Spectrum Occupancy Predictions Using Deep Learning Algorithms

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ABSTRACT

The fixed spectrum allocation (FSA) policy causes a waste of valuable and limited natural resources because a significant portion of the spectrum allocated to users is unused. With the exponential growth of wireless devices and the continuous development of new technologies demanding more bandwidth, there is a significant spectrum shortage under current policies. Dynamic spectrum access (DSA) implemented in a cognitive radio network (CRN) is an emerging solution to meet the growing demand for spectrum that promises to improve spectrum utilization, enabling secondary users (SUs) to utilize unused spectrum allocated to primary users (PUs). This study has addressed all the limitations of the previous studies by implementing a comprehensive approach that encompasses reliable spectrum sensing, potential candidate spectrum band identification, long-term adaptive prediction modeling, and quantification of improvements achieved in the prediction model. The Long-Short Term Memory (LSTM) Deep Learning (DL) model was proposed as a solution for this study to address the challenge of capturing temporal dynamics in sequential inputs. The LSTM model leverages a gating mechanism to regulate information flow within the network, allowing it to learn and model long-term temporal dependencies effectively. The dataset used for this study was obtained from a real-world spectrum measurement by employing the Cyclostationary Feature Detection (CFD) approaches in the GSM900 mobile network uplink band, spanning a frequency range of 902.5 to 915 MHz over five consecutive days. The dataset comprises a total of 225,000 data points. The five-day spectrum measurement data analysis yielded an average spectrum utilization of 20.47 %. The proposed model predicted the spectrum occupancy state for 5 hours ahead in the future with an accuracy of 99.45 %, improved the spectrum utilization from 20.47 % to 98.28 % and reduced the sensing energy to 29.39 % compared to real-time sensing.

Keywords: Cognitive radio spectrum, Deep learning, Dynamic spectrum access, Spectrum occupancy.

1. INTRODUCTION

The Radio Frequency (RF) spectrum is considered a limited and valuable natural resource used for various wireless communication systems, encompassing voice radio, digital terrestrial television (DTT), mobile telephony, and mobile broadband (MBB) [1]. The RF spectrum spans a wide range of electromagnetic waves demonstrating a direct relationship with their wavelength. Lower frequencies can propagate over longer distances and exhibit superior penetration through building walls. This characteristic makes them well-suited for applications such as broadcasting in expansive geographic areas. On the other hand, higher frequencies offer advantages in microelectronic devices like cell phones due to their shorter wavelengths that enable the use of proportionally smaller antennas, allowing these devices to transmit larger volumes of data [2].

As wireless technologies continue to advance, effective allocation and access remain essential for sustaining the growth and reliability of wireless communication systems because they are limited resources that cannot be simultaneously used for different services due to interference. The demand for spectrum has increased dramatically due to the exponential growth of wireless devices and the continuous development of new bandwidth-hungry technologies. This has resulted in a spectrum scarcity, further increasing its commercial value. Spectrum stakeholders must, therefore, develop adaptable strategies to use the spectrum efficiently, meeting both current and future spectrum standards [1], [2], [3]. The current fixed spectrum allocation (FSA) policy is not addressing the growing demand for spectrum due to its rigid command-and-control approach, which assigns channels to a single user. This inefficient allocation can lead to the wastage of spectrum and a decrease in the quality of service. However, studies have shown that significant portions of the spectrum assigned to licensed users are unused, indicating the need for a more dynamic and responsive spectrum allocation policy [4], [5], [6].

Dynamic spectrum access (DSA) implemented in (CRNs) has emerged as a solution to improve spectrum utilization and reduce spectrum waste by allowing secondary users (SUs) to share unused portions with (PUs) [7]. CRNs comprise two types of users i.e., PUs and SUs, where PUs have a higher priority than SUs in accessing the channels. The SUs logically divides the channels allocated to the PUs into slots. Within each slot, the SUs has to sense the PU channel slot and accordingly access the slot when idle. The idle slots are called spectrum holes or white spaces [4]. This approach enhances spectrum utilization, accommodating the growing demand for wireless connectivity that enables more devices to be connected [8], [9]. Spectrum sharing requires knowledge of spectrum usage patterns, which can be obtained through spectrum sensing. However, real-time spectrum sensing is considered unreliable because of energy and time consumption. Spectrum occupancy state prediction is a technique that forecasts the future states of the spectrum proactively and estimates the effective bandwidth in the next slot allowing SUs to adjust their data rates in advance used to improve spectrum sensing. Therefore, SUs can conserve energy and time by avoiding the busy portions of the spectrum and focusing on idle portions during sensing [4], [7]. Spectrum occupancy state prediction which infers the future states of the spectrum channel, is a key enabler for shared spectrum access in the DSA model. Proactive spectrum prediction allows SUs to identify and access idle spectrum channels before they become busy [7], [10], [11]. SUs in CRNs search for idle spectrum channels to use temporarily. They are equipped with the cognitive ability to effectively implement the CR, which performs the following cycle of functions: Sensing: to observe and sample spectral channels, Decision: to allocate suitable spectral holes, Sharing: to contend access with other SUs, and Mobility: to evacuate the spectral hole when a PU is present [11]. CRs have distinct characteristics that distinguish them from traditional radio systems and Software-Defined Radios (SDRs). These distinctive characteristics are a cognitive capability that enables the identification of the occupancy state and usage patterns of the spectrum channels and reconfigurability which allows them to adjust their operating parameters dynamically [12], [13], [14]. CRNs are intelligent networks capable of autonomously learning and dynamically adapting to optimize spectrum, which is inherent in the adaptability of DL models that excel in learning complex patterns from data to make informed decisions. The integration of DL models into CRNs with the capacity to analyze vast amounts of data and enhance the awareness of CRNs about their operating environment holds significant potential in spectrum-sharing models. The DL models can adapt and learn from the changing spectrum state conditions, allowing CRNs to dynamically optimize their communication parameters, spectrum channels, and transmission scenarios. Therefore, the synergy presents a relationship where DL's learning capabilities empower CRNs with enhanced situational awareness for intelligent decision-making [15], [16].

A distributed spectrum management framework for mobile edge computing (MEC)-based Cognitive Radio Internet of Things (CR-IoT) networks was proposed to integrates edge computing that enhance real-time decision-making and reduce latency in spectrum allocation [17]. Using a game-theoretic and optimization-based approach, it enables efficient and autonomous spectrum sharing among IoT devices while minimizing interference. Simulation results demonstrate improved spectrum utilization, energy efficiency, and network throughput compared to traditional centralized spectrum management methods.

A joint resource allocation and user association framework was proposed for multi-cell Integrated Sensing and Communication (ISAC) dense networks [18]. Interference models for sensing and communication were established, and a utility-maximization problem was formulated under SINR and power constraints. A greedy genetic sub-band allocation, Hungarian-based user association, and SCA-based power control were used to solve the non-convex problem. Simulations showed notable improvements in network utility and detection probability while balancing sensing–communication trade-offs.

Recent studies on machine learning-based spectrum occupancy prediction focus on improving the efficiency of spectrum utilization in CRNs [19]. Techniques such as SVM, Artificial Neural Networks (ANN), CNN, Recurrent Neural network (RNN), and ensemble models have been widely applied to predict temporal and spatial spectrum usage patterns. Researchers emphasize that deep learning models outperform traditional statistical methods in capturing nonlinear and dynamic spectrum behaviors. However, challenges remain in data scarcity, real-time prediction, and generalization across frequency bands.

This study has achieved promising results in solving the limitations of previous studies. In general, the main contributions of this study are:

1. Defining the PU channel characterization in a new mode in a time-domain approach called CFD to characterize primary user states.
2. Identifying the potential candidate spectrum band for a CR deployment through proper spectrum utilization and techno-economic analysis.
3. Developing an improved long-term spectrum occupancy state prediction that can predict the spectrum occupancy state of how long it will be busy and idle, which allows the SUs to improve spectrum access, reduce channel-switching costs, and increase the CRN throughput.
4. Quantifying the improvements achieved in the spectrum occupancy state prediction model.

2. STATEMENT OF THE PROBLEM

In spectrum sensing, parametric approaches rely on prior information about (PU) activity, whereas in many real-world cases, such information is unavailable. Consequently, nonparametric sensing methods, particularly Energy Detection (ED), are widely used due to their low computational complexity and ease of implementation [20]. However, the wireless environment introduces issues such as fading and hidden node problems, causing an exponential decay of field strength during transmission. This makes threshold selection difficult at low signal-to-noise ratios (SNRs), rendering ED inefficient and interference-prone in Cognitive Radio (CR) systems [8], [9], [13]. In contrast, the parametric sensing approach known as (CFD) outperforms ED because it exploits the spectral correlation of cyclostationary signals—a property absent in noise. This allows CFD to operate effectively in low SNR regions, remain robust to noise uncertainty, and deliver superior performance when prior information about the PU signal is available [13], [14].

Traditional statistical models such as Autoregressive Integrated Moving Average (ARIMA), Hidden Markov Model (HMM) and Markov Chains and machine learning algorithms assume spectrum occupancy states as stationary processes, implying that they remain constant over time and are suitable for short-term predictions [6], [21]. ANNs are less effective for modeling temporal data due to the absence of memory elements. RNNs have been employed for such tasks; however, they face challenges, such as the vanishing gradient problem, hindering their ability to capture long-term dependencies [7], [20]. LSTM neural networks have been introduced to address the vanishing problem. LSTMs overcome the vanishing gradient problem by incorporating memory cells, allowing them to retain information over extended periods. This feature is particularly advantageous for modeling temporal data, such as spectrum occupancy [15], [20], [21]. Long-term spectrum occupancy state prediction plays a crucial role in anticipating the channel idle period duration, which reduces channel switching costs and enhances channel selection in CRNs.

3. SYSTEM MODEL

The heterogeneous spectrum occupancy state model was used to implement a CRN for spectrum sharing in a DSA model [15]. The spectrum band has been divided into k contiguous channels. The channel states represent the spectrum channel state at time t and are denoted by a vector matrix. Each element in the matrix represents the corresponding channel is occupied or idle which is ready to be used by the SUs [22]. A heterogeneous spectrum occupancy state model has multiple PUs and SUs, which are centrally controlled by a database that identifies the spectrum occupancy states based on prediction [4]. This study has proposed a long-term spectrum occupancy state prediction model in a stationary location by exploiting the spectral and temporal correlation of the data. The occupancy of a channel is characterized by the presence of a primary user signal, while the presence of a spectrum hole characterizes the vacancy of a channel. These cases are formally stated as hypotheses (H0) and (H1).

$H_0: y[t] = w[t]$ when there is no PU

$H_1: y[t] = h[t]x[t] + w[t]$ when PU's signal is present (1)

where x[t] denotes the PU signal, w[t] is white noise and y[t] is the received signal at t^{th} time instant. H_0, the null hypothesis indicates the noise samples while H_1, the alternate hypothesis indicates the presence of PU signal along with noise t^{th} instant [6], [8], [12].

Figure 1 Spectrum channels occupancy state modeling

For the sequentially obtained time-series spectrum occupancy measurement data X_1, X_2, X_3, X_4,..., the long-term spectrum channel state prediction using the deep learning model can be done within the sequence-to-sequence neural network architecture based on the LSTM deep learning model is defined as (X_{t-n},...., X_{t-2},

$X_{t-1})$ to $(X_t, X_{t+1}, \ldots, X_{t+m})$ where *n* and *m* represents the historical observations and the future instants in time, respectively [23].

3.1 Time-Series Model Analysis

Time series data is composed of sequence data points measured over regular intervals. Time series models are designed to comprehend the patterns and trends inherent in the data that can feat the natural temporal ordering. This shows that observations closer in time are more similar than further apart observations because values in a time series data at a given time were derived from past values. Time series analysis is a methodology used to study time series data that identifies relationships and makes predictions of future values [24]. Time series data analysis begins by identifying whether the data is stationary or non-stationary. A stationary time series has consistent statistical properties, including mean, variance, and autocorrelation. This stability implies that the underlying data-generating process is predictable and stable. On the contrary, non-stationary time series data displays varying statistical properties over time, often influenced by trends, seasonality, or other non-random fluctuations. Time series prediction is a technique that estimates future values based on historical data. In spectrum occupancy state prediction, the objective is to forecast the spectrum occupancy state at the next time point [24], [25].

Time series data should be selected carefully, considering the different variations that can occur at different timescales. For example, a day can have four seasons (morning, afternoon, evening, and night), while a week can have only two (weekday and weekend). The spectrum occupancy data can vary significantly depending on the time of day, day of the week, and peak or trough times. Therefore, representative data must be chosen for the specific period and timescale of interest [26].

3.2 Privacy Concerns of Urban Spectrum Sensing

Urban spectrum sensing involves the collection and analysis of spectrum usage data from multiple SUs distributed across densely populated areas. While such collaborative or crowdsourced sensing improves the accuracy of spectrum occupancy prediction and the efficiency of spectrum utilization, it also introduces significant privacy concerns [27]. These arise primarily from the collection of user-related information that may inadvertently reveal sensitive details about a user's location, behavior, and communication patterns [27], [28].

Sources of Privacy Risks

i) **Location Disclosure:** Spectrum sensing data often includes information about the spatial position of participating SUs. Since sensing reports are typically associated with the geographical coordinates of the sensors, malicious entities or untrusted fusion centers can infer the exact location or movement patterns of users [29].

ii) **Activity Inference:** The frequency and timing of sensing reports can reveal user activities or communication habits. For example, consistent sensing from a specific location or time interval can indicate when a user is active, which networks they are connected to, or even which applications are being used [27].

iii) **Data Correlation and Identification:** Aggregated sensing data from multiple users may be correlated to re-identify individuals even when identifiers are removed. Advanced data mining or machine learning techniques can exploit these correlations to infer private user attributes [30].

iv) **Malicious Data Collection:** In cooperative sensing scenarios, untrusted or compromised nodes can collect data not only for spectrum purposes but also for unauthorized surveillance**,** traffic analysis**,** or profiling [28], [31].

Privacy Preservation Mechanisms

To mitigate these risks, several privacy-preserving spectrums sensing schemes have been proposed. These mechanisms aim to balance data utility with user confidentiality, ensuring that accurate spectrum decisions can still be made without compromising user privacy.

i) **Data Anonymization:** This technique removes or obscures identifiable information before transmitting sensing data to the fusion center. However, anonymization alone is often insufficient, as de-anonymization attacks can exploit contextual data [32].

ii) **Differential Privacy:** Differential privacy adds controlled random noise to sensing data, preventing adversaries from accurately inferring individual user contributions. It provides quantifiable privacy guarantees while maintaining statistical data utility [33].

iii) **Cryptographic Techniques: Homomorphic encryption** allows users to encrypt their sensing data so that the fusion center can perform computations without accessing the raw data, and secure **multiparty computation (SMC)** enables distributed users to collaboratively compute spectrum availability without revealing their individual inputs [28], [32].

iv) **Decentralized and Edge-Based Sensing:** Instead of central data aggregation, edge computing approaches process data locally on user devices or local base stations, transmitting only aggregated or decision-level information. This significantly reduces the exposure of raw sensing data [30], [32].

3.3 Proposed Deep Learning LSTM Architecture

The proposed model can accurately predict the spectrum occupancy state for the next time slot and several time slots ahead, implemented to facilitate a DSA. This model enables users to access spectrum channels that are not used by PUs, enhancing overall spectrum utilization efficiency. (Figure 2).

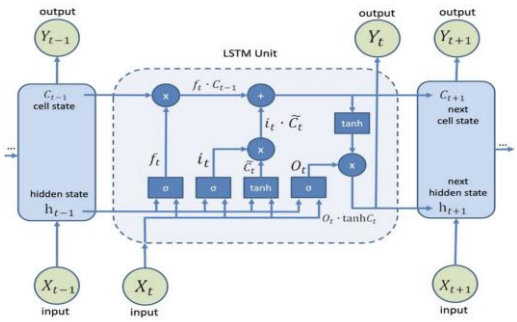

Figure 2 Basic Architecture of the LSTM model

The LSTM model used for long-term spectrum occupancy state prediction targets specific frequencies or channels, using known binary values for state estimation. Input and output data are constructed via a sliding window across both time and frequency axes, forming a 2D matrix where each element represents a time–frequency point with its binary state. This matrix constitutes the training dataset. During validation, the model demonstrates real-time prediction capability, using past spectrum measurements over time and frequency lags to predict the next state. The binary grid input yields corresponding binary outputs for the subsequent instant [34]. Unlike conventional RNNs, which struggle with long-range dependencies due to the vanishing gradient problem, LSTMs effectively model such temporal dynamics. LSTM networks address the problem of long-term dependency by introducing a gating mechanism that regulates the flow of information within the network. The mechanism consists of three gates the input**,** forget, and output gates and a cell memory used to retain information over long periods [7], [15].

1) **Input gate:** Controls how much new information is added to the LSTM's memory state.

2) **Forget gate:** Determines how much previous information is discarded.

3) **Output gate:** Regulates how much of the cell memory is passed to the next hidden state. The gates are mathematically formulated as:

$$i_t = \sigma\left(W_{ix}X_t + W_{ih}h_{t-1} + W_{ic}c_{t-1} + b_i\right)$$

$$f_t = \sigma\left(W_{fx}X_t + W_{fh}h_{t-1} + W_{fc}c_{t-1} + b_f\right)$$

$$c_t = f_t \circ c_{t-1} + i_t \circ \varphi\left(W_{cx}X_t + W_{ch}h_{t-1} + b_c\right)$$

$$o_t = \sigma\left(W_{ox}X_t + W_{oh}h_{t-1} + W_{oc}c_t + b_0\right)$$

$$h_t = o_t \circ \varphi\left(c_t\right) \tag{2}$$

Where i, f, o, and c denote the input gate, forget gate, output gate, and cell state, respectively. Each gate has the same dimension as the hidden vector h (N ×1). Here σ is a sigmoid function, and φ is a nonlinear function mapping to the range [-1, 1]. W_{ic}, W_{fc}, and W_{oc} are the peephole connection matrices linking the cell state to their respective gates, while W_{ix}, W_{fx}, Wox, and W_{cx} are input weight matrices connecting the input vector X_t (M × 1) to the gates and cell state. Because of the gates and the input vector X_t have the dimensions of N ×1 and M × 1 respectively. The matrices W_{ih}, W_{ic}, W_{fh}, W_{ch}, W_{oh}, W_{oc} are all of dimensions N × N, and W_{ix}, W_{fx}, W_{cx} and W_{ox} are of dimensions N × M.

4. RESULTS AND DISCUSSION

4.1 Data Description

The data used for this study was collected from a real-world spectrum measurement in Addis Ababa, Ethiopia using the TCI spectrum monitoring system in the GSM900 MHz mobile network uplink band spanning from 902.5 to 915 MHz for five consecutive days from January 28th to February 1st, 2021. The area of Bole was selected for the measurement because it is a commercial area that expects to have a high spectrum demand [35]. The data set comprised a total of 450,000 data points, captured with a resolution bandwidth of 100 kHz with 4 minutes resolution time. The GSM900 MHz uplink band was selected for this study to deploy a CR due to its underutilization from the sparse use of its users communicating on the network making it a promising potential candidate for a CR deployment [36], [37].The dataset contains features including Channel, Frequency, Maximum occupancy (%), Average occupancy (%), Maximum field strength, and Average field strength. However, all these features were not used for modeling spectrum occupancy due to their inability to capture unique information and their potential negative impact on the model's generalization. To address this issue, a feature reduction technique was employed to reduce the number of input variables, thus preventing excessive model complexity while preserving its ability to generalize effectively. In this study, a filter-based feature selection approach was utilized, which relies on statistical measures such as information gain, to identify features that contribute the most information about the target variable which exclusively considers the association between each feature and the class label [38]. Following the feature reduction process, the selected features for predicting spectrum occupancy state comprised frequency, average occupancy, and average field strength.

The spectrum measurement campaign that was conducted in the GSM900 MHz mobile network uplink band at four different regional cities in October 2021 has an average utilization of 21.45 % in Adama, 16.21 % in Bahir Dar, 18.87 % in

Hawassa, and 33.52 % in Jigjiga. Additionally, within Ethio-telecom's mobile network uplink bands in Addis Ababa, utilization was found to be 14.72 % in GSM 900MHz, 31.67 % in UMTS 900MHz, 25.32 % in LTE 1800MHz, and 6.75 % in LTE 2600MHz. The analysis indicates the underutilization of the spectrum. Even though all of the spectrum bands are underutilized, subscribers would migrate from 2G to 3G, 4G, and 5G to get the advanced technology features and services from these new-generation mobile networks because the 900MHz GSM offers only voice and short message services (SMS) [39]. For this reason, there is no need of considering 3G, 4G/LTE and 5G networks in our work.

The spectrum utilization analysis conducted in five days revealed distinct values for weekdays (Thursday, Friday, and Monday) and weekends (Saturday and Sunday). Specifically, the average spectrum utilization on weekdays was 19.13 %, 19.03 %, and 21.14 %, respectively. In contrast, the average spectrum utilization on weekends exhibits a variation, with values of 17.3 % on Saturday and a higher utilization rate of 25.76 % on Sunday.

The CFD-based spectrum sensing method was used in this study for defining PU channel characterization and modeling spectrum occupancy prediction due to its enhanced performance in challenging SNR conditions. In a five-day spectrum measurement campaign conducted using the CFD spectrum sensing method, the average spectrum utilization for the GSM 900 MHz uplink band was 20.47 %.

4.2 Results

This study utilizes data obtained via the CFD-based spectrum sensing method to develop the spectrum occupancy state prediction model. The dataset encompasses 225,000 data points, representing half of the five-day measurement dataset. Subsequently, this dataset is divided into training and validation sets, maintaining an 80 % to 20 % ratio, we should notice that this is done to minimize the risk of overstated generalizability. The spectrum occupancy state prediction model was implemented using Python programming with the Keras library. The model's configuration was evaluated based on metrics such as the loss function and accuracy (Figure 3). Throughout the training process, various hyperparameter combinations were explored to identify the most effective model that has the lowest loss and the highest accuracy. Finally, the model architecture comprises three LSTM layers with 128 units, followed by two dropout layers with a dropout rate set at 0.1. Additionally, two dense layers with 128 and 64 units, were incorporated, along with a final output layer. The model was configured with an activation function of rectified linear unit (ReLU) for all hidden layers and sigmoid for the output layer, adaptive moment estimation (ADAM) as an optimizer, binary cross-entropy as a loss function, 0.001 learning rate, 128 batch size, and 400 Epochs. Three sets of experiments designed to predict short-term and long-term (ranging from three to five hours) predictions conducted on the proposed LSTM model have exhibited consistent results across all performance evaluation metrics with an accuracy of 99.45 %.

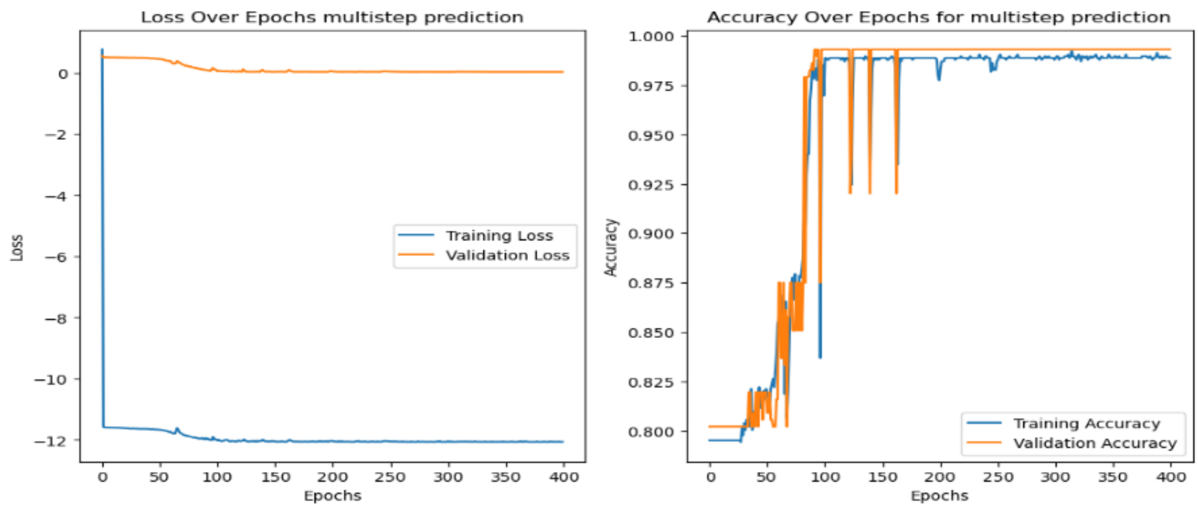

Figure 3 Training and validation, loss and accuracy for the LSTM model for 5-hours ahead prediction

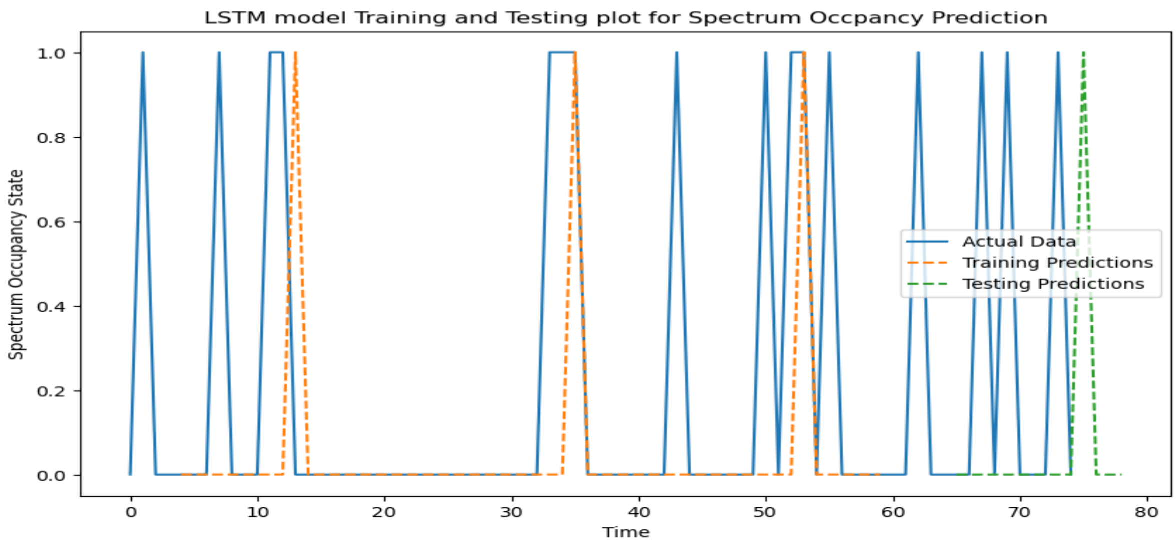

Figure 4 Spectrum occupancy state prediction in LSTM for the 904.1MHZ channel

Figure 4 compares the spectrum occupancy state actual data, training, and testing prediction performed for the 904.1MHZ channel. The LSTM network is trained to adapt new spectrum occupancy states, as shown in Figure 4, using the five-day spectrum measurement data for a one-channel 904.1MHz. In the graph, the brown dotted line representing the training data and the green dotted line representing the testing data closely match the actual observations depicted by the blue solid line. The test performance indicates an accuracy of 96 %.

A comparative analysis conducted on LSTM, Bi-LSTM, and ConvLSTM models for both short-term and long-term prediction revealed that LSTM and Bi-LSTM achieved equal results, with an accuracy of 99.45 %. In contrast, the ConvLSTM model outperforms them, achieving an accuracy of 99.72 %. Across all three models, each term of prediction has equal performance results. However, the short-term prediction achieved its targeted accuracy earlier than the long-term 3-hour and 5-hour predictions. The 3-hour long-term prediction achieved its targeted accuracy earlier than the 5-hour long-term prediction.

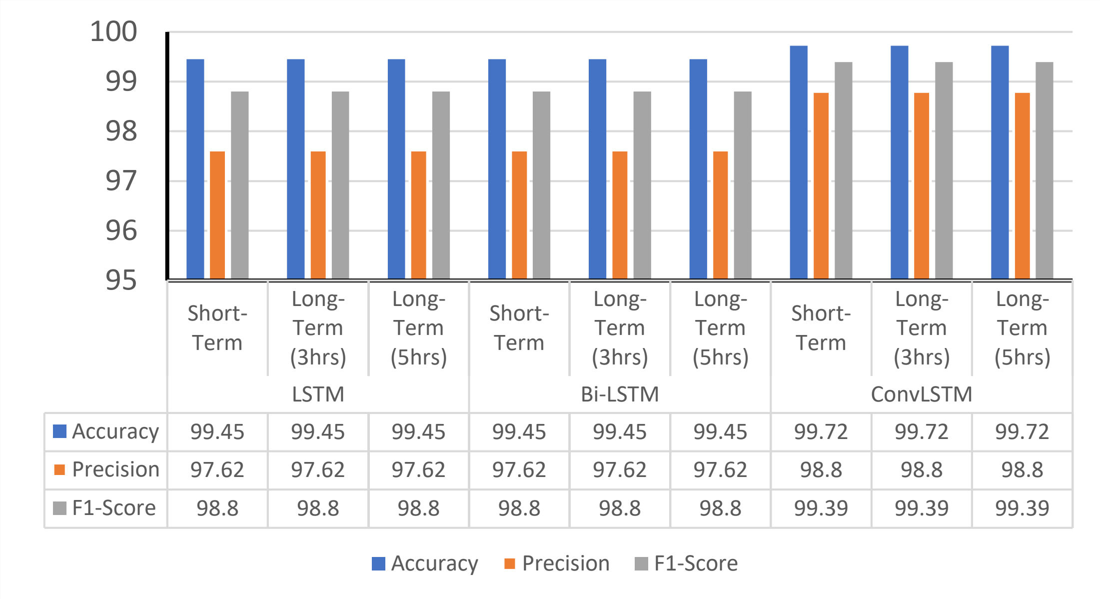

Figure 5 Comparison of models in Accuracy, Precision, and F1-Score

The Bi-LSTM model differs from the others by achieving its targeted accuracy earlier across all prediction scenarios. This may be attributed to its ability to process data in both forward and backward directions, potentially improving its ability to learn temporal relationships. Consequently, short-term predictions tend to achieve better accuracy earlier than long-term predictions. This tendency may arise from factors such as predicting the immediate future requires fewer data points and simpler relationships, and the available data for training the model can be enough for short-term prediction than for long-term prediction.

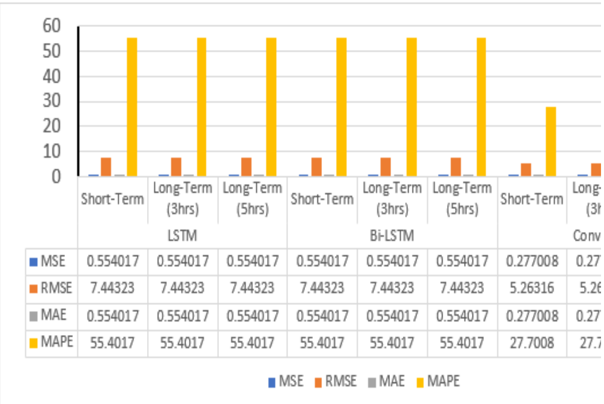

Figure 6 Comparison of models in MSE, RMSE, MAE, and MAPE

4.3 Discussions

Long-term spectrum occupancy state prediction using the LSTM model to implement a CR has improved spectrum utilization and reduced sensing energy.

Improvement in Spectrum Utilization

Spectrum occupancy state prediction can improve spectrum utilization by allowing SUs to select and use idle PU channels with appropriate time slots. This allows the SUs to select spectrum channels efficiently to reduce channel-switching costs and increase network throughput. In a CRN the PUs has two states, but the SU can sense only one channel at a time. The CRN has two types of SUs which are the CRsense and the CRpredict. The CRsense randomly selects a channel at every slot and senses the states of the channels, while the CRpredict device senses the states of the channels after prediction among those channels with an idle state. According to [4] spectrum utilization (SU) in the CRN can be defined as the ratio of the number of idle slots discovered by the SUs to the total number of idle slots available in the CRN.

$$SU = \frac{\text{Number of idle slots sensed}}{\text{Total number of idle slots in the band}} \quad (3)$$

The improvement in spectrum utilization due to spectrum prediction can be expressed as

$$SU_{imp(\%)} = \frac{SU_{sense}-SU_{predict}}{SU_{sense}} \quad (4)$$

Where SU_{sense} and $SU_{predict}$ represent the spectrum utilization for the CR_{sense} and the $CR_{predict}$ devices, respectively. Substituting (3) in (4), $SU_{imp(\%)}$ can be given by

$$SU_{imp(\%)} = \frac{I_{sense}-I_{predict}}{I_{sense}} \quad (5)$$

Where I_{sense} and $I_{predict}$ represent the number of idle channels sensed by the CR_{sense} and the number of idle channels predicted by the $CR_{predict}$ devices respectively. This analysis can be translated into a machine learning model and becomes equal with the specificity that measures the true negative rate, which is the fraction of negative values that were correctly predicted that can be calculated as expressed in (6).

$$SU_{imp(\%)} = Specifcity = \frac{TN}{TN+FP} \quad (6)$$

The $SU_{imp\ (\%)}$ in a CRN also improves the network throughput which shows the data rate achieved in the network due to the availability of more channels and can be calculated as expressed in (7).

Throughput = $SU_{imp(\%)}$* the number of channels in the spectrum band (7)

Reduction in Sensing Energy

The spectrum occupancy state prediction reduces the sensing energy required by the SUs. This is because the SUs in a CRN can sense only the idle channels. In a CRN the CR_{sense} device senses all the channels whereas the $CR_{predict}$ device only senses the channel that is predicted idle.

In other words, when the channel state is predicted to be busy, the sensing operation is not performed to reduce energy. Considering that one unit of sensing energy is required to sense one slot, the total sensing energy required for a CR_{sense} device in a finite duration of time can be calculated as expressed in (8).

$$SE_{sense} = \begin{pmatrix}\text{Toatal number}\\ \text{of slots}\\ \text{in the duration}\end{pmatrix} \times \begin{pmatrix}\text{unit sensing}\\ \text{energy}\end{pmatrix} \quad (8)$$

while the total sensing energy required by the $CR_{predict}$ device can be given by

$$\mathrm{SE_{predict}} = \left(\mathrm{SE_{sense}} - \left(\mathrm{B_{preidct}}\right)\right) * \ (\text{Unit sensing energy}) \quad (9)$$

Where $B_{preidct}$ is the total number of busy slots predicted by the $CR_{predict}$ device.

Therefore, using (8) and (9), the percentage reduction in the sensing energy can be given by

$$SE_{red(\%)} = \frac{SE_{sense} - SE_{predict}}{SE_{sense}} = \frac{B_{predict}}{Total\ no.of\ idle\ slots} \quad (10)$$

This can be translated to a machine learning model that measures a value by dividing the true positive value by the true negative plus the false positive values, even it doesn't have an equivalent machine learning metric it can be calculated and expressed as shown in (11).

It should be noted that Equation (11) is derived from analytical formulations reported in the literature. This study extends these formulations by quantifying sensing energy reduction using machine learning metrics. The resulting expression links the analytical energy model to classification outcomes—true positives (TP), true negatives (TN), and false positives (FP). While conceptually similar to standard ML metrics, it is **not** equivalent to precision or recall. Accordingly, we define this parameter as representing the proportion of sensing energy saved through accurate spectrum state prediction.

$$SE_{red(\%)} = \frac{TP}{TN+FP} \tag{11}$$

The $SU_{imp\,(\%)}$, the network throughput, and the $SE_{red\,(\%)}$ across all models for all terms of predictions calculated based on (6), (7), and (11) are presented in Table 1.

Table 1 Quantified improvements achieved in the spectrum occupancy state prediction

Model	Length of Prediction	$SU_{imp(\%)}$	Throughput	$SE_{red(\%)}$
LSTM	Short-Term	99.28	124.1	29.39
	Long-Term (3 hrs.)	99.28	124.1*45	29.39
	Long-Term (5 hrs.)	99.28	124.1*75	29.39
Bi- LSTM	Short-Term	99.28	124.1	29.39
	Long-Term (3 hrs.)	99.28	124.1*45	29.39
	Long-Term (5 hrs.)	99.28	124.1*75	29.39
Conv-LSTM	Short-Term	99.64	124.55	29.39
	Long-Term (3 hrs.)	99.64	124.55*45	29.39
	Long-Term (5 hrs.)	99.64	124.55*75	29.39

5. CONCLUSION AND FUTURE WORK

This study addresses the challenges posed by the rigidity of FSA policies. It paves the way for more effective and efficient spectrum utilization that optimizes scarce spectrum resources by predicting the spectrum occupancy state using a long-term adaptive LSTM model and a historical dataset obtained through a reliable spectrum sensing method. The proposed model has successfully predicted the spectrum occupancy state for the subsequent five hours with an accuracy of 99.45 % improved the spectrum utilization from 20.47 % to 98.28 % and reduced the sensing energy to 29.39 % compared to real-time sensing. Future studies can focus on enhancing the predictability of further occupancy lengths up to days for integrating CRN with the Internet of Things, which creates a synergistic system known as the (CRIoT). This integrated IoT and CR approach amplifies smart cities' capability, providing a comprehensive and interconnected infrastructure for effective and efficient urban management.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest in this work.

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