Coexistence of LTE-U duty cycle with WIFI in Unlicensed bands: A LSTM based approach

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***Abstract*—: An unprecedented growth in mobile data due to rapid development of mobile devices and wireless communications generates a large amount of data traffic everyday. In such a scenario, effective innovations are in need to enhance the network capacity and user-experience. Co-existence of Wi-Fi and LTE Unlicensed (LTE-U) in shared or unlicensed groups has drawn developing consideration from both scholarly community and industry to enable more efficient spectrum utilization and provide greater broadband capacity. The main point of consideration during this study is that both WIFI and LTE-U should co-exist fairly without interrupting routine WI-FI activities, as LTE-U can alter it's duty cycles accordingly with the motive of gaining a larger spectrum. In this paper we develop RNN based LSTM network to learn WIFI traffic demands i.e. the idleness/business of WIFI channels. WIFI signals are captured using an empirical setup which is then feed into LSTM model, this way the model trains itself to get acquainted regarding WIFI activites. Based on this knowledge, LTE-U will thereby learn priorly about the WIFI activities as the model train itself and will allocate itself on channels which are kept idle for a longer time or un-occupied. This way both WI-FI and LTE-U will not have to compromise for their duration and can access the unlicensed band efficiently. This results are than compared with an algorithm for duty cycle estimation of LTE where a threshold is set at WIFI AP to check whether it misbehaves or not. The main goal of this article is to prove how the LSTM network can prove to be an efficient approach in comparison with the duty cycle method where both WI-FI and LTE-U have to compromise for their duration.**

***Index Terms*—Long term evolution, LSTM model, 5GHZ unlicensed band, WIFI**

I. Introduction

Since the demand of smart phones and other mobile applications are becoming prevailing, mobile traffic is growing explosively resulting in the need for additional wireless network capacity. Licensed bands for LTE are expensive and difficult in expanding [4]-[6]. LTE operators are thus interested in utilizing the 5GHz unlicensed bands mainly used by WIFI. From the user perception this mean high data rate, high reliability and robust mobility [1]. However the coexistence between WIFI and LTE is not an easy task because the two technologies completely employ different medium access protocols. WIFI follows the CSMA/CA protocol, senses the medium and allows others to complete their transmission before attempting it's own [7]-[8], while LTE transmits continuously without sensing. This results in a serious degradation of WIFI activities performance. Thus the main challenge is to enable coexistence with high LTE throughput and zero degradation in routine WIFI activities.

A. Motivations

For LTE-U duty cycle method that has been mentioned in [2], where both WIFI and LTE transmits for equal duration for fair coexistence. LTE-U duty cycles have been calculated and thereafter compared with a threshold to check whether it misbehaves i.e. try to access a larger spectrum with more duty cycle [3]-[5]. However a drawback of this approach turns out is both WIFI and LTE tries to access the same spectrum without identifying vacant frequency bands in the spectrum. Resulting in condense transmission duration for both the technologies. A mechanism whereby one of the technologies is trained to identify vacant frequency bands during transmission and allocated itself to such bands will result in higher data rate and increase in efficiency of spectrum utilization. One such algorithm is proposed in this article.Since long machine learning algorithms are used to extract valuable information from data. Survey in comprehensively describes survey in CR architectures using machine learning. The traditional Artificial Neural Networks is widely used where it trains every example with forward pass. The serious shortcoming of ANN's is they cannot process time series data as they cannot store information due to absence of memory elements and cannot model long term dependencies [9]-[10]. The former shortcoming is resolved by Recurrent Neural Networks as they process sequences of data. In order to solve the shortcoming of long term dependencies LSTM networks are used [11].

B. Contributions

The design objective of this paper is to maximize LTE throughput without interfering with routine WIFI activities. WIFI demand activities are time varying and unknown to the LTE. However, if LTE can monitor WIFI activities to learn about the idle/busy slots about WIFI channels it can utilize the spectrum band more effectively. For this LSTM networks are used in this paper which trains itself from historical data of WIFI signals and acknowledges LTE about WIFI activities to optimize its transmission accordingly. The main contribution of this paper are summarized below.

- LSTM approach to solve the problem of coexistence of WIFI and LTE where model trains itself on the basis on input WIFI signals

- Model learns about the idle/busy slots and acknowledges LTE
- Results are compared with duty cycle approach of LTE.

C. Organization of the Paper

In Section II we provide the system model and the basics of LSTM, Section III discusses the proposed RNN-LSTM scheme. In Section IV we discuss analytical and simulation results. Finally Section V draws conclusion.

II. II.SYSTEM MODEL

A. LTE/WIFI Spectrum Sharing

We consider an LTE/WIFI spectrum sharing as depicted in Fig.1, WI-FI standard employs CSMA/CA that implements the Distributed Co-ordination Function(DCF) – a distributed slotted medium access scheme with an exponential backoff [12]. In DCF each node attempting to transmit must ensure the medium has been idle for period of 34us, whereas LTE never stops it's transmission. For the WI-FI system there exists a WI-FI AP and several WI-FI user equipments (W-UEs) to transmit data whereas LTE BS shares the same unlicensed band to serve some users.

LTE system is saturated due to tremendous mobile traffic demands, meanwhile due to private access WI-FI system has limited active users and unsaturated traffic. In fact WI-FI systems are underutilized and thus leaves a lot of unoccupied spectrum bands [13]-[14]. Hence LTE can exploit the unlicensed band under-utilized by WIFI to enhance LTE network capacity.

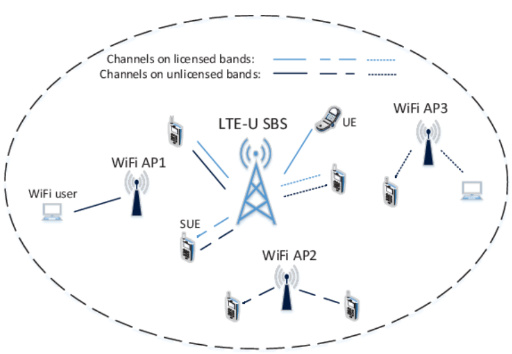

Fig. 1. LTE/WI-FI spectrum sharing system.

B. LSTM based framework

The problem of WI-FI spectrum sensing can be formulated as binary classification problem.

$$H0 : y^t : w^t \tag{1}$$

$$H1 : y^t = h^t x^t + w^t \tag{2}$$

where x^t denotes WI-FI signal, w^t is white gaussian noise with zero mean and variance and y^t is the received signal at t^{th} time instant. $H0$ the null hypothesis indicated the noise samples while $H1$ indicated the presence of WI-FI signal along with noise at t^{th} instant. In order to exploit the temporal dependencies the previous sensing event is fed along with the current sensing event and thus the received signal, in general can be expressed as metioned in [15]:

$$Y = [y^1 y^2 \dots y^n y^{N+1} y^{N+2} .. y^{2N}]^T \tag{3}$$

where N is the signal sample size. Fig 2 shows the internal structure of a LSTM cell [11],where $x_{(t)}$ denotes the input, $h_{(t-1)}$ denotes previous LSTM output and $c_{(t)}$ and $c_{(t-1)}$ are the current and previous cell states, respectively. The key elements of LSTM are described as follows:

- Update Gate: Decides when to update the current cell, denoted as the output $i_{(t)}$
- Forget Gate: Decides when to discard the current cell, denoted as the output $f_{(t)}$
- Output Gate: Controls the output, denoted as the output $o_{(t)}$

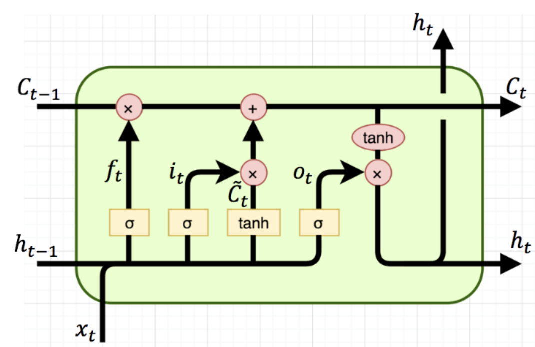

Fig. 2. Internal structure of LSTM cell.

C. LSTM cell

The tanh activation is used to help regulate the values flowing through the network. The tanh function squishes values to always be between -1 and 1 as shown in Fig3. The

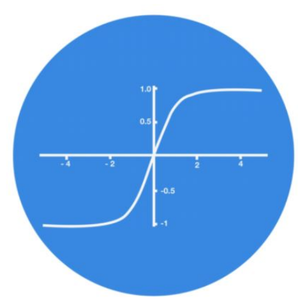

Fig. 3. Tanh squishes values to be between -1 and 1

sigmoid activation is similar to the tanh activation. Instead of squishing values between -1 and 1, it squishes values between 0 and 1 as shown in Fig4. The compact forms of the equations for the LSTM cell are:

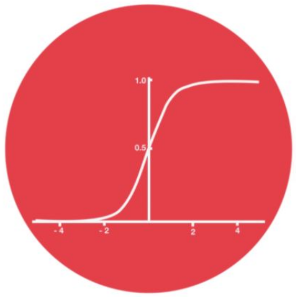

Fig. 4. Sigmoid squishes values to be between 0 and 1

$$f_t = \sigma_g(W_f x_t + U_f ht - 1 + bf)$$
$$i_t = \sigma_g(W_i x_t + U_i ht - 1 + bi)$$
$$o_t = \sigma_g(W_o x_t + U_o ht - 1 + bo)$$
$$f_t = \sigma_g(W_f x_t + U_f ht - 1 + bf)$$
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III. RNN-Long short term based memory approach

Although the LTE system cannot know exact WIFI traffic demands, the LTE system can monitor WIFI channels to obtain WIFI channel activity i.e. the number of busy and idle slots. In this section we develop LSTM based algorithm to correctly identify WI-FI signals from a dataset. This algorithm will make it easy for a LTE system to monitor WIFI traffic demands.

A. Dataset construction

In this study, the proposed LSTM model is trained and validated based on spectrum data. The data has been generated synthetically in NS3 simulator. An environment of WI-FI nodes was created and packets were transmitted from between WI-FI nodes. WI-FI protocols were then used to calculate the transmission time of packets, using which energy values have been obtained. This energy values were then used to train LSTM model using Deep Learning simulator.The generated data was divided into three classes training, validation and test datasets. A detailed description of NS3 parameters has been mentioned in Section IV.

B. Evaluation Of Performance Metrics

Algorithm 3 shows the detailed evaluation for classification of WI-FI signals from a dataset consisting of WI-FI signals and AWGN noise. Signals data is fed in small number of batches one after the other to train the LSTM model [17] the present sensing event becomes the previous sensing event for the upcoming batch and thus LSTM model proves to be more useful compared to traditional RNN schemes and the LTE system will be able to monitor the WI-FI activity from these results.

Later, P_d which is the detection probablity for number of times WI-FI signaals are correctly identified and P_f which is the false alaram probablity for number of times WI-FI signaals are not correctly identified

Algorithm1:Prediction Model

$i \leftarrow 1$
for $i \leftarrow 1$ to length(WIFI$_{Signal}$ **do**
example,label $\leftarrow extract(Dataset, 1)$
$H0\_examples \leftarrow 0$
$H0\_false \leftarrow 0$
$H1\_examples \leftarrow 0$
$H1\_correct \leftarrow 0$
if $labelisH1$ **then**
$H1\_examples \leftarrow H1\_examples + 1$

if Output is H1 **then**
H1_correct $\leftarrow H1\_correct + 1$
end if
if label is H0 **then**
H0_examples$\leftarrow H0_examples + 1$
if $OutputisH1$ **then**
$H0\_false \leftarrow H0\_false + 1$
$P_d \leftarrow H1\_correct/H1\_examples$
$P_f \leftarrow H0\_false/H0\_examples = 0$

IV. Experimental Results

A. Dataset Construction

Dataset was contructed in ns3 , a widely used network simulator [16]. We considerthe coc-channel coexistence of a LTE-U cell and a WiFi network that consists of an AP and 20 clients, allof which are located close to each other. Simulation parameters are provided in Table I.

NS3 parameters	
Parameters	Values
Wi-Fi standard	802.11n (Mixed Format)
Channel 20MHz	(5170-5190MHz)
Wi-Fi AP/client Tx power	24/18 dBm
CCA-CS/ED threshold	-82/-62dBm
Traffic model	Full buffer UDP
RTS/CTS	Disabled
Frame aggregation	A-MSDU enabled
Min./max. continuous ON period	6/20ms
Idle gaps between ON periods	2ms
LTE-U cycle period (T)	80-480ms
Max. Wi-Fi packet duration (Lmax)	300-1100µs
Max. duty cycle (max)	0.5

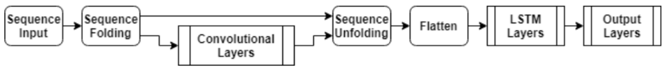

Fig. 5. Architecture of LSTM network

WI-FI dataset was obtained by simulating the above parameters in NS3 in values of tranmission time of packets. This values were then converted into energy values to get a complete dataset along with AWGN noise samples.

In order to generate a larger dataset an another LSTM model namely Vanilla LSTM was impelmentd using keras library [17]. A Vanilla LSTM is an LSTM model that has a single hidden layer of LSTM units, and an output layer used to make a prediction.In this case, we define a model with 50 LSTM units in the hidden layer and an output layer that predicts a single numerical value.The model is fit using the efficient Adam version of stochastic gradient descent and optimized using the mean squared error, or 'mse' loss function.Once the model is defined, we can fit it on the training dataset.After the model is fit, we can use it to make a prediction.We can predict the next value in the sequence by providing the input.

B. Training LSTM model using dataset

After the dataset was constructed a LSTM model was created using deep learning toolbox in Matlab.An LSTM layer learns long-term dependencies between time steps in time series and sequence data. The layer performs additive interactions, which can help improve gradient flow over long sequences during training.An LSTM layer with 100 hidden units was created.The LSTM layer parameters are mentioned in Table2.

LSTM layer parameters	
Parameters	Values
InputSize	'auto'
NumHiddenUnits	100
OutputMode	'sequence'
StateActivationFunction	'tanh'
GateActivationFunction	'sigmoid'
InputWeights	[]
RecurrentWeights	[]
Bias	[]
HiddenState	[]
CellState	[]

After creating the LSTM layer the deep learning LSTM network is trained using the constructed dataset.Mini-batch size is set to 27 and the maximum number of epochs is set to 100. This way an execution environment has been created with specific training options and the results are shown in Fig3

It is evident from Fig3 that as the training time and iterations increases the model keeps on training it and more accurate results are obtained making loss almost zero in the end.

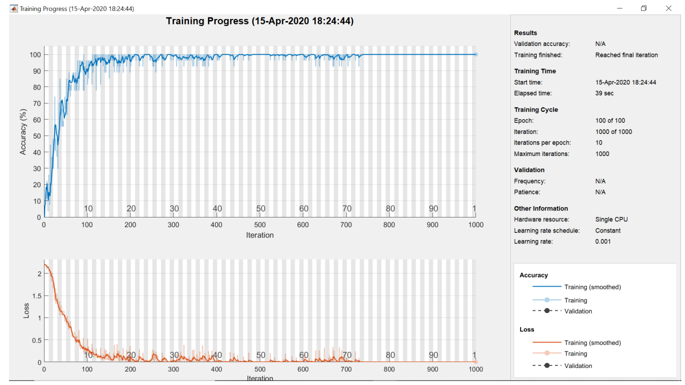

Fig. 6. Training model of WI-FI signals using LSTM network.

This result is can be used by LTE system to monitor WI-FI activities and identify the idle/busy slots.[18]

C. Duty Cycle Estimation Using LSTM results

In this section we compare the results of duty cycle estimation for LTE mentioned in article [2].
The duty cycle in article is calculated using the following equation.

$$\hat{\alpha} = 1/T \sum_{i=1}^{m} \hat{ON_i} \tag{4}$$

where $\hat{ON_i}$ is the transmission duration of LTE.

After obtaining $\hat{\alpha}$, the spectrum manager needs to determine whether the LTE-U AP violates the rule i.e. try to gain more spectrum by transmitting for a duration longer then the decided threshold.Its performance is measured by probability of detection P_d and probability of false alarm P_f , i.e.,

$$P_d(\alpha, \gamma) = Pr(\hat{\alpha} > (1+\gamma)\alpha_{max} | \alpha > \alpha_{max}) \tag{5}$$

$$P_f(\alpha, \gamma) = Pr(\hat{\alpha} > (1+\gamma)\alpha_{max} | \alpha < \alpha_{max}) \tag{6}$$

where α_{max} is set to 0.5. A detailed description of parameters and their derivations have been mentioned in article [2] .
Analytical results have been obtained by plotting eqn(5) and eqn(6) as shown in fig4 where L_{max} is set to 0.5
Note that if the true duty cycle α is greater than α_{max},the probability in Eqn(5) is P_d; otherwise, it becomes P_f . For instance, with L_{max} = 0.5ms, T = 160ms and γ = 0 if the LTE-U AP transmits with a duty cycle of 0.498, the probability of mistakenly identifying that AP as misbehaving is 14.0%. If α = 0.502, the probability of correctly detecting that misbehaving user is 83.4.

D. Simulation Setup

The simulation of duty cycle scheme proposed in article [2] was done in NS3 simulator [16] as shown in Fig6
In order to compare the results of Fig6, we have used the transmission time values of WI-FI signals which were predicted using Vanlilla LSTM model in kerras library. Using

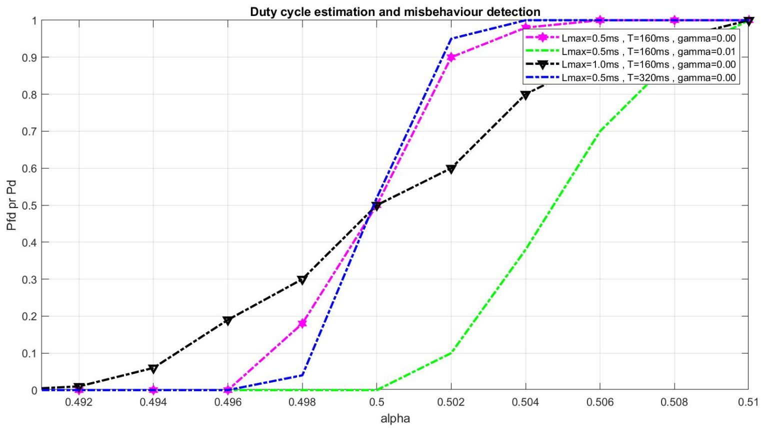

Fig. 7. Analytical results

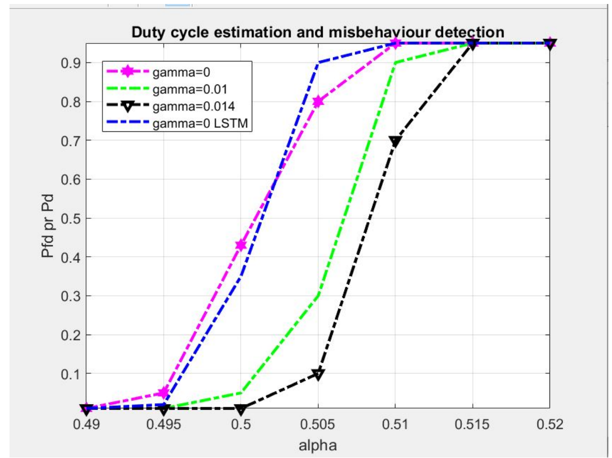

Fig. 9. Comparison of simulation results withs simulation results obtianed using LSTM framework

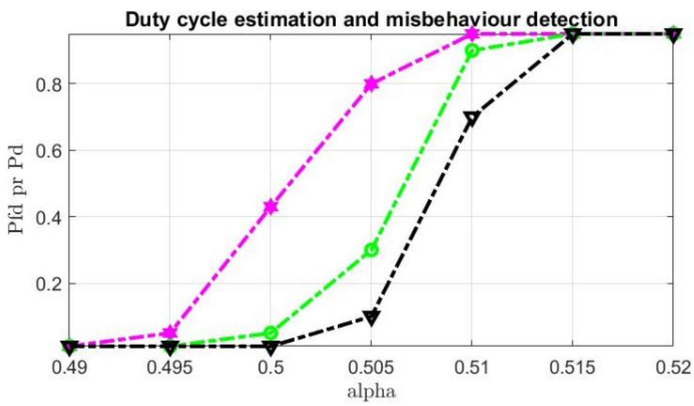

Fig. 8. Simulation results

this values we have calculated new duty cycles for LTE for the scheme proposed in article. This values were then used to plot new values of P_d and P_f and again simulation was done in NS3 simulator.

We consider a typical cycle period of 160ms , and set α_{max} to 0.5, L_{max} to 1100ms. The true α is varied from 0.49 and 0.52. For each value, the experiment is repeated 200 times. The new results obtained are shown in Fig.7 where gain is obtained for the case where $\gamma = 0$. It is evident from Fig.7. that using LSTM model for WI-FI signals and thereby calculating their duty cycles gain is obtained in comparison to the results mentioned in article

V. Conclusion

In this paper we have proposed deep learning based algorithm LSTM for the LTE system to allocate itself to unoccupied bands by learning the demand of WI-FI channels from observed WI-FI channel activity. Further this results were compared with a proposed duty cycle approach to detect possible misbehavior, and analyzed its performance in terms of detection and false alarm probabilities. Our results show that the proposed LSTM scheme have a higher detection probability and lower false alarm probabilities [1]. Hence LSTM model proves extremely efficient for time series data and long term dependencies. The way for fair co-existence of WIFI and LTE is an important issue of prospect research.

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