A LEVENBERG-MARQUARDT BASED NEURAL NETWORK SPECTRUM OCCUPANCY PREDICTION FOR UHF (470-670) MHz BAND SERVICES IN OSOGBO METROPOLIS

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Abstract: A study on the Levenberg-Marquardt Neural Network model *was aimed at predicting UHF band services spectrum occupancy in the Osogbo metropolis, Nigeria. Four locations were used: Firestation, Uniosun campus, National Control Centre (NCC), and Fountain University campus. Energy detection was used for data capture and analysis. The prediction metrics included Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). Parametric values considered included channel vacancy duration versus time, Power Spectral density versus time, Channel vacancy duration versus frequency, Power spectral density versus frequency, power spectral density versus channel vacancy duration (Time Domain), and power spectral density versus channel vacancy duration (Frequency Domain). The highest RMSE and MAPE recorded were 39.94 and 28.59 %, respectively, for Fountain University, while the lowest RMSE and MAPE were 0.269 and 0.09 %, respectively, for UNIOSUN. The fire station and National Control Centre locations had 0 RMSE and 0 % MAPE, which were the most accurate predictions of all parametric values.*

1. INTRODUCTION

The Levenberg-Marquardt back-propagation algorithm optimizes the model, producing solutions with comparable statistics. The LM-based ANN model performs significantly better in accuracy and has the lowest error rates compared to previous research. Some research uses an Artificial Neural Network (ANN) based on Levenberg-Marquardt (LM) to anticipate short-term electrical load for smart grids accurately. The model considers meteorological factors and historical load data divided into winter and summer seasons and divides the data for each season between workdays and weekends. Historical load data spanning three years estimates load demand for the next week and day.
Electric load datasets from the USA Power Industry were gathered between 2019 and 2021 to train the model. However, there is still room for parameter optimization to increase computation efficiency [1].

Based on the Levenberg-Marquardt Back-Propagation (LMBP) Algorithm, the feed-forward neural network forecasts electrical load in Jammu. However, the data gathered needs to accurately represent the demand due to the greater demand in Jammu than the supply. Regularly scheduled power outages are necessary to meet the need, but the supply has historically lagged behind demand due to factors like time, weather, and past load on power availability [2].

Continuous spectrum measuring requires a significant time investment in addition to financial hardship which spurred the use of prediction methods and algorithms to spectrum data. By using historical spectrum measurements, spectrum prediction predicts future channel states, such as whether they will be occupied or vacant. There are benefits to using spectrum prediction tools for spectrum management, the estimate of available channels is expected to have a low probability of mistakes; there is a higher bandwidth utilization. Also, the data rates can be adjusted considering the available bandwidth, as it is possible to forecast the bandwidth for the upcoming time frame [3].

2. LITERATURE REVIEW ON NEURAL NETWORK BASED PREDICTION

In [3], it was emphasized that constant spectrum sensing is necessary for an effective use of the available spectrum, yet it is expensive. A solution to continuous spectrum sensing has been suggested: spectrum prediction. In theory, spectrum prediction predicts the future status of the channel by using historical spectrum measurements. The prediction of spectrum occupancy for a 925–960 MHz link in a particular site in Ilorin, Nigeria, was investigated in the research work using Artificial Neural Networks (ANN). Various sample partitions were investigated. With regard to the anticipated power spectral densities based on frequency points and time instances, the sample produced the best Mean Square Error of 3.9090 and MSE of 0.0025, respectively.

In [4], research was carried out on "A Neural Network Based Spectrum Prediction Scheme for Cognitive Radio", and it was revealed that Cognitive Radio (CR) technology enables the coexistence of unlicensed and licensed users in spectrum usage. However, unlicensed users rely on spectrum sensing, which consumes energy. Predictive approaches can reduce this by identifying spectrum gaps. A reliable prediction technique helps unlicensed users identify inactive channels. A neural network model, specifically the multilayer perceptron (MLP), was used to develop a spectrum predictor. The model's performance was evaluated through extensive simulations. Channel status prediction in CR networks can significantly decrease energy consumption during sensing operations and enhance spectrum use.

In [5], the investigation was carried out on “Learning and Adaptation in Cognitive Radio Using Neural Networks” The study focuses on optimizing cognitive radios by accurately estimating transmission performance under specific environmental conditions and setup factors. Multilayered feed-forward neural networks (MFNNs) are used to assess communication efficacy in real time. Experiments show the versatility of MFNNs in various applications and situations, maintaining high modelling accuracy. The study demonstrated the use of MFNNs for optimizing CR configurations in a practical 802.11 devices for evaluation context. Future research should explore the application of MFNN techniques to various protocols and scenarios, as well as implementing the system on commercial

In [6], the investigation was carried out on ‘’A New Approach to Signal Classification Using Spectral Correlation and Neural Networks” The integration of channel sensing and spectrum allocation into wireless communications systems in license-free bands has been a long-standing goal. Traditional cyclic spectrum analysis techniques are used for signal classification when carrier frequency and bandwidths are unknown, but they pose computational challenges and require extensive observation time. Neural networks are used when the baseband signal is present. The study re-examined signal categorization using neural networks and spectral coherence, evaluating its efficacy through Monte Carlo simulations. Cyclic spectrum analysis was applied to extract distinct characteristics from each signal type, and a neural network was developed to classify signals according to these attributes. Future attempts should focus on other signal types, higher-order QAM and PSK, and incorporate higher-order spectral analysis for feature extraction.

In [7], another research on “Comparative Analysis of Artificial Neural Network (ANN) Techniques for Predicting Channel Frequencies in Cognitive Radio” analyzes the increasing demand for bandwidth in cellular and wireless bands that necessitates optimal spectrum usage. Cognitive radio can help by sharing licensed user bands with unlicensed users. Machine learning methods evaluate the availability of unoccupied channels and license user bands based on factors like power, bandwidth, and antenna characteristics. A neural network was implemented to improve resource allocation decisions for secondary users in specific frequency bands. Feed-forward networks showed superior performance compared to radial basis networks and Elman networks. Implementing this technology enhances service quality, minimizes interference, and increases the reliability of the Cognitive radio system. ANN exhibit the highest predictive accuracy in cognitive contexts.

In [8], the investigation was carried out on "Neural Network-Based Learning Schemes for Cognitive Radio Systems" it was analyzed that cognitive radio systems are intelligent software modules that manage and allocate restricted radio spectrum in various scenarios. They participate in a cognitive cycle that involves modifying operational parameters, monitoring outcomes, and implementing appropriate actions. A study introduces learning methods based on artificial neural networks (NNs) that can predict the capabilities of a specific radio configuration. Two NN-based learning approaches are built and analyzed: "basic" and "extended." The primary objective is to establish a comprehensive framework for developing and implementing these learning schemes in cognitive radio-based systems. The study emphasizes the importance of integrating further data into the learning process to enhance the accuracy and resilience of the neural network-based method. The learning process involves the ongoing adjustment of the neural network's free parameters in response to external inputs.

3. METHOD

The following four locations within Osogbo metropolis in Nigeria were the subject of a measurement campaign for the spectrum occupancy: the Fire station (longitude 7.8545°N, latitude 4.5457°E), Fountain University campus (longitude 7.7437°N, latitude 4.5460°E), National Control Centre (longitude 7.8026°N, latitude 4.5786°E), and Uniosun campus (longitude 7.7616°N, latitude 4.6012°E). The band spectrum is (470-670) MHz band, which gives a bandwidth of 200 MHz for frequency of operation. The data collected was analyzed using Microsoft Excel.

3.1 Specification of the Measuring Equipment

A spectrum analyzer is a piece of equipment used for the measurement setup, and it has to be able to identify any signal inside the specified frequency range, no matter how strong. The experimental setup includes an Android-based global positioning system (GPS) to record all coordinates of selected locations within Osogbo metropolis, as well as a field strength analyzer with variable parameters (BK PRECISION 2640 with 500ms sweep time, 50 input impedance, variable resolution bandwidth, 3.125Hz resolution, maximum accuracy of 3ppm and minimum accuracy of 1.5 ppm and 0.1GHz -2.0 GHz frequency range).

3.2 Equations Analysis

CVDs are deduced based on Equation (1)

$$CVD_l = t_s(1 - U_m) \quad (1)$$

t_s =Duration of spectral observation
U_m = the observed duty cycle of the m^{th} spectrum segment
CVD_l = Channel Vacancy Duration of the l^{th} spectrum segment
Equations (2) – (7) are modifications from [9] and [10],

$$U_k = \sum_{l=m=1}^{n} Z_l \, W_{lm} + b \quad (2)$$

b= the bias offset for the activation function

U_k= the output from the hidden layer that was fed as the input to the activation function;

U_k= the weight for the connection from the input layer $l \in n$ to the hidden layer $m \in n$;

$$F_{CVD_k}(f) = \frac{1}{1 + e^{-u_k(f)}} \quad (3)$$

The residuals or error signals

$$e_k = A_{CVD_k} - F_{CVD_k} \quad (4)$$

Where, $A_{CVD_k} =$ The actual channel vacancy duration and
$F_{CVD_k} =$ The Forecasted channel vacancy duration
In order to train (update) the weights link between the hidden layer k and the output layer of each iteration, the error signal e_k is transferred from the output layer k to the hidden layer of Equation (5) ;

$$W_{lk}(f+1) = W_{lk}(f) + \Delta W_{lk}(f) \quad (5)$$

Where, $\Delta W_{lk}(f)$ *is* the weight correction parameter deduced from Equation (6);

$$\Delta W_{mk}(f) = \beta F_{CVD_k}(f)\partial_k(f) \quad (6)$$

Where $\beta =$the learning rate and $\partial_k(f)$ = the gradient error in neuron k deduced from Equation (7)

$$\partial_k(f) = F_{CVD_k}(f)\left(1 - F_{CVD_k}(f)\right)e_k \quad (7)$$

new ones and the expression for the LM algorithm is given in eqn. (8) after modification of [11] and [12].
update (small values of λ) and the Gauss-Newton update (large values of λ).

$$[HW = \lambda diad(HW)]\partial_k(f) = J^T W(e_k) \quad (8)$$

H= The Hessian matrix of the weights, given as $J^T J$
$J^T =$ The transpose of Jacobian matrix; W= The weight matrix; $\lambda =$ The damping parameter that adaptively updates between the gradient descent.

The root mean square errors (RMSE) in each band is noted as indicated in equation (9):

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(A_{CVD_k} - F_{CVD_k})^2} \quad (9)$$

$$for\ k = 1,2,3 \ldots\ldots\ldots\ldots n$$

The Levenberg-Marquardt (LM) algorithm is used in training and adjustment of the weights and getting
Where A_{CVD_k} and F_{CVD_k} are the actual target and forecasted targets, the mean absolute percentage error (MAPE) in each band is computed as indicated in Equation 10.

$$MAPE = \frac{1}{n}\sum_{k=1}^{n}\frac{|A_{CVD_k} - F_{CVD_k}|}{A_{CVD_k}} \quad (10)$$

Table 1 shows the LM-ANN model architecture prediction algorithms for the LM-ANN spectrum occupancy for parameters used while Table 2 shows the UHF (470-670) MHz Band Services within Osogbo Metropolis.

Table1:LM-ANN Model Architecture Parameter

Parameter	***Value***
No of layers	*3(Input layer, hidden layer, output layer)*
Hidden layer neurons	*100*
Input layer neurons	*3*
Output layer neurons	*1*
Activation function	*Sigmoid function*
Training Algorithm	*Levenberg-Marquardt(LM)Back-Propagation*
No of epochs	*1000 (default)*
LM learning rate	*0.05*
LM Batch sizes	*16-256*
LM Decay rate	*0.98*
LM Number of units in the dense layer	*5*
LM Dropout	*15%*

Table 2: The Proposed algorithm for a Levenberg-Marquardt Based Neural Network Spectrum Occupancy prediction for UHF (470-670) MHz Band Services in Osogbo Metropolis

1. Implement Data Capturing of the band with BK precision2640 spectrum analyzer
2. Carry out spectrum sensing with energy detection approach and deduce power spectrum densities
   $P(t_i, f_j)$ over a period of 48 hours
3. Analyze the data with Excel sheet application into matrix form $Z = \begin{Bmatrix} P(t_1 f_i) & P(t_1 f_j) \\ P(t_1 f_i) & P(t_1 f_j) \end{Bmatrix}$
4. Create a decision threshold $\lambda_{TH} = \eta Z(f) + p_i$ And apply the hypothesis rule for each entry in 3:

$$I_{ED}(t_i f_j) = \begin{cases} 0, if P(t_{i,} fj) < \lambda_{TH} \\ 1, if P(t_{i,} fj) \geq \lambda_{TH} \end{cases}$$

5. Evaluate the average spectrum duty cycle and acquire spatio-temporal variations of duty cycle across all the four locations within specified period of 48 hours and within the specified band limit

   for each link using $\Delta(loc, t, f) = \frac{1}{N_{time} N_{freq}} \sum_{i=1}^{N_{time}} \sum_{j=1}^{N_{freq}} I_{ED}\left(t_i, f_j\right)$
6. From 5, deduce the Channel Vacancy Durations (CVD) according to $CVD_l = t_s(1-\mu_m)$
7. Initialize ANN-LM algorithm to obtain the predicted CVDs
8. Implement time series data set from 3-6 to generate training, test and validation set
9. Choose the best set of LM parameters for the model
10. Train, test and validate ANN-LM model of Equations (1-8)
11. Set up a threshold for the channel vacancy duration CVD_{THR}
12. From 10, is the model optimized from $CVD_l \geq CVD_{THR}$, move to 13, if not go back to 8 for rework.
13. Evaluate using the model to determine the RMSE and MAPE from Equation (9-10)
14. Post process the Evaluated model
15. Set the model for deployment
16. End the Algorithm

4. RESULTS AND DISCUSSION

Section 4.1 showed the Levenberg-Marquardt RMSE prediction's results for Figures 1-5, results for Figures 4-10 while Section 4.2 showed the Levenberg-Marquardt MAPE prediction's

4.1 LEVENBERG-MARQUARDT RMSE PREDICTION'S RESULT

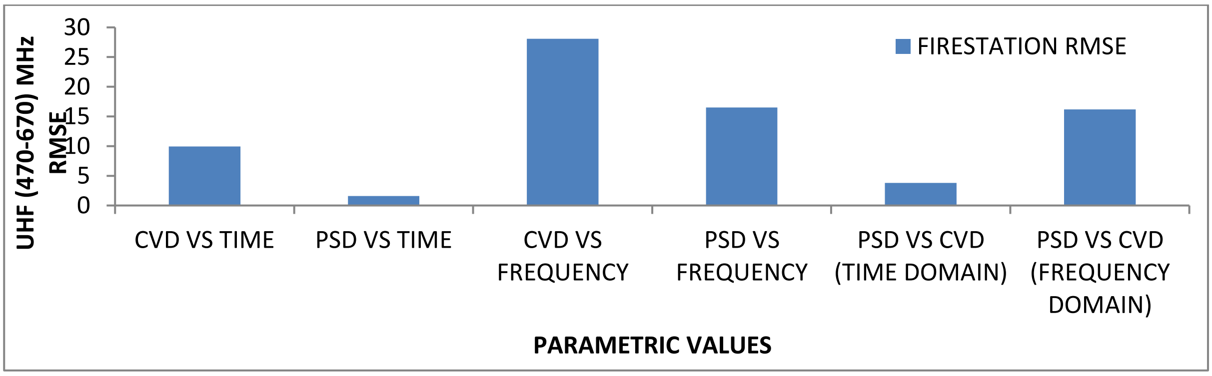

Figure 1: Fire station RMSE versus Parametric values for UHF (470-670)MHz

Figure 1 indicates the Comparison of Firestation Root Mean Square Errors. The highest root mean square error of 28.0548 occurs at the channel vacancy duration versus frequency column, while the lowest root mean square error of 1.5919 occurs at the channel vacancy duration versus time column

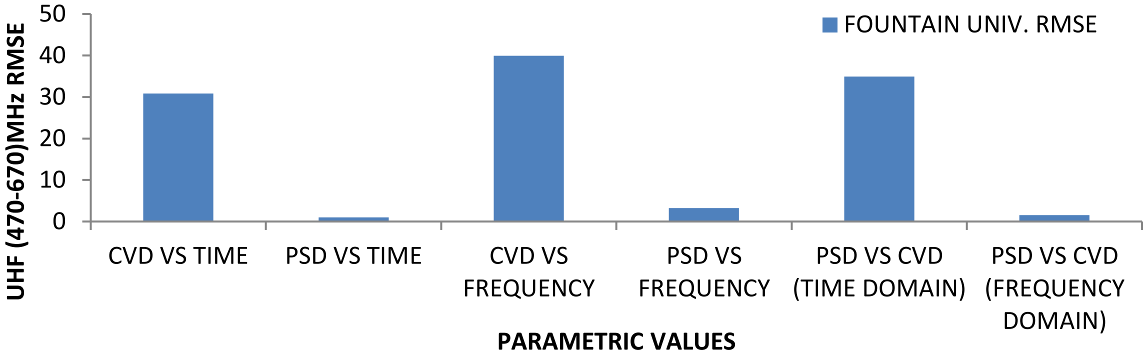

Figure 2: Fountain university RMSE versus Parametric values for UHF (470-670) MHz

Figure 2 indicates the Comparison of Fountain University Root Mean Square Errors.

The highest root mean square error of 39.94 occurs at the channel vacancy duration versus frequency column, while the lowest root mean square error of 1.03 occurs at the power spectral density versus time column.

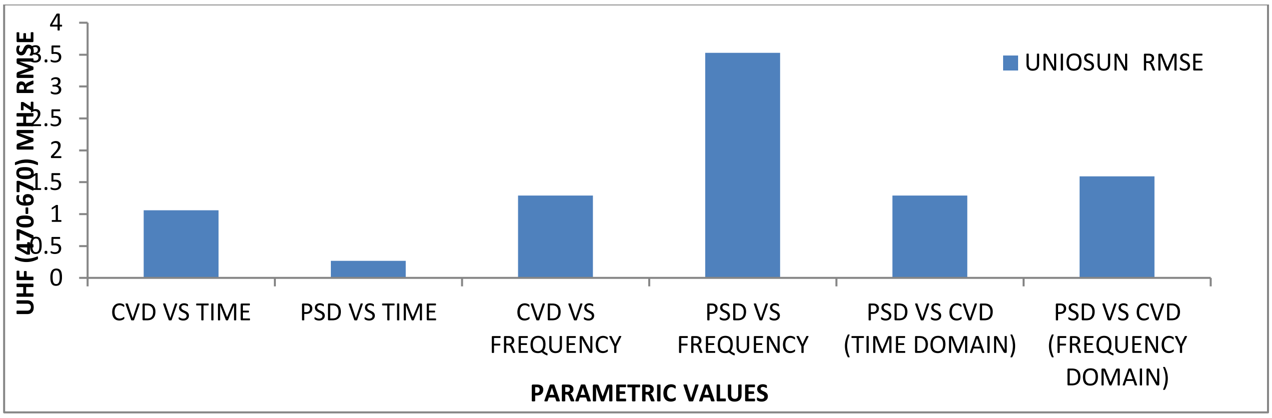

Figure 3: Uniosun campus RMSE versus Parametric values for UHF (470-670) MHz

Figure 3 indicates the Comparison of UNIOSUN campus Root Mean Square Errors.

The highest root mean square error of 3.53 occurs at the power spectral density versus frequency column, while the lowest root mean square error of 0.2686 occurs at the power spectral density versus time column.

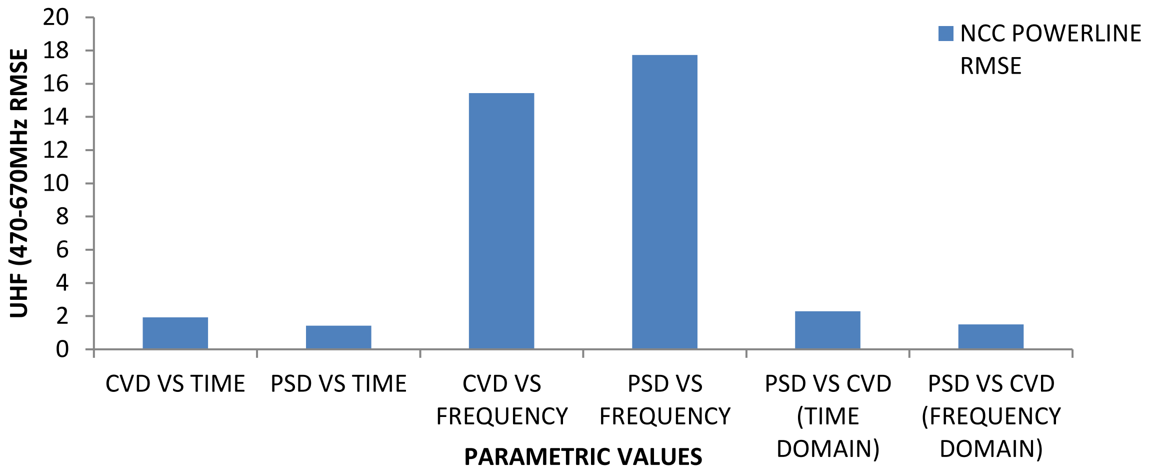

Figure 4: National Control Centre Power-line RMSE versus Parametric values for UHF (470-670)MHz

Figure 4 indicates the Comparison of the National Control Centre Power-line Root Mean Square Error. The highest root mean square error of 15.43 occurs at the power spectral density versus frequency column, while the lowest root mean square error of 1.4219 occurs at the power spectral density versus time column.

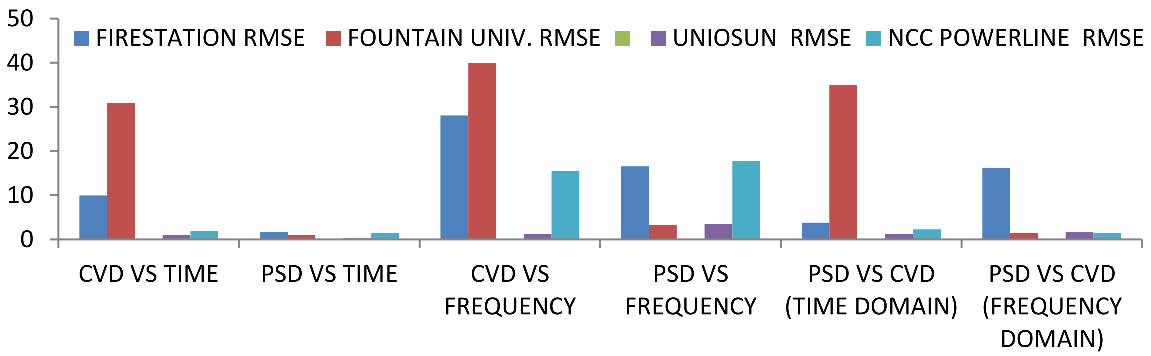

Figure 5: Comparison of RMSE for all locations RMSE versus Parametric values for UHF (470-670) MHz

Figure 5 indicates the Comparison of all locations' Root Mean Square Errors. The highest root mean square error of 39.94 occurred at Fountain University with the channel vacancy duration versus frequency column, while the lowest root mean square error of 0.269 occurred at UNIOSUN with the power spectral density versus time column.

4.2: LEVENBERG-MARQUARDT MAPE PREDICTION'S RESULT

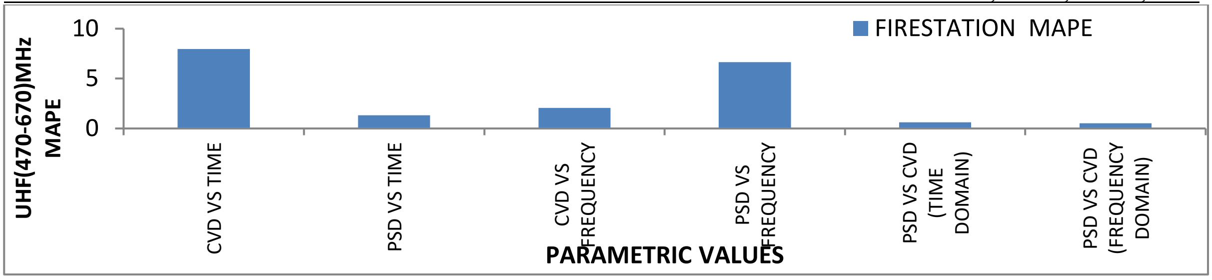

Figure 6: Fire station MAPE versus Parametric values for UHF (470-670) MHz

Figure 6 indicates the Comparison of Fire station Mean Absolute Percentage Errors versus Parametric values histogram graph. The UHF band has the highest mean absolute percentage error of 7.95 at the channel vacancy duration versus time, while the lowest mean absolute percentage error is 0.61 at the power spectral density versus channel vacancy duration column (time domain).

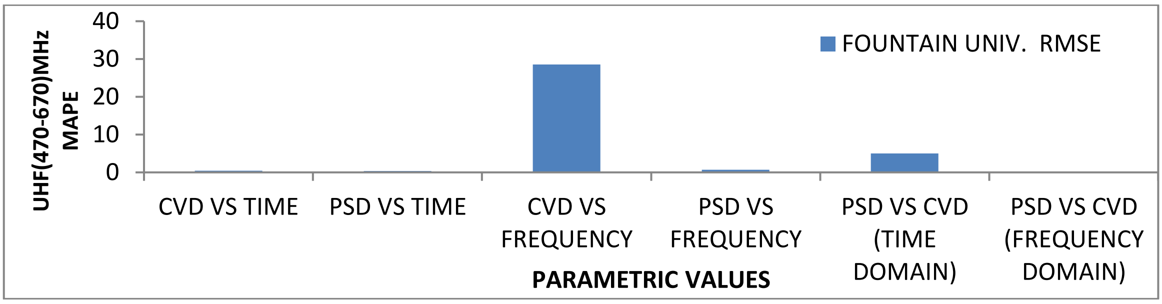

Figure 7: Fountain University MAPE versus Parametric values for UHF (470-670) MHz

Figure 7 indicates the Comparison of Fountain Mean Absolute Percentage Errors versus Parametric values histogram graph; the band has the highest mean absolute percentage error of 28.59 at the channel vacancy duration versus frequency column while the lowest mean absolute percentage error of 0.02 at the power spectral density versus channel vacancy duration column (frequency domain.

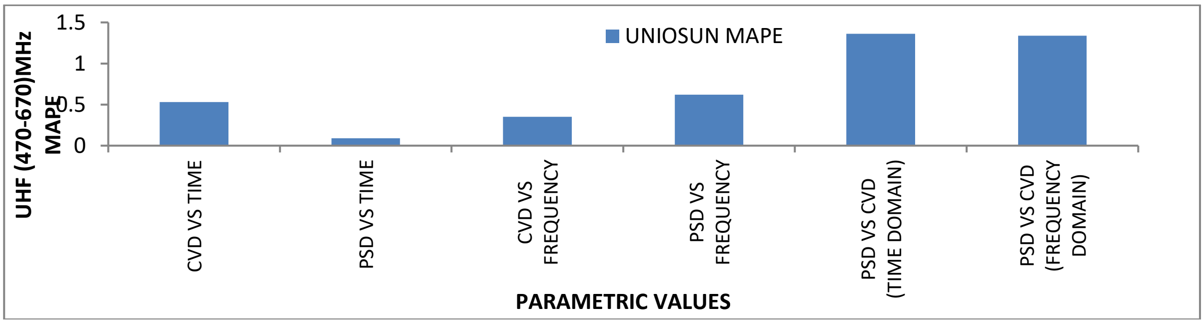

Figure 8: Uniosun campus MAPE versus Parametric values for (470-670 UHF) MHz

Figure 8 indicates the Comparison of Uniosun campus Mean Absolute Percentage Errors versus parametric values histogram graph; the UHF band has the highest mean absolute percentage error of 1.36 at the power spectral density versus channel vacancy duration column (frequency domain) and power spectral density versus channel vacancy duration column (time domain) respectively. In contrast, the lowest mean absolute percentage error of 0.09 occurs at the power spectral density versus the time column.

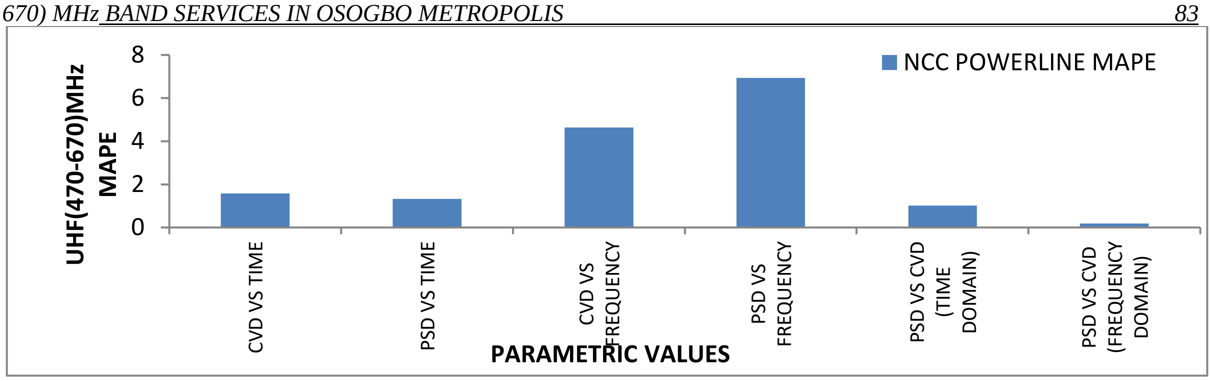

Figure 9: National Control Centre Power-Line MAPE versus Parametric values for UHF (470-670) MHz

Figure 9 indicates the Comparison of the National Control Centre Mean Absolute Percentage Errors versus the parametric value of the histogram graph. The UHF band has the highest mean absolute percentage error of 6.94 at the power spectral density versus frequency domain. In contrast, the lowest mean absolute percentage error of 1.01 occurs at the power spectral density versus channel vacancy duration (time domain).

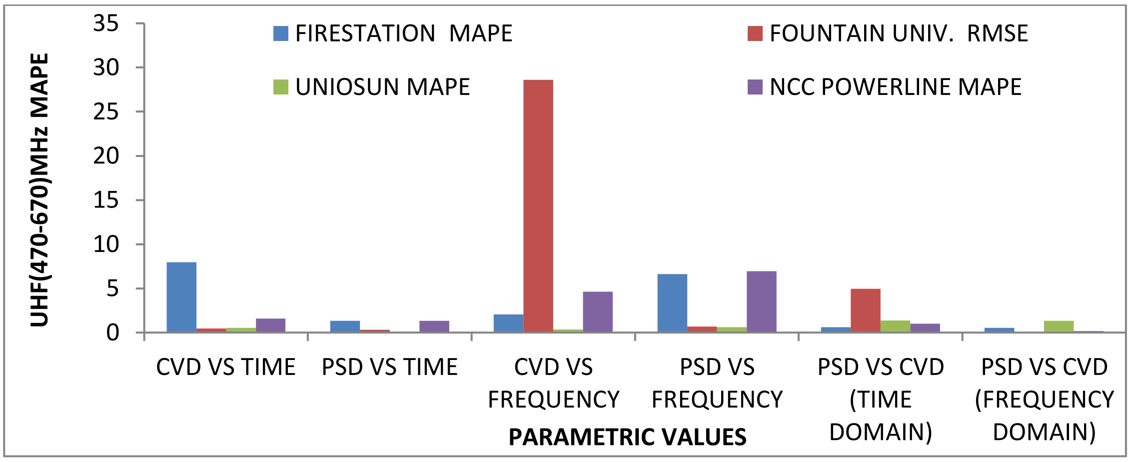

Figure 10: Comparison of MAPE for all locations versus Parametric values for UHF (470-670) MHz

Figure 10 indicates the Comparison of all locations' Mean Absolute Percentage Errors. The highest mean absolute percentage error of 28.59 occurred at Fountain University with the channel vacancy duration versus frequency column. In contrast, the lowest root mean square error of 0.09 occurred at UNIOSUN with the power spectral density versus time column.

4. CONCLUSION AND RECOMMENDATION

The paper investigated the Levenberg-Marquardt-based Neural Network spectrum occupancy prediction for UHF (470-670) MHz. The Method of prediction with Levenberg-Marquardt (LM) Algorithm was compared with traditional means of prediction of actual values of spectrum occupancy deduced from the analysis with Excel application, and LM algorithm outperforms better than traditional means of prediction.

The result showed that the fire station and national control center locations with 0 RMSE gave the most accurate prediction of all parametric values. Fountain University had the highest root mean square error of 39.94 with the channel vacancy duration versus frequency column. UNIOSUN had the lowest at 0.269 with the power spectral density versus the time column. Fountain University had the highest mean absolute percentage error of 28.59 for the channel vacancy duration versus frequency column. In contrast, UNIOSUN had the lowest root mean square with 0 MAPE accurately predicted all parametric values. The result of the work will be useful for the broadcasting stakeholders in frequency allocation planning and possible deployment for emergency communications network and other cognitive usage that require necessary frequency allocation. In the future work, deep learning neural network with more predictive power will be subjected to the same process to create more spectral opportunities for cognitive usage and deployment.

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