Machine Learning-based Module for Monitoring LTE/WiFi Coexistence Networks Dynamics

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Abstract*—Long-Term Evolution (LTE) technology is expected to shift some of its transmissions into the unlicensed band to overcome the spectrum scarcity problem. Nevertheless, in order to effectively use the unlicensed spectrum, several challenges have to be addressed. The most important of which is how to coexist with the incumbent unlicensed WiFi networks. Incorporating the "intelligence" component into the network radios is foreseen to resolve the intrinsic network challenges, rather than conventional non-adaptive action plans. Specifically, an intelligent cognitive engine (CE) that continuously monitors the environment, and dynamically decides upon the best mechanisms and their configuration to suit a given scenario, is essential. In this work, we propose a machine learning-based monitoring module that provides real-time situational awareness that is envisaged to provide the necessary adaptivity, intelligence, autonomy, and learning capabilities. The objective of the proposed intelligent monitoring module is to sense, assess and select the most appropriate scheduling and resource allocation (SRA) algorithm at each LTE base station, according to the different coexistence scenarios. We propose a random forest classifier that maximizes the overall LTE throughput without degrading that of the WiFi network. Numerical simulations are presented to demonstrate the effectiveness of the monitoring module in achieving robust adaptive results under new unfamiliar network environments. Furthermore, we shed some lights on the comparison between the performance of multiple SRA algorithms under dynamic network settings.

***keywords*—** Coexistence, network monitoring, LTE unlicensed (LTE-U), licensed-assisted access (LAA), CSAT, LBT, NS-3, machine learning, random forest.

I. Introduction

Throughout the past few decades, cellular networks have been required to accommodate exponentially growing numbers of connected devices. Undoubtedly, the scarcity of licensed spectrum introduces crucial challenges that hinder providing the connected users with a sustained performance and/or the anticipated quality of service [1]. Towards this end, carrier aggregation (CA) has received immense attention from both academia and industry to open new horizons for future cellular networks. Particularly, exploiting the unlicensed spectrum bands, some of the networks transmissions are to be offloaded to decongest the licensed spectrum [2]–[4]. However, this necessitates investigating the arising coexistence issues between the various technologies being deployed in the unlicensed spectrum and the incumbent technologies (e.g., IEEE 802.11 (WiFi), Bluetooth, IEEE 802.15.4 (Zigbee), LORA, SIGFOX, ..., etc) [5]. One of which is the fact that such coexistence entails that no significant deterioration is imposed on the performance of the main incumbent unlicensed technologies [2], [6], [7]. Current standardization efforts hence focus on the need for efficient and dynamic spectrum access techniques to maintain adequate performance for coexisting systems.

LTE-unlicensed (LTE-U) and LTE-licensed assisted access (LTE-LAA) have been introduced as variants for the LTE standard to operate over the unlicensed spectrum. With particular focus on the LTE-LAA/LTE-U and WiFi coexistence scenario, as a promising solution to the sharp shortage of licensed spectrum resources, several research attempts have been investigating the challenges and limitations imposed by such coexistence [8]–[12]. The LTE is a schedule-based technology, where the LTE Evolved Node B (eNB) schedules during each LTE subframe some resources to each one of its associated user equipments (UEs), without the need for sensing the channel. Contrarily, the WiFi is a contention-based technology that has to sense the carrier before any transmission and perform a complete clear carrier assessment (CCA) by using sensing mechanisms, such as a request to send/clear to send (RTS/CTS), carrier sensing multiple access/collision avoidance (CSMA/CA), ..., etc. This major difference between the two technologies in both the MAC and PHY layers gives the LTE the privilege to access the medium more frequently than the WiFi, causing severe starvation and performance degradation to the latter [1], [6], [7].

To this end, the LTE network has to change its schedule-based behavior by applying new channel access mechanisms. Listen-before-talk (LBT), carrier sensing adaptive transmission (CSAT), almost blank subframe (ABS) and channel selection algorithms are some of the main scheduling and resource allocation (SRA) algorithms that have been proposed for the LTE-LAA/LTE-U networks [13]–[15]. They offer an uncoordinated, yet friendly, coexistence with WiFi. We briefly overview the main state-of-the-art SRA mechanisms that we will build upon throughout this work as follows.

A. Overview of the state-of-the-art SRA mechanisms for LTE/WiFi Coexistence

1) Listen-before-talk (LBT): Listen-before-talk is an energy-detection based channel access scheme. That is, an LTE-LAA transmitter senses the unlicensed carrier before its transmission to avoid collisions with other LAA or WiFi nodes, for a fixed or random contention window (CW) [16], [17]. Upon detecting an idle channel, a transmission opportunity (TXOP) of fixed duration is assigned for transmitting the eNB's packets.

2) Carrier Sensing Adaptive Transmission (CSAT): Unlike the LTE-LAA, LTE-U uses carrier sensing adaptive transmission (CSAT) which is based on duty cycles that define the channel occupancy ratio between the LTE-U and WiFi networks [15]. The eNB has to monitor the WiFi network activity for a long enough time (10 to 200 ms) in order to decide upon its optimal duty cycle ratio to guarantee fair spectrum sharing with WiFi. Particularly, CSAT-based schemes schedule periodic "on/off" durations, during which the eNB gains/defers access to the channel. Thus, the main challenge in CSAT scheduling mechanisms is the optimal fair allocation of the "on" and "off" periods within each CSAT cycle.

B. Related work

Several research works have proposed enhancements and modifications to the aforementioned basic SRA mechanisms to tackle the LTE/WiFi coexistence problem. In [8], the authors introduced a fairness framework between LTE-LAA and WiFi devices based on finding the optimal channel occupation time ratio between the two systems. In [9], a trade-off between energy usage and throughput is considered to guarantee fairness and efficient band-sharing by allowing the receivers to join the channel sensing process with its transmitters. By studying the effect of CCA energy detection (ED) threshold in the coexistence case, the authors in [10] concluded that increasing the CCA threshold reduces the sensing range of the eNBs. Another SRA algorithm of interest is the channel observation-based LBT (CoLBT), which is based on the CW size adaptation [18]. In [19], a varying LTE TXOP is introduced together with a variable muting period, during which WiFi has the opportunity to transmit, thereby achieving fairness between both networks.

In [11], the authors discuss fair channel access via chance constraint optimization based on CSAT algorithm. In [12], the authors propose a Q-learning based CSAT to optimally adapt the LTE-U duty cycle based on Markov decision process (MDP) for the purpose of maximizing the aggregated LTE-U and WiFi throughputs.

Despite the significant performance gains brought by the proposed SRA mechanisms and their modified versions, practical coexistence setups will still inherently suffer from other unaddressed challenges. The ongoing dynamic changes in the network imply that no specific SRA algorithm is preferable all the time, which gives rise to the need for adapting the selected SRA algorithm according to the network scenario at hand. In that regard, machine learning plays a vital role in incorporating an intelligence component that acts as a promising solution to include knowledge about *when* and *how* to use particular coexistence strategies. In this paper, we propose an eNB-based monitoring module that is responsible for sensing the current network environment for the purpose of optimizing the overall network performance. Such monitoring module will be continuously monitoring and assessing the real-time performance of the deployed networks. It is noteworthy that such task is indeed challenging owing to the critical need for carrying out such evaluation as generically as possible to account for all the possible disparities. Moreover, the monitoring module should continuously be updating the operating scenarios categorization. The devised module aims at selecting the fittest coexistence mechanism that is capable of maximizing the overall system performance. For this purpose, we implement a random forest (RF) classifier which has the potential to distinguish between the diverse underlying wireless environments with different network setups. Once the encountered network is classified by the proposed monitoring module, the eNB is thereby able to select the optimum coexistence mechanism to operate. To the best of the authors' knowledge, this is the first work to compare the performance of multiple SRA algorithms under different and dynamic network settings.

The rest of the paper is organized as follows. Section II presents the proposed system model. In Section III, the implemented SRA algorithms are demonstrated. Section IV, proposes the machine learning based monitoring module. Simulation results and main insights are discussed in Section V. The paper is concluded in Section VI.

II. System Model

A. Network and Traffic Model

We consider an indoor setup of LTE-LAA/LTE-U and WiFi coexistence in the 5 GHz unlicensed spectrum within an area of dimensions $120\text{m} \times 50\text{m}$. The coexistence network consists of N eNBs and M WiFi APs sharing an unlicensed channel of bandwidth $\mathcal{B} = 20$ MHz. The offloaded eNBs from the licensed to the unlicensed spectrum are determined by the LTE operator, and the mechanism of such offloading is beyond the scope of this paper. We study the downlink transmissions since the uplink transmissions are to be assigned to the licensed bands, and are hence not accounted for in this work. Each eNB serves U UEs, whereas each WiFi AP has S stations (STAs) randomly deployed within its coverage area. We consider the users' traffic arrivals to follow a Poisson process under the file

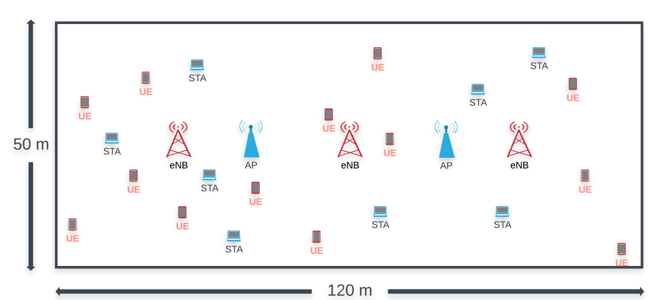

Fig. 1: Snapshot of the L/L layout of 3 eNBs and 2 WiFi APs placed along the same line.

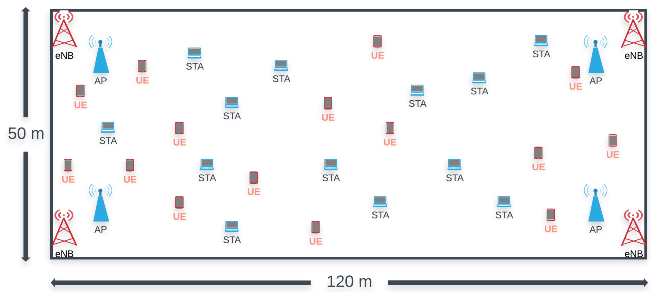

Fig. 2: Snapshot of the C/C layout of 4 eNBs and 4 WiFi APs placed at the corners.

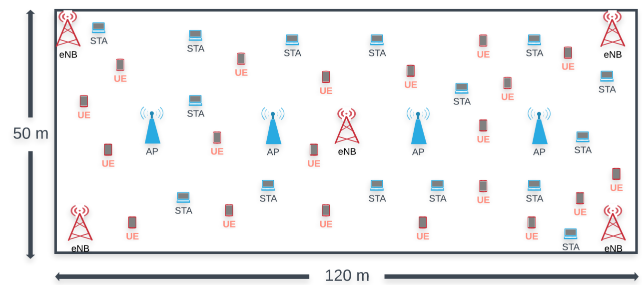

Fig. 4: Snapshot of the C/L layout of 5 eNBs located at the corners and 4 WiFi APs placed along the same line.

transfer protocol mode 1 (FTPM 1). Let λ denote the traffic arrival rate for each of the collocated networks.

We consider four different layouts of the unlicensed LTE and WiFi coexistence. Line-line (denoted as L/L) and corner-corner (denoted as C/C) layouts, imply a linear and corner deployments, respectively, of all the eNBs and APs in the network, as shown in Fig. 1 and Fig. 2. The C/C layout is of particular interest since it has the potential to account for the impact of the hidden nodes on the overall performance. For more generalized settings, we further consider a line-corner setup, which we hereafter denote as L/C, where eNBs are deployed along a line, while APs are located at the corners of the area of interest, as depicted in Fig. 3. Moreover, the corner-line setting, denoted as $C-L$, has the eNBs deployed at the corners while the APs are located across a line, as demonstrated in Fig. 4. All of the eNBs are assumed to transmit at the same power level P_L, while the WiFi APs and UEs transmit at power P_W.

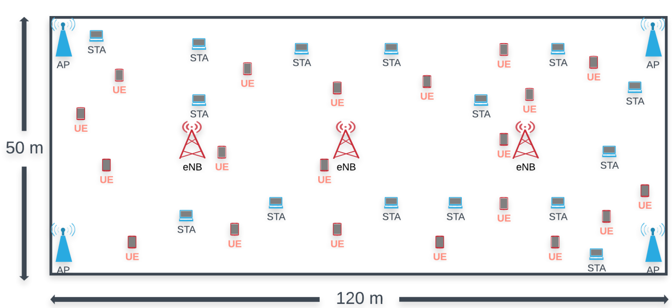

Fig. 3: Snapshot of the L/C layout of 3 eNBs placed along the same line and 4 WiFi APs placed at the corners.

B. *LTE and WiFi transmissions model*

LTE transmissions are scheduled centrally at the eNB. We consider a cognitive setting, in which each eNB can exploit multiple diverse SRA algorithms that operate differently according to the encountered environment setup. For this purpose, and motivated by the continuous dynamic changes of the environment, we propose equipping each eNB with a monitoring module. The function of this prospective module is to provide real-time situational awareness of the time-varying environment. Accordingly, the eNB is able to decide upon the best scheduling and resource allocation strategy to be carried out, and thereby, achieves the optimum performance, for both the LTE and WiFi networks. In this setup, a CE is one from a set of different LTE-LAA/LTE-U scheduling and resource allocation mechanisms to be explained in more details in Section III.

III. Overview of the Implemented SRA algorithms

In what follows, we present the operations of a number of SRA algorithms that we adopt in this work.

A. *Traditional LBT engine*

The conventional Listen-before-Talk (LBT) cognitive engine implements the traditional LBT algorithm demonstrated in [20]. If the eNB selects this engine to operate, a complete clear channel assessment (CCA) channel sensing process will be required. In this engine, the CW adjustment procedure, described in 3GPP Release 14 [21], is adopted. Initially, an integer number is selected as the CW size, then it is adapted according to the received Hybrid-ARQ (HARQ) feedback. That is, the percentage of received negative acknowledgements (NACKS) with respect to the number of ACKs and NACKs altogether represents the adopted threshold, typically set to 80%, according to which the CW size is adjusted. The bigger such percentage, the more likely the CW is to be increased in order to overcome the detected collisions. Typically, the maximum size for the CW takes values from $[7, 1023]$. Otherwise, if the percentage of NACKS does not cross this 80% threshold, the CW is reset to its minimum value, which typically varies from 3 to 15. Obviously, the configuration of the CW size and TXOP duration is of utmost importance to the performance of the LBT engine.

B. *Channel Observation-based LBT (CoLBT) engine*

This engine is basically a variant of the traditional LBT algorithm that employs an update rule based on the NACKs to adjust the CW size [18]. In fact, the LTE protocol stack induces inevitable latency that results in a delay of at least 4 ms for the users' HARQ feedback after the transmission of the subframe. This is the main reason subsequent feedbacks after the first subframe of a TXOP are ignored. To overcome such drawbacks, channel observation is performed to estimate the channel collision probability. The CoLBT algorithm proposed in [18] adaptively scales up or down the traditional LBT CW from CW_{pre} to CW_{current}, based on the channel collision probability observation. Each eNB can estimate the channel observation-based collision probability, denoted as ν, by observing the number of NACKs, S_{nack}, in recent TXOP, as well as the number of busy slots during the extended CCA (ECCA) period, S_b. The collision probability ν can then be calculated as

$$\nu = \frac{S_b + S_{\text{nack}}}{S_{\text{nack}} + B_{\text{obs}}}, \tag{1}$$

where B_{obs} is the total number of backoff slots between two consecutive ECCA periods. When the eNB detects an unsuccessful transmission, it will scale the CW up, otherwise, it will be scaled down. The update rule is hence expressed as

$$CW_{\text{current}} = \begin{cases} \min\left((CW_{\min})^{\nu} \times 2CW_{\text{pre}}, CW_{\max}\right), & \text{if } \nu > 0 \\ \max\left(\frac{(CW_{\min})^{\nu}}{2} \times CW_{\text{pre}}, CW_{\min}\right), & \text{if } \nu = 0 \end{cases}, \tag{2}$$

where $CW_{\max}$ and $CW_{\min}$ are the maximum and minimum contention windows size, respectively.

C. Dynamic (Adaptive) CSAT engine

In dynamic CSAT, known as Qualcomm's CSAT [22], the eNB monitors the channel to detect the number of active WiFi APs during a period called AP-scan monitoring time. The AP-scan time is initially set to 160 ms. This means that each LTE-U eNB has to spend some time for monitoring the environment before determining its CSAT duty cycle ratio, defined as $\frac{T_{\text{ON}}}{T_{\text{ON}}+T_{\text{OFF}}}$, where T_{ON} and T_{OFF} are the "on" and "off" periods within the cycle duration, respectively. In [22], the selection of the CSAT duty cycle, is carried out by the following procedure. The averaged medium utilization, denoted by $\overline{\mu}$, is defined as a weighted moving average of the WiFi activity over the monitoring window. It is measured by summing the durations of all WiFi transmissions detected during the AP-scan period. Then, $\overline{\mu}$ is compared to two thresholds, the lower threshold μ_{low}, and the upper threshold μ_{high}. Accordingly, T_{ON} is adjusted as follows

$$T_{\text{ON}} = \begin{cases} T_{\text{ON}} + \delta_{\text{up}}, & \text{if } \overline{\mu} > \mu_{\text{high}} \\ T_{\text{ON}} - \delta_{\text{down}}, & \text{if } \overline{\mu} < \mu_{\text{low}} \end{cases}, \tag{3}$$

where δ_{up} and δ_{down} are the increment and decrement values that adjust T_{ON}. If the measured $\overline{\mu}$ lies in between both thresholds, T_{ON} will remain unchanged.

In the context of this work, we will consider switching between the aforementioned scheduling strategies in order to achieve optimized performance according to the network setting at hand.

IV. Proposed Machine Learning Based Monitoring Module

The proposed monitoring module is required to detect whether the network has undergone any changes, and how. Thus, it has to distinguish between the different environment scenarios, thereby, the system can properly tune the operating parameters to best adapt to the detected changes. To this end, we will first make some reasonable assumptions that will render this process viable:

1) **LTE eNBs cooperation:** We assume the eNBs within the same operator cooperate together. Consequently, the LTE operator knows the number of the collocated eNBs.
2) **The number of WiFi APs is known to the eNBs:** Within the WiFi network, the APs are assumed to broadcast a beacon signal that is transmitted every 100 msec [20]. The eNBs are able to listen to these beacon signals, and hence, they will have the ability to determine the number of the coexisting APs. It is to be emphasized that only the WiFi APs numbers are known, while their deployments are not.
3) **Traffic arrival rate is known to the eNB and is the same for both LTE and WiFi**: We assume that each eNB knows the traffic load of users' requests. This traffic load specifies whether the user is browsing, streaming, or downloading files. Therefore, it indicates whether the network experiences heavy traffic that needs higher attention from the coexistence algorithms or not.

By exploiting these assumptions, the proposed module will have the potential to ensure fair coexistence between both systems. In order to be able to distinguish between different environment scenarios, we implement a classifier that predicts the most appropriate SRA engine that best matches the current operating scenario. Basically, a classification algorithm tries to learn from the data features, to be able to distinguish between the different classes. In our model, the data features are the network states and the classes are the different SRA algorithms. In this regard, we have implemented different classifiers streamline machine learning (ML) classifiers (i.e., logistic regression, support vector machine, naive Bayes, decision tree, random forest) as illustrated by Table I. The performance of each classifier in terms of the training accuracy and validation accuracy is demonstrated. We decide to use the random forest (RF) classifier as it offers the highest accuracy. In addition, it works efficiently for the categorical and heterogeneous datasets. It is one of the well known bagging technique with a predefined number of decision trees. Each tree in the forest gives a classification output. The impact of randomly selecting a subset of training samples and isolating variables at each tree node will produce a large number of decision trees. Therefore, the sensitivity level of the RF classifier is less with respect to other streamline ML classifiers because of the quality of training samples and the robust decision trees.

Algorithm Name	Training Accuracy	Validation Accuracy
Logistic Regression	71.7%	63.6%
Support Vector machine	67.0%	72.7%
Naive Bayes	74.1%	63.6%
Decision Tree	91.7%	95.4%
Random Forest	98.8%	95.4%

TABLE I: Training and validation accuracies for the different environment classification algorithms.

Hyperparameter	Value
Number of trees	10
Classes weights	$\{\text{LBT} = 0.7, \text{CoLBT} = 1, \text{CSAT} = 0.6\}$
Decision Tree kernel	Entropy
Maximum depth	7
Minimum samples per leaf	3

TABLE II: Random forest hyperparameters values

V. Experimental setup and Random Forest Training Results

A. Simulations Setup

We demonstrate proof-of-concept numerical results that are obtained using the NS-3 (the Network Simulator Version 3) in LTE/WiFi coexistence environment, and specified by the following parameters unless otherwise stated. In the NS-3 "laa-wifi-coexistence" module, the number of eNBs is $N \in \{2, 3, 4, 5\}$, and the number of APs is $M \in \{2, 3, 4, 5\}$ in the L/L deployment scenario. For the C/C layout, we consider $N \in \{4, 5\}$ and $M \in \{4, 5\}$. We assume that the number of UEs per eNB is $U = 5$ and the number of assigned STAs per AP is $S = 5$. We assume the traffic load to be $\lambda = \{0.5, 2.5, 5\}$ files per second. The size of one file to be transmitted is 0.5 MB. The main control parameters of the coexistence engines that are based on LBT are: TXOP $= 10$ ms, the ED threshold $\gamma_{\text{th}} = -72$ dBm, and the transmit powers of the LTE and WiFi nodes are $P_L = 18$ dBm and $P_W = 18$ dBm, respectively. As for the dynamic CSAT-based algorithm, the control parameters are as follows. The cycle duration $T_{\text{ON}} + T_{\text{OFF}} = 640$ ms, $\delta_{\text{up}} = \delta_{\text{down}} = 0.05$ ms, and the transmit powers P_L and P_W which are similar to those of the LBT-based engines.

Adopting the aforementioned simulation setup, we could come up with 108 scenarios that can be shared between the different implemented coexistence algorithms. Those scenarios differ from one another in the number of eNBs, N, the number of the APs, M, the traffic load, λ, and the eNBs/APs deployments. We represent each scenario by the 4-tuple $(N, M, \text{"deployment type"}, \lambda)$, where the "deployment type" $\in \{L/L, C/C, L/C, C/L\}$.

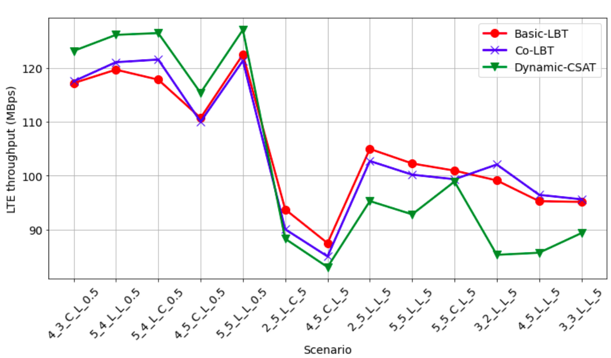

Fig. 5: The LTE throughput obtained by the basic LBT, CoLBT, and dynamic CSAT algorithms under different environment settings.

In Fig. 5, we show the LTE throughput of each coexistence algorithm versus the 4-tuple representing the environment setup. As evident from the figure, for the scenarios that experience low traffic load, the dynamic CSAT engine outperforms the basic LBT and the CoLBT. This is because CSAT enforces the LTE system to be silent during T_{OFF} which is enough to serve the low traffic load of the WiFi network. This in turn decreases the collisions with the LTE during T_{ON}, and hence offers performance gains over the LBT and CoLBT schemes. This performance trend changes as the traffic load increases, where the basic LBT and/or CoLBT engines have shown to offer performance gains up to 16% over the dynamic CSAT. As clear from Fig. 5, the LBT and the CoLBT achieve very near LTE throughput, since both rely on CSMA/CA. For some scenarios, the CoLBT provides performance gains over the LBT due to accounting for the collisions occurring due to concurrent transmissions in an adaptive fashion.

B. Random Forest (RF) Training

In order to implement our random forest classifier, we use Python-3 and the Scikit-Learn open source library, so we just tune the hyperparameters of the RF classifier to achieve better performance. The RF classifier hyperparameters we have used are listed below [23]:

- Classes weights: By observing the statistical results obtained by employing each of the coexistence algorithms under the different network setups, we could find that the data is imbalanced. We could then come up with adequate weights for the loss of each class (algorithm) in order to enforce the model to distinguish between the different classes.
- Decision tree kernel: the criterion whereby the impurity of data is reduced. Hence, data is split according to the information gain.
- The maximum depth and minimum samples per leaf: we define for each decision tree within the RF classifier the maximum depth and minimum number of samples per leaf to reduce overfitting.
- The number of trees within the RF classifier.

The searched out hyperparameters values are demonstrated in Table II. These values have been shown to provide the best training and validation results. Accordingly, the RF classifier achieves 98.8% training accuracy, and 95.4% validation accuracy. This means that our RF classifier is robust for new unfamiliar datasets exhibiting similar network setups.

For the purpose of testing the RF classifier with unexplored environment settings, we design different scenarios as shown in Fig. 6. We found that the scenarios defined by high traffic load, $\lambda \geq 2.5$ are classified to carry out basic LBT. On the other hand, for scenarios with intermediate traffic load, $1 \leq \lambda \leq 2$, the RF classifier selects the CoLBT engine. When the traffic load is low, the network employs the dynamic CSAT engine. As evident from Fig. 6, the proposed RF classifier is able to detect the network scenario at hand, and thereby select the fittest coexistence mechanism providing the optimum LTE performance. It is of utmost importance to emphasize that the optimized LTE performance does not deteriorate that of the WiFi network. In light of the above discussion, it is obvious that the proposed module is able to dynamically switch between the different SRA strategies as the network setting varies.

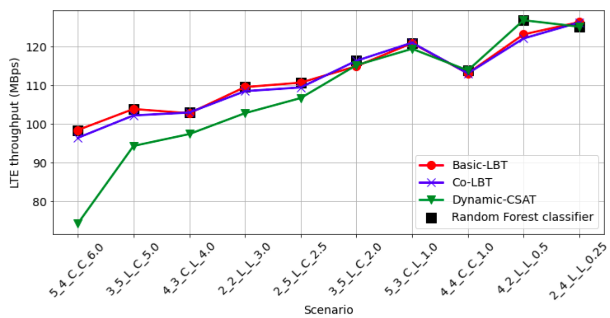

Fig. 6: Predicted LTE throughput based on Random forest classifier for unfamiliar network scenarios.

VI. Conclusion

This work aims at providing a proof-of-concept framework, adopting machine learning for LTE/WiFi coexistence. Furthermore, it is extremely critical to take into account the vast network variations due to mobility of users, varying traffic loads and other channel conditions. To this end, we propose a machine learning-based monitoring module that senses the surrounding network environment. Having received real-time measurements of the operating environments, the monitoring module is then responsible for comparing multiple SRA algorithms and quantifying their respective efficiency. In addition, via the monitoring module, the operating scenario is continuously characterized. Numerical simulations have shown the proposed random forest classifier to offer robust performance that effectively deals with unexplored environments. Finally, we have highlighted several insights for the performance of the different engines under different network scenarios.

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