MACHINE LEARNING BASED PUBLIC SAFETY APPLICATIONS USING DEVICE-TO-DEVICE COMMUNICATION PROTOCOL

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Abstract — **The underutilised portion of the wireless spectrum will need to be better utilised due to the expected exponential growth in traffic volume in 5G-based networks. Apps for smartphones have caused an increase in data traffic on cell phone networks recently. As a result, expanding the network's capacity to accommodate new applications and services is critical. D2D communication with multiple hops requires more nodes for data transmission, especially when cooperatively-operated relays are used. Long-Term Evolution (LTE) is the most recent and most technologically advanced cell phone technology that is about to be introduced to the market. LTE and its advanced version appear to be an appealing solution for many businesses since they offer exceptional peak data speeds in both the uplink and downlink directions. Public safety communications is currently one of the fastest-growing fields in the world. In accordance with two homogeneous Poisson Point Processes, beacon-enabled and simple LTE terminals are dispersed in the vicinity of a significant event. This research looks into direct-to-device (D2D) communications. In this paper, we explore the likelihood of LTE mobile terminals forming in D2D networks using a stochastic geometry technique, and we then build an unique D2D protocol.**

Keywords—LTE, Machine Learning, Device to Device Communication, Public Safety Applications

I. INTRODUCTION

The term "cognitive radio" (CR) has been used to characterise radio systems that are capable of learning and adapting to their environment [1]. Knowledge and comprehension are acquired by cognoscere (to know), which is Latin for "to know." Acquiring knowledge and comprehension, which includes thinking, knowing, remembering, judging, and problem solving (cognition), is defined by cognoscere (to know). Self-programming, often known as autonomous learning, is a key component of all CR systems. [4] and [5]. In accordance with [6,] Haykin predicted that CRs would be brain-enhanced wireless devices whose goal would be to improve the utilisation of the electromagnetic spectrum. Haykin adopts an understanding-by-building strategy, which is intended to achieve two key goals: dependable communications and efficient spectrum use (or utilisation of available spectrum). [6]. It was with this new interpretation of CRs that the dynamic spectrum sharing (DSS) period began, with the goal of improving the utilisation of the crowded radio frequency spectrum. Evolution of a number of communications and signal processing techniques was demanded by the development of DSA networks [6–38]. The underlay, overlay, and interweave paradigms were used for secondary CRs in licenced spectrum bands, and they were all used in conjunction with each other. In order to carry out its cognitive duties, a CR must be aware of its radio frequency environment. It should be capable of detecting and distinguishing between all sorts of radio frequency (RF) activity in its immediate vicinity. As a result, it was discovered that spectrum sensing is an important component of CRs. A slew of new sensing approaches have been developed during the previous decade, including the matching filter, energy detection, cyclostationary detection, wavelet detection, and covariance detection [30, [41]–[46], among others. It has been proposed in [15], [33], [34], [42], [47]–[49] that cooperative spectrum sensing could improve the accuracy of wireless network sensing by addressing the hidden terminal problems that are inherent in wireless networks. Cooperative spectrum sensing has been proposed in [15], [33], [34], [42], [47]–[49]. cooperative CRs have also been examined recently, according to the authors [50]–[53]. [41], [54], and [55] are some of the most recent surveys on CRs that have been conducted. [39] provides a complete evaluation of spectrum sensing approaches for CRs, which is available online. The DSA and MAC layer operations for the CRs are investigated in numerous surveys, according to [56–60]. In addition to being aware of its environment, a CR must be able to learn and reason in order to be considered cognitive in the true sense. ([1] In accordance with the pioneering idea of [2, the cognitive engine [63]–[68] has been designated as the heart of a CR. Coordination of the CR's actions is accomplished by machine learning methods implemented by the cognitive engine. Machine learning methods have just lately gained popularity when it comes to CRs [38–72]. The process of learning is required when the precise effects of inputs on the outputs of a particular system are not understood in advance. Because of this, learning approaches are required to predict the input-output function of the system in order to ensure that the system's inputs are optimised. In wireless communications, for example, non-ideal wireless channels may cause uncertainty due to the fact that they are not ideal. In order to predict the wireless channel characteristics and to establish the precise coding rate that is required to achieve a certain likelihood of error across a wireless link [69], learning approaches can be applied. [69, 70] [69, 70] The problem of channel estimation is, according to [73], a comparatively simple one to tackle. Concerning cognitive radios (CRs) and cognitive radio networks (CRNs), the complexity of wireless systems rises with the introduction of highly reconfigurable software-defined radios, notably in the case of CRs and cognitive radio networks (CRNs) (SDRs). In this instance, a simple formula may not be able to calculate all of the setup parameters at the same time (for example, transmitting power, coding scheme, modulation scheme, sensing algorithm, communication protocol, sensing policy, and so on). This is due to the complex interplay between these components as well as the surrounding RF environment. This allows for the application of adaptive learning approaches that allow for efficient adaptation of CRs to their environment, but without the need for a thorough understanding of the relationship between these parameters [74].

According to some, threshold-learning algorithms, such as those described in [71] and [75], can be used to reconfigure spectrum sensing devices when they are operating under unknown conditions. In the case of diverse CRNs, the problem becomes far more difficult to manage. It is necessary for a CR not only to adapt to its environment, but also to coordinate its actions with the activities of other radios in the network while doing so. CRs are compelled to make educated guesses about what other nodes are up to as a result of the limited number of paths through which they can learn about their peers' behaviour. According to the DSA, for example, the CRs strive to access idle primary channels while avoiding clashes with both licenced and other secondary cognitive users. For example, in the case of Markov Decision Processes (MDPs), it is feasible that CRs operating in an unknown RF environment will be pushed to utilise unique decision-making strategies, such as Dynamic Programming in the case of MDPs [76]. Specific learning techniques such as reinforcement learning (RL) [38, [74], and [77] can assist you in solving the MDP problem even if you do not know the transition probabilities of the Markov model at the outset. Because of the need for self-adaptation in an uncertain and diverse RF environment, as well as the requirement for reconfigurability in RF environments, learning algorithms may be implemented by CRs. It is possible to incorporate low-complexity learning algorithms into the system in order to further lower the overall complexity of the system. Several learning approaches, both supervised and unsupervised, have been proposed for a range of learning tasks in recent research on CRs. These approaches include: [65], [78], and [79] [supervised learning], numerous researchers have examined CR applications that make use of neural networks and support vector machines (SVMs) for supervised learning in the context of [65], [78], and [79]. [80, 81] also discuss DSS applications for unsupervised learning, such as reinforcement learning, which have been addressed in the literature. In accordance with [77], the distributed Q-learning technique has been found to be successful in a variety of applications. The application of Q-learning to improve the identification and categorization of primary signals in the environment was demonstrated by CRs in [82]. Along with the examples in [14], [83]–[85], and others, there are countless additional instances in which RL has been used in conjunction with CRs as well. In [86], a weight-driven exploration technique was used to introduce new techniques to enhancing the efficiency of RL's performance, and the results were promising. When it comes to signal classification, it was proposed in [13] to use Bayesian non-parametric learning based on the Dirichlet process, which was later employed for signal classification [72]. Using an unsupervised learning strategy, such as that described in [87], it is possible to categorise signals, which is also beneficial for signal classification. RL algorithms, such as Q-learning, have been shown to be beneficial when used in conjunction with autonomous unsupervised learning [88–91]. While their performance in non-Markovian and multiagent systems has been demonstrated [88–91], it has been proven to be inadequate. The methodologies of evolutionary learning [89], [92], imitation, instruction, and policy-gradient approaches have all been shown to outperform RL on certain difficulties when used in this environment. Many studies have proved that the policy-gradient approach is more efficient in partially observable settings than other approaches [90, 91], primarily because it searches directly for optimal policies within the policy space [90, 91]. Recent years have seen an increase in the number of studies conducted on multi-agent learning, which has implications for the development of learning algorithms for CRNs. Several studies have compared the behaviour of human civilizations that exhibit both individual and group behaviours to cognitive networks [95], and a strategic learning framework for cognitive networks has been proposed. [pages 94 and 95] [page 94] It was in [96] that adaptive learning in cognitive users during strategic interactions was originally proposed, employing an evolutionary game paradigm to explain how they learn. The distributed nature of CRNs, as well as their interactions with one another, must be taken into consideration while attempting to obtain effective learning approaches based on cooperative schemes. Individual nodes in a CRN are less likely to behave selfishly as a result of this. When dealing with scattered CRNs, coordination of actions is a key challenge [88]. [numbers 89 and 90]. Network-wide policies that are centralised can be used to generate the greatest possible cooperative activities for the benefit of the entire network, hence maximising its overall efficiency. However, implementing centralised systems in a distributed network is not always feasible due to the nature of the network. The goal of cognitive nodes in distributed networks is to apply decentralised laws that ensure near-optimal behaviour while simultaneously minimising communication costs, which is referred to as decentralisation. Knowing how to convey knowledge (i.e., teach) across a wireless media has been discussed in depth in [3] and [97], and it is based on the concept of "docitive networks," which is derived from the Latin word docere, which literally means "to instruct" (to teach). Docitive networks are designed to reduce cognitive complexity, accelerate learning, and generate better and more trustworthy judgements, among other things. Radios in a docitive network are able to learn from one another because they are exchanging information with one another. [3] The radios are meant to teach not only the end results, but also how to get there. It is possible for new radios in a docitive network to pick up certain policies from older radios. There is, of course, a communication overhead in the transfer of knowledge. However, as shown in [3] and [97], the policy improvement achieved through cooperative docitive behaviour compensates for this overhead.

A new technology called cognitive radio (CR) can dynamically allocate spectrum to each device in order to maximise the capabilities of each one in low-bandwidth areas. There are devices that can be programmed to change their frequency based on a programme, like software-defined radios (SDR). Dr. Joe Mitola at the University of Stockholm introduced cognitive radio in a research paper. Cell networks and handsets were designed to adapt their communication methods based on their immediate surroundings. Figure 3 depicts the behaviour in more detail. The Radio Knowledge Representation Language was designed to provide "a standard language within which such unanticipated data exchanges can be defined dynamically". This, in turn, could be used in cognitive radios to increase battery life and performance. System selection of "the most appropriate network based on user service requests" is another feature. Wi-Fi calling is a recent addition to mobile phones that incorporates this feature.

II. PROPOSED DESIGN

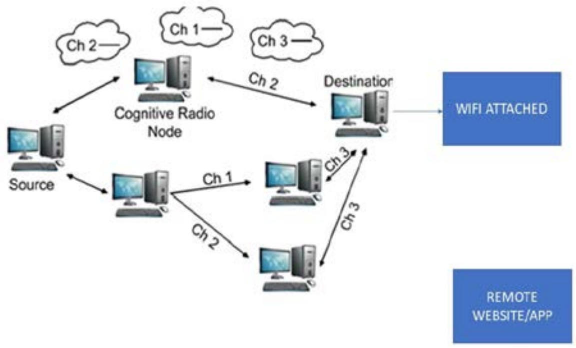

Figure 1 Design of multihop protocol

Using multi-channel and multi-hop protocols, the efficiency of communication will be increased as shown in Figure 1. We can monitor online network dynamics from a remote location using a website or an Android app that connects to the system via wifi.

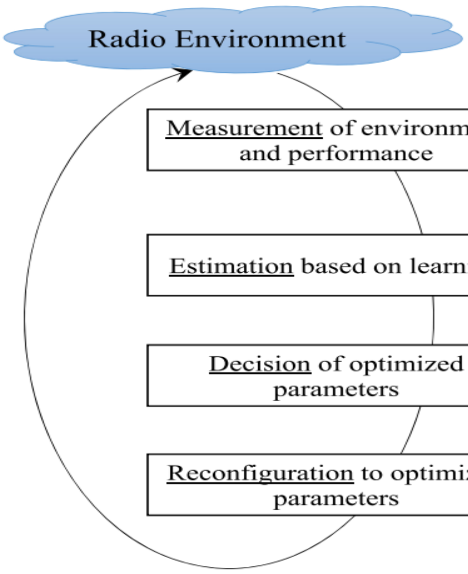

Figure 2. Concept of Cognitive Cyles

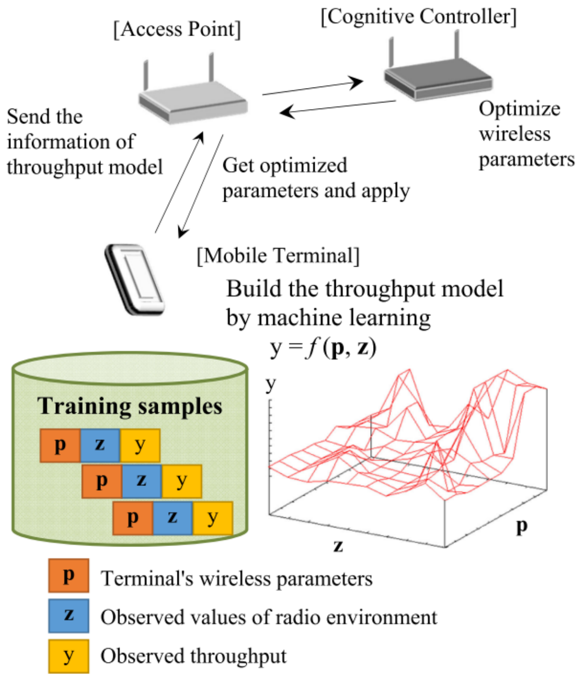

Figure 3. Proposed System concept Design

In a number of studies [100-102], it has been demonstrated that machine learning may improve the performance of wireless networks. In an experimental testbed, it has been demonstrated that using a neural network to choose channels in IEEE 802.11 WLAN access points (APs) can boost throughput [103-105]. Despite the fact that this approach is intriguing, it only takes into consideration one AP at the time. However, rather of concentrating on a few key metrics (MTs), our strategy seeks to improve the overall system's performance. The proposed approach is depicted in action in Fig. 3. Mobile terminals collect information about the radio environment and use it to develop a performance model that reflects the relationship between wireless parameters and throughput. This is accomplished through machine learning. Access points provide information about the throughput model to the cognitive controller, which is then used to make decisions. The cognitive controller is represented by the network reconfiguration manager. This system determines the wireless parameters for all MTs and transmits those parameters to the MTs through the access points. The wireless parameters are relayed to mobile terminals, which then adjust their settings in accordance with the new information. MTs collect information about the status and performance of the wireless network by repeating the cycle described above. As more training data is collected, the performance of the network increases, resulting in a more accurate throughput model being produced.

A. *A machine learning-based approach to parameter optimization.*

ThisSystem follows the previous research in [5] by using support vector regression (SVR) as a learning algorithm. It is an analogue output version of support vector machines (SVMs) Function f can be expressed as follows in SVR. [99].

$$f(\mathbf{x}) = \sum_{i=1}^{l} (\alpha_i' - \alpha_i) K(\mathbf{x}, \mathbf{x}_i) + b,$$

It is necessary to note that this equation contains two unknown input sets for the learning algorithm (p and z), as well as one unknown training sample input set (xi). The unknown parameters are obtained, according to [9], by the use of an optimization technique, with the training samples p, Z, and Y being used as the training samples. In order to establish the ideal wireless parameters p for the MTs, the cognitive controller must solve the following optimization problem for it to be success

$$\arg\max_{\boldsymbol{p}} \sum_{n=1}^{N} \log(1 + f(\boldsymbol{p}_n, z_n)),$$

It can be expressed in terms of how many MTS there are and how many parameters each MTS can have. For example, for MTS-1, we can say that there are N possible parameter sets, while for MTS-2 we can say that there are N possible parameter sets for MTS-1 and MTS-2. Consider the fairness of MTs when using the logarithmic utility function for throughput. When it comes to objective function, MTs with lower throughputs have larger gains compared to MTs with higher throughputs. **Figure 4 shows** Probability a D-beacon is received correctly by a UE varying the probability (p) a b-UE is active for a threshold and Figure 5 shows path loss exponent.

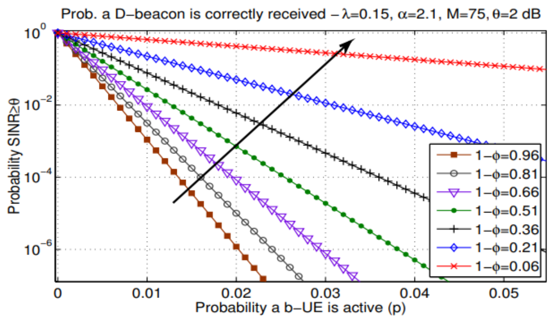

Figure 4 Probability A D-beacon is appropriately received by a UE by altering the likelihood (p) that a b-UE is active for a threshold period of time.

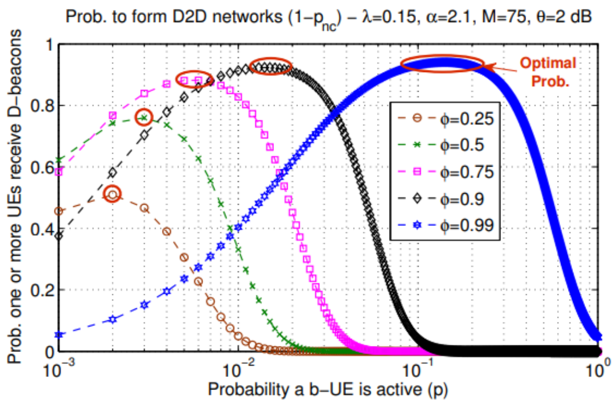

Figure 5 Path loss Exponent

III. CONCLUSION

Wireless communication quality has deteriorated as a result of the extensive use of mobile devices and the restricted availability of radio resources. It has been created cognitive radio technology in order to address these challenges. For the purpose of developing a wireless network optimization approach in this paper, we applied a machine learning algorithm based on the cognitive cycle. To put the proposed optimization approach through its paces, wireless LANs were deployed and the throughput performance was tested. Tests carried out in a real-world scenario demonstrated that the proposed strategy was effective.

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