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Enhanced LBT Mechanism for LTE-Unlicensed using Reinforcement Learning

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***Abstract*—The amount of connected devices has been growing tremendously over the past decade. These connected devices range from the traditional smart phones to electrical appliances, solar panels, converters, electric vehicles and wearables. Satisfying their connectivity demand is adding pressure to the wireless networks which are already pressed with serving their bandwidth-hungry mobile users. LTE Unlicensed (LTE-U) aims to exploit the unlicensed spectrum to offload mobile user (LTE users) traffic, increase capacity, and hence improve the user/device experience in an era of inflated demand. Meanwhile, WiFi is the dominant technology operating at the unlicensed spectrum. Therefore, LTE-U needs to ensure the performance of WiFi users do not degrade as LTE users offload their traffic. In this paper, we propose a Q-learning based medium access approach to enhance the Listen Before Talk (LBT) mechanism of LTE-U. Q-learning based LBT helps with the co-existence issue by enhancing the performance of WiFi users at times when LTE-U users try to access the unlicensed bands. Our results show that the proposed Q-learning based LBT reduces the end-to-end delay of WiFi users in the order of several tens of seconds in comparison to the standard LBT implementation. It also increases the delivery success rate of WiFi traffic by up to 71%.**

***Index Terms*—Medium access, Listen before talk (LBT), LTE-U, Q-learning.**

I. Introduction

User expectations from wireless networks are constantly increasing. However, the capacity of wireless networks is limited due to the scarce spectrum resources. Mobile applications on smart devices along with the addition of Internet of Things (IoT) devices increase the demand for high data rates, low delay and better coverage. Even though cellular networks are traditionally designed for mobile outdoor users and wireless personal area networks (WLANs) are for satisfying the high bandwidth demand of indoor stationary users, recently there is growing interest for adoption of Long Term Evolution (LTE) cellular technology in WLANs. LTE Unlicensed (LTE-U) technology aims to seamlessly persist indoors and make use of the unlicensed bands by allowing LTE users to offload their traffic to the global Industrial, Scientific and Medical (ISM) channel at 5GHz. Since WiFi has long been the dominating technology for WLANs and a primary user in the ISM band, LTE-U base stations are expected to co-exist with WiFi access points.

LTE-U exploits the Listen-Before-Talk (LBT) mechanism for channel access where the transmitter first senses the medium and transmits only if the medium is idle, i.e. other LTE or WiFi devices are not transmitting. This mechanism has been defined in 3GPP release 13 for random channel access of Licensed Assisted Access (LAA) [1]. LAA aims to enhance LTE performance by carrier aggregation in the downlink by combining the unlicensed spectrum with the licensed LTE bands. LTE-U adopts the LBT mechanism of LAA but the major concern for LTE-U is the co-existence of LTE users with the WiFi users. The existing LBT mechanism is designed in such a way that LTE users defer transmission if the channel is busy. Thus, LTE avoids dominating the unlicensed band. However, there is still room for improvement in spectrum sharing, in particular by learning the deferring behavior.

In this paper, we propose a Q-learning based LBT mechanism that aims to improve the performance of WiFi traffic while still giving LTE traffic a reasonable amount of bandwidth. Our technique uses a Q-table to store the defer period of an LTE user. The defer period is increased using a reward mechanism when WiFi users experience increase in backoffs. According to this reward, the Q-table is updated. The reward function seeks to reward higher defer periods for LTE traffic for the benefit of the overall WiFi performance. In our simulations, we show that the proposed Q-learning based LBT scheme significantly improves the end-to-end delay and delivery success rate of WiFi. This comes with a tradeoff in LTE performance. We also evaluate the impact of contention window (CW) on the performance and further show that both WiFi and LTE can perform better at $CW = 30$ rather than the default CW set to 15.

The paper is organized as follows: Section II provides background on related studies. Section III presents the system model and the proposed Q-Learning based LBT mechanism. In Section IV, we show the performance of our proposed scheme and conclude the paper in Section V.

II. Related Work

There is a growing interest from the academia and the industry for LTE-U technology. MulteFire Alliance provides an LTE-U solution which aims to provide LTE-like performance with the WiFi-like simple deployments [2]. The major challenge is the coexistence and fairness issues between LTE and WiFi. In [3], a relay-based communication scheme is proposed in which LTE would announce its presence when it would like to use the unlicensed spectrum. In [4], the authors replace LBT with a Q-learning based carrier selection and discontinuous transmission mechanism. Meanwhile, in [5], the authors tune the contention window to achieve fair spectrum sharing between LTE and WiFi as well as for fair service differentiation. Furthermore, reinforcement learning has been used for resource allocation in LTE-U in [6]. The authors propose a new LTE-U frame structure where blank sub-frames are allocated using Q-learning. Reinforcement learning has been also used for LAA where the authors use a time duplex modulation assuming the IEEE 802.11n beacon transmission mechanism [7]. In our work, we use LBT mechanism and enhance it by learning the defer durations. We use the existing frame structures with minimal changes to the standard. We also evaluate the impact of contention window on the performance of our proposed scheme.

III. Proposed Scheme

A. System model

The network consists of one LTE access point and one WiFi access point which share the ISM band at 5GHz. D_{LTE} denotes the set of LTE users with the number of LTE users given as $|D_{LTE}|= N_{LTE}$. D_{wifi} denotes the set of WiFi users with the number of WiFi users given by $|D_{wifi}|= N_{wifi}$. Each $n_{LTE} \in D_{LTE}$ accesses the unlicensed spectrum using the Q-learning based LBT mechanism. Each $n_{wifi} \in D_{wifi}$ uses the CSMA/CA medium access mechanism of IEEE 802.11. According to LBT, each n_{LTE} first senses the medium and transmits only if the medium is idle which is also called as Clear Channel Assessment (CCA). The LTE device is assumed to have an access manager object that can listen for WiFi users' state transitions and that can observe WiFi backoffs.

B. Q-learning based LBT Mechanism

The proposed scheme uses Q-learning to adaptively learn the user traffic on the unlicensed spectrum and coordinate the access of LTE and WiFi users. The goal is to schedule LTE traffic such that the performance of WiFi users is not degraded while LTE users maintain acceptable access to the medium.

The first step of the Q-learning based LBT mechanism is the initialization of the Q-table with state-action pairs which are randomly generated defer periods for LTE base station (eNodeB-eNB). In LBT, the defer period is defined as the duration an eNB waits after a successful CCA. At each iteration of the learning stage, a value from the Q-table is picked for deferring LTE transmission while observing the backoff for WiFi. If the selected value increases the backoff for WiFi, then a larger defer period is set using the reward function. The Q-table is updated as follows [8]:

$$Q[s,a] \leftarrow (1-\alpha)Q[s,a] + \alpha\{R(s,a,s') + \gamma(max_a Q[s',a'])\}$$

Here, s and s' denote the current and new states while a and a' denote the current and new actions, respectively. α is the learning rate and γ is the discount rate. $R(s,a,s')$ defines the reward received for the transition from the state s to the new state s' by executing the action a. The proposed scheme only impacts the medium access mechanism of LTE. The reward for LTE devices increase, if their defer time is increased when the observed backoff of WiFi is increasing. This means if WiFi is experiencing higher backoffs, LTE devices are given larger defer times so that they would yield to WiFi traffic.

The performance of the proposed scheme is compared with the existing LBT mechanism. In the LBT mechanism originally designed for LAA [9], a transmitter first performs CCA. If during the CCA, the medium is sensed busy, an extended CCA (ECCA) is invoked where the channel is monitored for multiples of the CCA time [10]. This allows the traditional LBT to yield to WiFi however it does not observe the performance of the WiFi and learn from the traffic conditions unlike the proposed scheme.

IV. Performance Evaluation

We present the performance of our reinforcement learning based technique in terms of end-to-end delay and packet delivery success. We compare our scheme with the existing LBT mechanism which is referred to as the 'Base scheme' in the plots. The simulations are conducted using NS3 network simulator [11]. N_{LTE} and N_{wifi} vary between 1 and 10. The energy detection threshold is set to -72dB according to LAA specifications [12]. The rest of the simulation settings are given in Table I. We provide the averaged results of 5 runs with 95% confidence intervals. The training period of Q-learning is set to 1000 iterations. The presented results are the following 1000 iterations after the training period.

TABLE I
Simulation settings.

LTE Base station transmit/receive antenna gain	5 dB
WiFi Base station transmit/receive antenna gain	3 dB
LTE Base station transmit power	18 dBm
WiFi Base station transmit power	14 dBm
Base station noise figure	5 dB
User equipment transmit/receive antenna gain	0 dB
LTE User equipment transmit power	18 dBm
WiFi User equipment transmit power	14 dBm
User equipment noise figure	9 dBm
Propagation Loss Model	Log Distance
Energy Detection Threshold	-72.0 dB
Contention window size	15,30
Transport protocol	UDP
Traffic Type	Constant Bitrate

In Fig. 1, we provide the end-to-end delay for varying number of LTE and WiFi users. In these simulations, each set of runs include equal number of LTE and WiFi users with a mixture ratio of 1:1. Base WiFi and Base LTE show the performance of WiFi and LTE users under the existing LBT mechanism, respectively. The contention window is set 15 which is the default setting. Our results show that the proposed Q-learning based LBT scheme is able to reduce the delay of WiFi users significantly in most cases. This comes with a tradeoff for LTE users in particular for $N_{LTE} < 14$. Since LTE users are considered as secondary users of the unlicensed spectrum, the Q-learning algorithm makes them yield to WiFi users. When $N_{LTE} > 14$, the two schemes converge in performance because the network reaches saturation. In Fig. 2, we increase the contention window (CW) size to 30, to observe its impact on end-to-end delay. Our results show that even further improvements are achieved when $CW = 30$. For clarity, the same curves from Fig.1 and Fig. 2 are plotted in

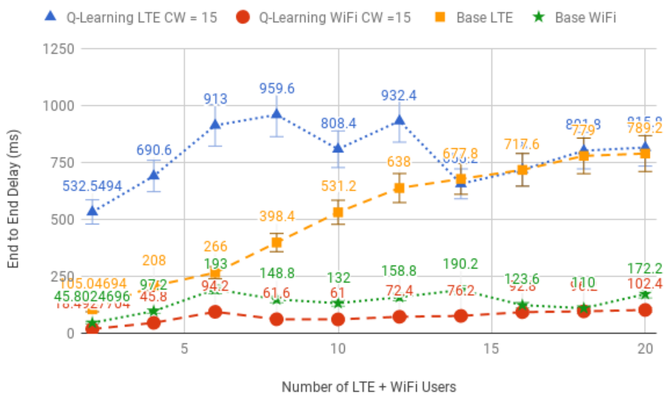

Fig. 1. End to end delay for increasing number of LTE and WiFi users for the proposed Q-learning based LBT and standard LBT mechanism (denoted by 'Base'). The number of LTE and WiFi users is set to be equal.

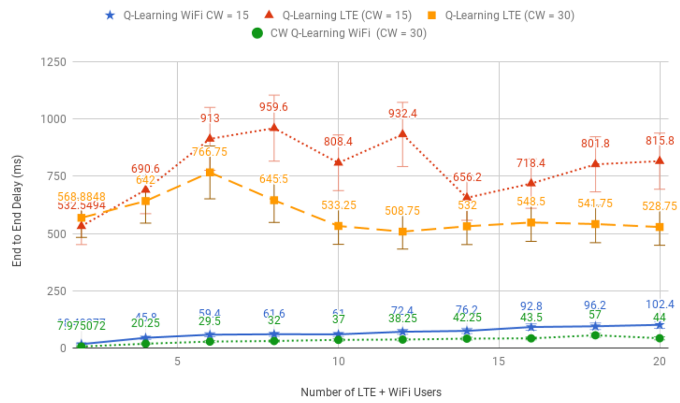

Fig. 3. End to end delay under varying number of LTE and WiFi users, and $CW = 15$ and $CW = 30$.

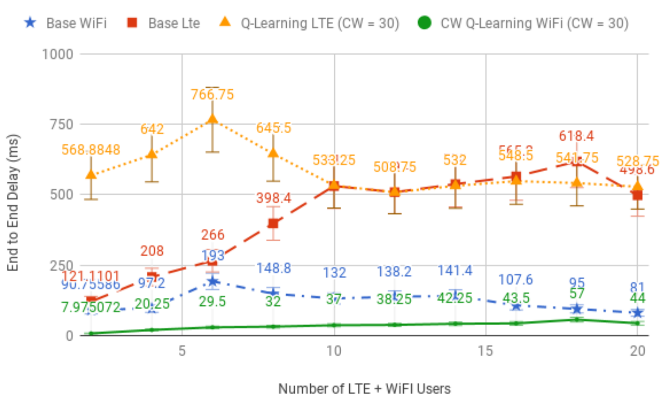

Fig. 2. End to end delay for increasing number of LTE and WiFi users.

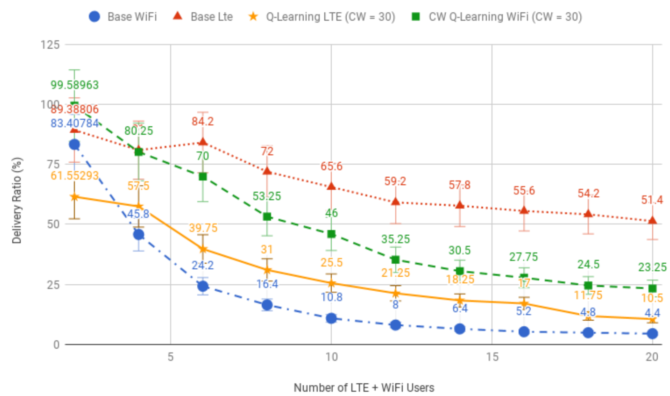

Fig. 4. Delivery success rate under increasing number of LTE and WiFi users.

Fig. 3, which compares the Q-learning algorithm for CW=15 and CW=30. In particular, LTE users can benefit from a higher contention window when the number of LTE users exceed 6. For 20 users (10LTE:10WiFi), our results show an improvement in reduction of delay as high as 286ms for LTE users while WiFi users experience a delay reduction reaching 58ms. Note that, these delays may be tolerated by delay-tolerant applications but not by mission critical applications. Based on this observation, we use $CW = 30$ for the remaining set of simulations.

In Fig. 4, we show the delivery success rate for WiFi and LTE traffic with respect to increasing number of WiFi and LTE users (using the 1:1 ratio). The success rate achieved by WiFi using the proposed Q-Learning based approach is always greater than that of the existing LBT scheme. This comes at the expense of performance degradation for LTE users, as seen in the figure. In the following set of results, we consider only 1 WiFi user competing with increasing number of LTE users to eliminate the impact of multiple WiFi users competing with each other. In Fig. 5, we present the end-to-end delay for both WiFi and LTE traffic as the number or LTE users increase in the network. As more LTE users try to share the unlicensed spectrum, the delay for the WiFi user increases. Our proposed approach incurs less increase in delay for WiFi, in comparison to traditional LBT mechanism. As for the end-to-end delay of LTE, the Q-learning based scheme incurs higher delay for few LTE users but eventually the delay approaches to the delay of the base scheme as the number of LTE users increase to 6. The reason for this behavior has been explained before. Once again,the existing LBT scheme defers LTE transmission as well, but not as aggressive as ours. For higher number of nodes the deferral inevitably incurs high delays. In Fig. 6, we present the delivery success rate of the traditional LBT scheme and the Q-learning scheme under increasing number of LTE users. The contention window is set to 30. In these set of results, the WiFi user is able to attain 100% success rate with our proposed scheme which is a significant improvement (60% improvement over the Base WiFi). Meanwhile, LTE traffic experiences almost 30% losses as they yield to WiFi.

In Fig. 7, we compare the results for $CW = 15$ and $CW = 30$ for the integrity of our evaluation. Even for $CW = 15$, the delivery success rate of WiFi reaches 75%-80% while in this case LTE performance is not impacted. Our results, show that both the proposed Q-learning-based approach and the existing LBT mechanism favor WiFi users which is desired. However, our approach has better performance for WiFi, achieving less delay and higher delivery success rate. This naturally impacts

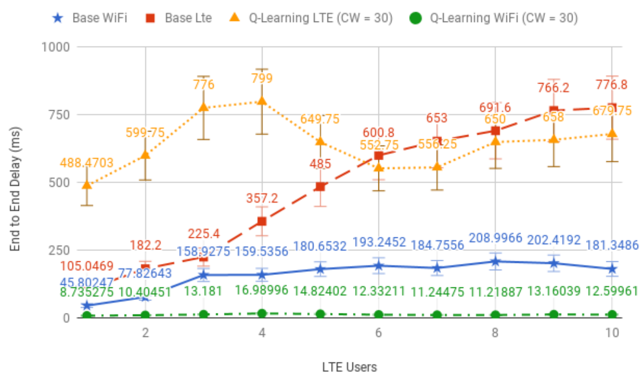

Fig. 5. End to end delay under increasing number of LTE users.

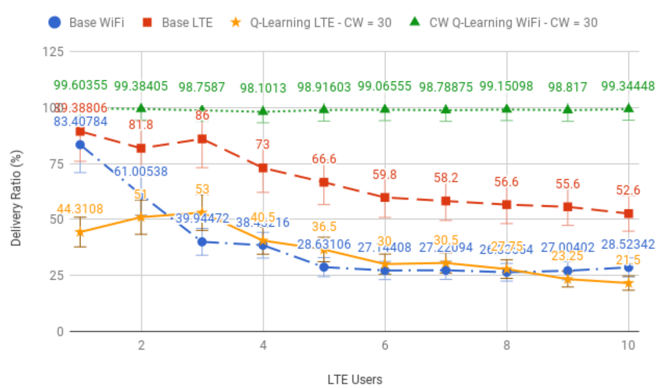

Fig. 6. Delivery success rate under increasing number of LTE users.

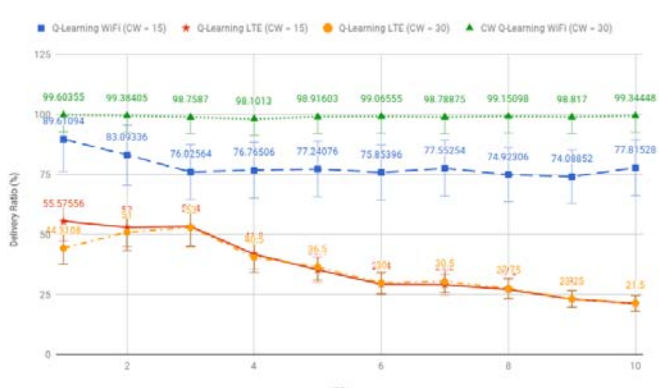

Fig. 7. Delivery success rate under increasing number of LTE users and varying size of contention window (15 and 30).

the performance of LTE users which indicates that LTE traffic would use the licensed bands under heavy WiFi existence.

V. Conclusion

In this paper, we proposed a Q-learning based Listen Before Talk (LBT) mechanism that increases the delivery success rate and reduces the end-to-end delay of WiFi traffic. The proposed scheme observes the backoff for WiFi users which is an indication of how well users make use of the shared medium. If the backoff is increasing, then the defer period of LTE users is increased so that they can yield to WiFi traffic. The Q-learning mechanism help the LBT mechanism to learn the defer times. Our results show that, the proposed scheme reduces the end-to-end delay of WiFi significantly while increasing its delivery success rate. This comes at the expense of performance degradation of LTE. However, in many countries LTE-U mechanisms are required to yield to WiFi in the unlicensed spectrum. Therefore, this behavior is expected. In our simulations, we further investigate the impact of contention window on the performance. Our results show that larger contention window favors WiFi performance.

In our future work, we plan to optimize the Q-learning algorithm and the training of the network. There is room for improvement in the fairness of the proposed approach. Therefore, we plan to design the objective of the Q-learning algorithm to consider fairness in addition to other metrics.

VI. Acknowledgement

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