (5G) envisioned to address these challenges are thus required to incorporate cognition and intelligence to resolve the aforementioned issues. Cognitive radios (CRs) and self-organizing wireless networks are two major technologies that are envisaged to meet the future needs of such next generation wireless networks.

CRs are intelligent and fully programmable radios that can dynamically adapt according to their prevalent environment. In other words, they sense the spectrum and dynamically select the clearer frequency bands for better communication in the most prevailing conditions. In this way, CRs can adaptively tune their internal parameters to optimize the spectrum usage, transmission waveform, channel access methods and modulation schemes with enhanced coverage. However, it is due to the recent advancements in machine learning, software defined radio (SDR) that CR is able to emerge from simulation environment to the real-time applications [3].

The overwhelming traffic growth coupled with the greedy approach towards high quality of service (QoS) has been a major challenge for current wireless systems in terms of network resources and QoS. A new paradigm for wireless communication called 5G has been envisioned to address these challenges. The major component of the envisioned 5G scheme is Self-Organizing Network (SON). SON is a relatively new concept in perspective of wireless cellular networks, it refers to an intelligent network that learns from its immediate environment, while autonomously adapting accordingly to ensure reliable communication. In fact, SON underlines new aspect for automation of future networks in 5G era.

The sensing, learning and reasoning behavior of both CRs and SON is achieved by extensively using artificial intelligence (AI) and machine-learning techniques. The CRs are an evolved form of SDRs, realized by the embodiment of cognitive engine (CE) that exploits the AI techniques for the cognitive behavior to decide optimally.

The CR network (CRN) follows the cognitive cycle, for unparalleled resource management and better network performance. Cognitive cycle, as illustrated in figure[1] begins with sensing of dynamic radio environment parameters, subsequently observing and learning recursively the sensed values for reconfiguration of the critical parameters in order to achieve the desired objectives.
Cognitive cycle is elaborated in figure 2 which highlights the parameters that CR needs to quantify in order to utilize the available spectrum without affecting primary user’s performance. The sensed parameters are treated as stimuli for achieving different performance objectives, for instance, minimizing the bit error rate or minimizing the power consumption etc. [4]. To achieve the aforementioned objectives, CR adaptively learns deciding optimal values for various significant variables such as power control, frequency band allocation, etc. [4].

CR incorporates machine learning techniques for dynamic spectrum access (DSA) and capacity maximization. AI-based techniques for decision making such as optimization theory, Markov decision processes (MDPs), and game theory is used to encompass a wide range of applications [3]. The popular learning techniques used in cognitive cycle are support vector machine (SVM), artificial neural networks (ANNs), metaheuristic algorithms, fuzzy logic, genetic algorithms, hidden Markov models (HMMs), Bayesian learning, reinforcement learning, multi-agent systems. Fuzzy logic theory has been used for effective bandwidth, resource allocation, interference and power management [3], [5], [6], [7]. Genetic algorithms (GAs) have been employed for CRs spectrum and parameters optimization [8], [9], [10]. ANNs have been incorporated to improve the spectrum sensing and adaptively learn complex environments, without substantial overhead [11], [12]. Game theory enables CRNs to learn from its history, scrutinize the performance of other CRNs, and adjust their own behavior accordingly [13], [14]. In multi-agent domain, reinforcement learning (RL) a reward-penalty based technique, which reinforces immediate rewards to
maximize long term goals has been employed for efficient spectrum utilization [15], minimum power consumption [16] and filling the spectrum holes dynamically [17]. SVM, a supervised classification model, is being utilized for channel selection [18], adaptation of transmission parameters [19] and beam-forming design [20]. In CRNs, HMMs have been widely used to identify spectrum holes detection [21], spectrum handoff [22], and competitive spectrum access [23]. The range of AI-based techniques are not limited to the above mentioned applications, other applications of AI in CRNs are expressed in [3], [4]. By combining increasing spectrum agility, context aware adaptability of CR and AI techniques, CR has become an increasingly important feature of wireless systems. IEEE 802.16h has recommended CR as one of its key features and a lot of efforts are being made to introduce CR features in 3GPP LTE-Advance.

The rapid proliferation of multi-radio access technology-disparate smart devices has resulted in complicated heterogeneous mobile networks thus making configuration, management and maintenance cumbersome and error-prone. 5G, expected to handle diverse devices at a massive scale, is foreseen as one of the most complicated networks and hence extensive efforts are being carried out for its standardization. In the recent years, SONs, as depicted in figure 3, have gained significant attention regarding self-configuration, self-optimization and self-healing of such complex networks. The idea behind SONs is to automate network planning, configuration and optimization jointly in a single process in order to minimize human involvement. The planning phase, which includes ascertaining cells locations, inter-cell connecting links and other associated network devices as well as parameters, precedes the configuration phase [24]. Self-configuration means that a newly deployed cell is able to automatically configure, test and authenticate itself and adjust its parameters such as transmission power, inter-cell interference etc. in a plug and play fashion [24]. Self-healing allows trouble-free maintenance and enables networks to recover from failures in an autonomous fashion. In addition, it also helps in routine upgrades of the equipments in order to remove legacy bugs. Self-optimization is the ability of the network to keep improving its performance with respect to various aspects including link quality, coverage, mobility and handoff with an objective to achieve network level goals [23]. Since AI-based techniques are capable to handle complex problems in large systems intrinsically, these techniques are now being proposed to achieve Self Organization (SO) in 5G.

Fig. 3: Illustration of AI-based self-organization in the networks

Self-configuration, in cellular networks, refers to the automatic configuration of initial parameters—neighbouring cells list,
IP Addresses and radio access parameters—by a node itself. AI techniques like Dynamic Programming (DP), RL and Transfer Learning (TL) may be employed in 5G to automatically configure a series of parameters to render best services. RL, as opposed to DP which initially builds the environment model to operate, is a model free learning technique that iterates through to reach optimal strategy and may yield superior results in dynamically changing radio conditions [25]. Self-healing is about automatic fault detection, its classification and initiating necessary actions for recovery. Irregularities and anomalies in network may be timely spotted to further restore the system by leveraging different AI based sensing techniques like Logistic Regression (LR), SVM and HMM [25]. Self-optimization includes continuous optimization of parameters to achieve system-level objectives such as load balancing, coverage extension, and interference avoidance. AI techniques that may be exploited to optimize provisioning of QoS to various services mainly belong to the class of unsupervised learning. Besides Gradient Boosting Decision Tree (a supervised learning technique), Spectral Clustering, One-class SVM and Recurrent Neural Networks are few examples in this regard [25]. Figure 4 summarizes the AI algorithms that can be utilized to enhance cellular networks performance.

AI techniques may also exploit network traffic patterns to predict future events and help pre-allocate network resources to avoid network overloading. Furthermore, user-centric QoS-provisioning across tiers of heterogeneous cells may also be granted using AI [25]. Similarly, GAs are employed for cell planning and optimization of coverage with power adjustment [26]. GAs are also suited for the problem of finding the shortest path routing in a large scale dynamic networks [27]. Wenjing et al. in [28] proposed an autonomic particle swarm compensation algorithm for cell outage compensation. The study in [29] introduces the self-optimization technique for the transmission power and antenna configuration by exploiting the fuzzy neural network optimization method. It integrates fuzzy neural network with cooperative reinforcement learning to jointly optimize coverage and capacity by intelligently adjusting power and antenna tilt settings [29]. It adopts a hybrid approach in which cells individually optimize respective radio frequency parameters through reinforcement learning in a distributed manner, while a central entity manages to cooperate amongst individual cells by sharing their optimization experience on a network level [29]. Cells iteratively learn to achieve a trade-off between coverage and capacity through optimization, since increase in coverage leads to reduction in capacity, while additionally improving energy efficiency of the network [29]. ANNs can also be
effectively utilized for the estimation of link quality [30]. Mobile devices in an indoor environment have also been localized through the use of ANNs [31]. In fact, AI-based techniques enable network entities to automatically configure their initial parameters before becoming operational [24], adaptively learn radio environment parameters to provide optimal services [25], autonomously perform routine maintenance and upgrades and recover from network failures [24], [25].

In view of the continued proliferation of smart devices, we anticipate that CRs and SON will soon become the basic building blocks of future wireless networks. These technologies will transform future networks into an intelligent network that would encompass user preferences alongside network priorities/constraints. AI, being the basis of both these technologies, will continue to drive ongoing 5G standardization efforts and therefore be the cause of a major paradigm shift. AI techniques will continue to intervene future networks finding their usage in from radio resource management to management and orchestration of networks. In fact, we anticipate that future wireless networks would be completely dominated by AI.

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