I. J. Computer Network and Information Security, **2022, 3, 63-74**
Published Online June 2022 in MECS (http://www.mecs-press.org/)
DOI: 10.5815/ijcnis.2022.03.05

Cascade Forward Neural Networks-based Adaptive Model for Real-time Adaptive Learning of Stochastic Signal Power Datasets

Odesanya Ituabhor
Department of Physics, Federal University Lokoja, Lokoja, Kogi State, Nigeria
E-mail: Ituabhor.odesanya@fulokoja.edu.ng

Joseph Isabona and Jangfa T. zhimwang
Department of Physics, Federal University Lokoja, Lokoja, Kogi State, Nigeria
E-mail: Joseph.isabona@fulokoja.edu.ng, Ituabhor.odesanya@fulokoja.edu.ng

Ikechi Risi
Department of Physics, River State University Port Harcourt, Nigeria
E-mail: ikechi.risi@ust.edu.ng

Received: 25 December 2021; Revised: 20 January 2022; Accepted: 06 February 2022; Published: 08 June 2022

Abstract: In this work, adaptive learning of a monitored real-time stochastic phenomenon over an operational LTE broadband radio network interface is proposed using cascade forward neural network (CFNN) model. The optimal architecture of the model has been implemented computationally in the input and hidden units by means of incremental search process. Particularly, we have applied the proposed adaptive-based cascaded forward neural network model for realistic learning of practical signal data taken from an operational LTE cellular network. The performance of the adaptive learning model is compared with a benchmark feedforward neural network model (FFNN) using a number of measured stochastic SINR datasets obtained over a period of three months at two indoors and outdoors locations of the LTE network. The results showed that proposed CFNN model provided the best adaptive learning performance (0.9310 RMSE; 0.8669 MSE; 0.5210 MAE; 0.9311 R), compared to the benchmark FFNN model (1.0566 RMSE; 1.1164 MSE; 0.5568 MAE; 0.9131 R) in the first studied outdoor location. Similar robust performances were attained for the proposed CFNN model in other locations, thus indicating that it is superior to FFNN model for adaptive learning of real-time stochastic phenomenon.

Index Terms: Stochastic phenomenon, Neural networks, Adaptive modelling, Adaptive learning, Practical SINR.

1. Introduction

Unlike the wired or cable communication channel that is stationary and relatively predictable, the wireless communication channel is unstable and difficult to analyze due to its stochastic nature [1, 2]. Particularly, radio frequency wireless broadband channels are complex phenomenons that are largely impacted by diverse radio frequency propagation mechanisms, such as scattering, diffraction, and reflection. For instance, reflection occurs when a travelling radio wave comes in contact with a large obstruction. For diffraction, it is experienced when the obstructing object blocks the propagated radio wave path, thus resulting in the meandering of the radio wave around the obstructing object. On the hand, scattering occurs when the communication channel in which the radio waves broadcast are non-uniformities and irregularities owing to different environmental blockades. Owing to these phenomena, copies of received signal and signal quality are random variables and these make them very difficult to be modelled [3]. This phenomenon is also accompanied by the wireless radio communication channel that is frequency selective, time-varying and space-varying. Thus, to effectively model and characterize the signal quality and the entire wireless communication systems performance, the aforementioned possible variation must be well articulated.

The concept of applying parametric and non-parametric mathematical models to examine the behavior of time-dependent and stochastic phenomena has been widely established globally. Neural Networks models belong to a family of nonparametric models with massively parallel architectures and computational tools that can adaptively learn and solve complicated engineering problems. Till date ANNs remained a broad and robustly applied learning and modeling tools, ranging from catering for simple to complex function approximation problems, pattern recognition problems, classification and time series problems. The exceptionality and distinctiveness of ANNs came in the 80s' when its basic back propagation network learning algorithm was first introduced. It was a ground-breaking tool for researchers and academics, paving way for a widespread application in the scientific world [4].

1.1. Related Works

There exist a number of ANNs models. Among the key ones are Hopfield neural network (HNN), Elman neural network (ENN) cascade forward neural network (CFNN), Multilayer perceptron neural network (MLP), hybrid multilayer perceptron network (HMLP), cascade forward neural network (CFNN) and feedforward neural network (FNN). These diverse neural networks have been explored in previous works by different authors to solve a number of classical, seasonal and functional approximation problems in literature. In [5], comparative prediction study of daily rainfall and seasonal time series data are provided. In [6], the modelling of temperature retention in Ion Chromatography is studied using back propagation and cascade forward neural networks. Many studies related to the modelling of seasonal and time series occurrence are contained in [7–15]. The results reveal that the tractability of neural network models is assertively influenced by the nature of input variables and phenomenon. In [16, 17], the authors engaged cascade forward neural network for ECG signal classification/detection and their results showed 99.9 % and 96.69% classification accuracy, respectively. In [18, 19], cascade forward neural network architecture was also explored by the researchers to access and improve signal quality information processing and analysis. Their overall experimental results displayed 92.7% and 91.8% recognition accuracy.

This work explores the adaptive learning capability of CFNN model to examine the stochastic SINR phenomenon in LTE Broadband Networks. The optimal architecture of the model is explored and implemented computationally in the input and hidden units by means of incremental search process.

Particularly, the core contributions of this study are presented as follows:

- We proposed an adaptive-based cascaded forward neural network model for optimal leaning and monitoring of real-time stochastic phenomenon.
- We have applied the proposed adaptive-based cascaded forward neural network model for realistic learning of practical signal data taken from an operational LTE cellular network.
- The optimal architecture of the model has been implemented computationally in the input and hidden units by means of incremental search process.

The remaining part of this research paper is provided as follows. Section 2 presents the detailed research methodology, and this contains method of data collection, Multilayer Perception Forward Neural Network model, Cascaded Forward Neural Network and Levenberg-Marquardt (LM) Algorithm. Also contained in this section is the data training and testing procedure adopted using the proposed Cascaded Forward Neural Network model in comparison with the standard Multilayer Perception Forward Neural Network model. Section 3 provides the results, analysis and valued discussions. Lastly, Section 4 contains the concise conclusion to the study.

2. Methodology

2.1. Data Collection

A cellular mobile subscriber can be within a good network coverage area but still be unable to communication effectively owing to the interference from within the cells or nearby cells [20]. A key parameter to access the amount and nature of interference in the physical layer of LTE networks is the Signal to Interference plus Noise Ratio (SINR).

The real-time SINR data used in this work, have been obtained from commercial LTE broadband networks operator by means of field walk test using Samsung mobile phone monitoring device. The Samsung phone is equipped with TEMS and Network Info signal software tools which enable it to automatically probe, access and acquire practical signal coverage and quality data over the LTE radio network interface. The walk test measurement campaign was conducted between the month of May and June 2019 in Adamkolo campus of Federal University Lokoja, and environs. A total of three cellular locations were engaged for data collection. Each location possesses an eNodeB base station transmitter. All the base station transmitters are empowered with three sectored directional antennas each, which transmit and receive broadband signals from the LTE mobile subscribers in space or time at 2600MHz frequencies. More details of each antenna transmission parameters can be found in [21].

The measured *SINR* can be defined mathematically as:

$$SINR = \frac{S}{1+N} \tag{1}$$

where I, S and N_b indicate the interference power, signal coverage power and background noise, respectively.

According to 3GPP [22], *SINR* can also be expressed as [23]:

$$RSRQ = N_{rb}\frac{RSRP}{RSSI} \tag{2}$$

where

$$RSSI = I_{tot} + S_{tot} + N_{tot} \tag{3}$$

$$S_{tot} = \rho * 12 * N_{rb} * RSSR \tag{4}$$

$$\rho = RE / Rb$$

$$I_{tot} + N_{tot} = \frac{I_{tot} + N_{tot}}{12.N_{rb}} \tag{5}$$

And RSRP and RSRP indicate the Received Signal Reference Power and Received Signal Reference Quality. N_{rb} designates the number of Resource Blocks (RB).

Now, inserting Eqs. (4) and (5) into (1) gives

$$SINR = \frac{\rho.12N_{rb}.RSRP}{(I_{tot} + N_{tot})/12Nrb} \tag{6}$$

After some simplification, Eq. (6) can be rewritten as:

$$SINR = \frac{12N_{rb}.RSRP}{(I_{tot} + N_{tot})} \tag{7}$$

Also, considering the expression in equation (3) in Eq. (7) gives:

$$SINR = \frac{12N_{rb}.RSRP}{(RSSI + S_{tot})} \tag{8}$$

Also, by means of Eq. (2), the expression in Eq. (8) can be articulated as:

$$SINR = \frac{12N_{rb}.RSRP}{N_{rb}\frac{RSRP}{RSSI} - (x.12N_{rp}.RSRP)} \tag{9}$$

2.2. Multilayer Perception Forward Neural Network

The multilayer feedforward networks (FNN) which are the most largely used one, is considered in this work. The training process of FNN is a stepwise adaptation of the connection weights which link or transmit information between simple processing units known as neurons.

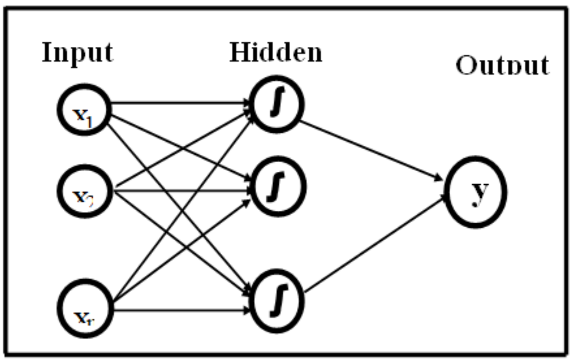

Fig.1. Feed Forward Back propagation Network

By means of mathematical model, the FNN architecture of Fig. 1 can be expressed as:

$$y_p = f^0\left(\sum_{j=1}^{n}\omega_i^o x^i f_j^H\left(\sum_{i=1}^{n}\omega_{ji}^H x_i\right)\right) \tag{10}$$

where f^0 and f_j^h designate the output layer activation function and the hidden layer activation function, respectively. Considering the addition of bias to both the input layer and the hidden layer, Eq. (10) turn into:

$$y_p = f^0\left(\omega^b + \sum_{j=1}^{n}\omega_i^o x^i f_j^H\left(\omega_i^o + \sum_{i=1}^{n}\omega_{ji}^H x_i\right)\right) \tag{11}$$

for p=1, 2, 3…n
where ω_j^H and ω_b indicate the respective weight from bias to hidden layer and output layer.

2.3. Cascaded Forward Neural Network

CFNN is a superb manifold layered neural network. It principally comprises of input and output layers with one or more hidden layers in-between the first and last layers. Each of these layers is made up of a set of neurons.

Specifically, the CFNN architecture differs from the FNN architecture because of the weight connection which exists between the input and every preceding layer. As a distinctive feed-forward network and with enough hidden neurons, CFNN possess the capability to accommodate and learn any set of linear and nonlinear input-output relationship.

In this study, we employ a four layered CFNN network model to investigate the Stochastic SINR data phenomenon obtained from operational LTE Broadband Networks. The optimal model architecture was obtained computationally by means of incremental search method in correspondence with both input and hidden units.

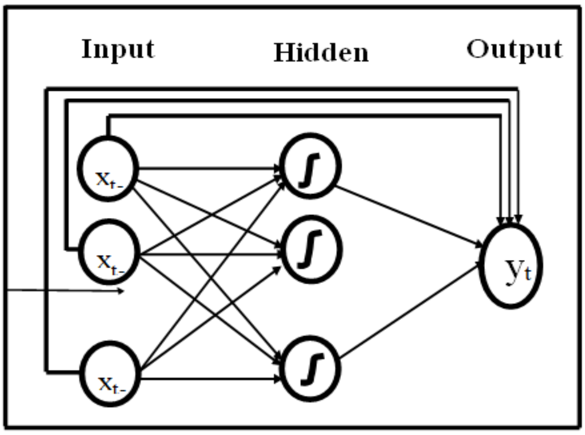

Fig.2. Cascade Forward Back propagation Network

By means of mathematical model, the CFNN architecture of figure 2 can be expressed as:

$$y_p = \sum_{i=1}^{n} f^i\omega_i^o x^i + f^0\left(\sum_{j=1}^{n}\omega_i^o x^i f_j^H\left(\sum_{i=1}^{n}\omega_{jh}^H x_i\right)\right) \tag{12}$$

where f^i and f_j^H designate the output layer activation function and the hidden layer activation function, respectively. Adding bias to both the input layer and the hidden layer, Eq. (12) becomes:

$$y_p = \sum_{i=1}^{n} f^i\omega_i^o x^i + f^0\left(\omega^b + \sum_{j=1}^{n}\omega_i^o x^i f_j^H\left(\omega_i^o + \sum_{i=1}^{n}\omega_{jh}^H x_i\right)\right) \tag{13}$$

for p= 1, 2, 3…n
where ω_j^H and ω_b indicate the respective weight from bias to hidden layer and output layer.

The learning phase involves the use of a robust learning algorithm to minimize of the cost function; it can be expressed as:

$$E = \frac{1}{2}\sum_{p=1}^{n}(y_p - q_p) = \frac{1}{2}\sum_{p=1}^{n}(e_p)^2 \tag{14}$$

where q_p represent the expected value and y_p indicates the calculated output value by the network.

2.4. Levenberg-Marquardt (LM) Algorithm

To minimize the cost function (i.e. the error function) expressed in Eq. (14), the LM algorithm [24], is considered in this work. The LM algorithm is special and fast learning algorithm which combined Gauss–Newton and gradient descent methods to speed up error function minimization problems. The Newton's method weight update is defined by:

$$\Delta w = -[H(w)]^{-1} g(w) \tag{15}$$

with $g(w)$ and $H(w)$ denoting the gradient vector and Hessian matrix, respectively.

Also, for:

$$g(w) = J(w)^T e(w) \tag{16}$$

$$H(w) = J(w)^T J(w) + Q(w) \tag{17}$$

with $J(w)$ being the Jacobian matrix, we have:

$$Q(w) = \sum_{i=1}^{N} \nabla^2 e(w) e(w)^T \tag{18}$$

Taking $S(w) = 0$ for the Gauss- Newton method, the gradient method would turn to:

$$\Delta(w) = -[J(w)^T J(w) + \mu I]^{-1} J^T(w) e(w) \tag{19}$$

Eq. (19) represent the LM weight update, where μ and I indicate the damping parameter and identity matrix, respectively.

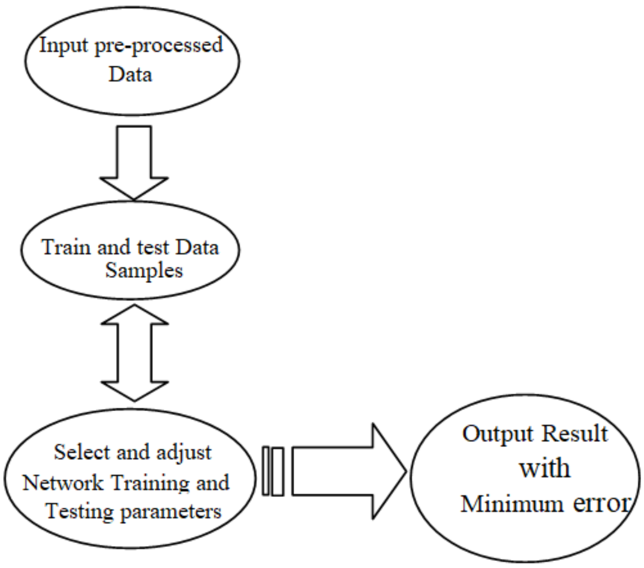

Fig.3. FNN and CFNN Data Training and Testing Process

2.5. CNFF and FFNN Model Network Training

The Matlab 2018a neural network toolbox was explored to model, train and simulate the measured SINR data. The neural network training and testing approach adopted is shown in figure 3. Different syntheses of parameters in terms of hidden layer neurons number, transfer function, error goal, and among others, were considered for the FNN and CFNN training. In order to enhance network training, mapminmax function and Levenberg-Marquardt function were explored for input/output processing function and training algorithm, respectively. Each network had *purelin and tansig* as an activation function for the output layer and hidden layer. Location 1 contains 100 training datasets, while locations 2 and 3 contained 234 and 455 training datasets respectively. For effective training, testing and validation, the input data were randomly divided into 75%:15%:15% using a default dividerand function. The early stopping procedures were involved to outwit over training, testing and validation.

3. Results and Analysis

To ascertain the level of CFNN and FFNN models performances, their networks were appraised using Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Correlation coefficient (R) as defined in Eqs. (20) to (23). So, the acceptable criteria for a model performance are based upon these indices [25, 26]:

$$MSE == \frac{1}{N}\sum_{p=1}^{N}\left[y_p - q_p\right]^2 \tag{20}$$

$$RMSE = \sqrt{MSE} = \frac{1}{N}\sqrt{\sum_{p=1}^{N}\left[y_p - q_p\right]^2} \tag{21}$$

$$MAE = \frac{1}{N}\sum_{p=1}^{N}\left|y_p - q_p\right| \tag{22}$$

$$R = \frac{\sum_{P=1}^{N}(y_P - \bar{y}_P)(y_P - \bar{d}_P)}{\sqrt{\left[\sum_{q=1}^{N}\left[(y_P - \bar{y}_P)^2\right]\right]\left[\sum_{P=1}^{N}\left[(y_P - \bar{d}_P)^2\right]\right]}} \tag{23}$$

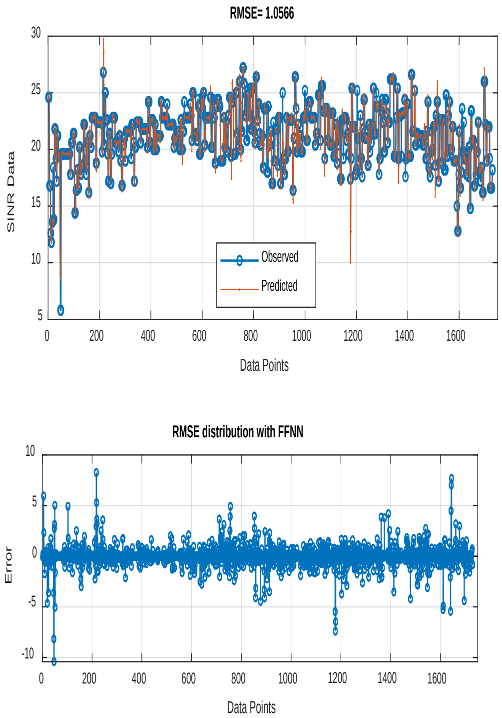

Fig.4. RMSE Performance with CFNN model in Physics Lab (Outdoor)

Displayed graphs of Figs. 4 to 11 are RMSE performance distribution plots for both outdoor and indoor locations in Physics laboratory and Conference Hall using CFNN and FFNN models.

From the graphs, the results indicate 0.9529; 0.658 RMSEs for outdoor locations and 0.9624; 0.9520 RMSEs for indoor locations with CFNN model compared to FFNN model which attained 0.9131; 0.9844 RMSEs for outdoor locations and 0.9531; 0.9483 RMSEs for indoor locations, respectively. It clears from the RMSE performance plots that the proposed CFNN model outperforms the benchmark FFNN model in both studied outdoor and indoor locations of Physics laboratory and Conference hall.

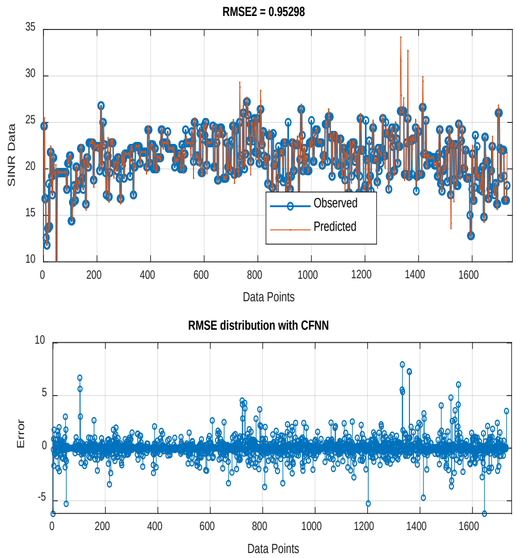

Fig.5. RMSE Performance with CFNN model in Physics Lab (Outdoor)

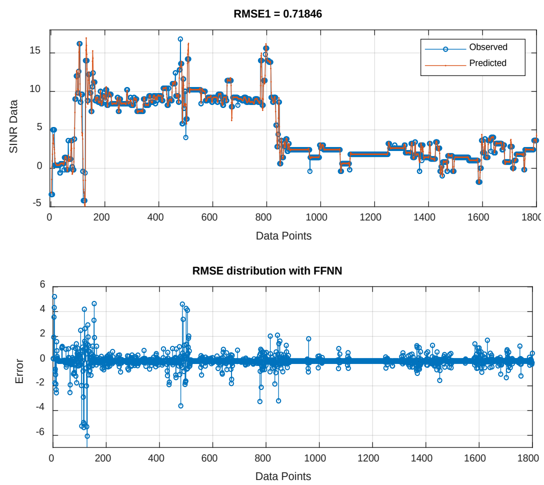

Fig.6. RMSE Performance with FFNN model in Physics Lab (Indoor)

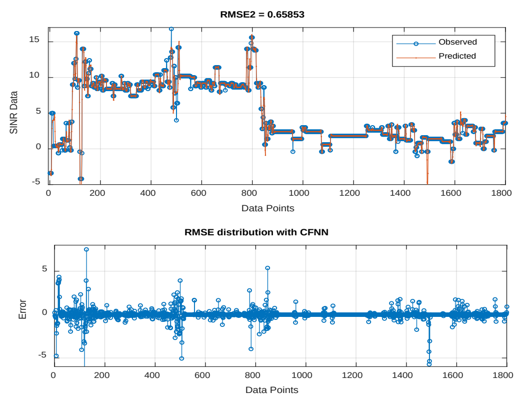

Fig.7. RMSE Performance with CFNN model in Physics Lab (Indoor)

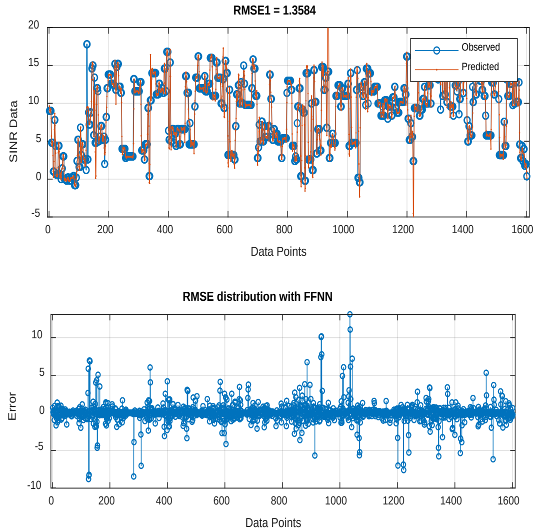

Fig.8. RMSE Performance with FFNN model in Conference Hall (Outdoor)

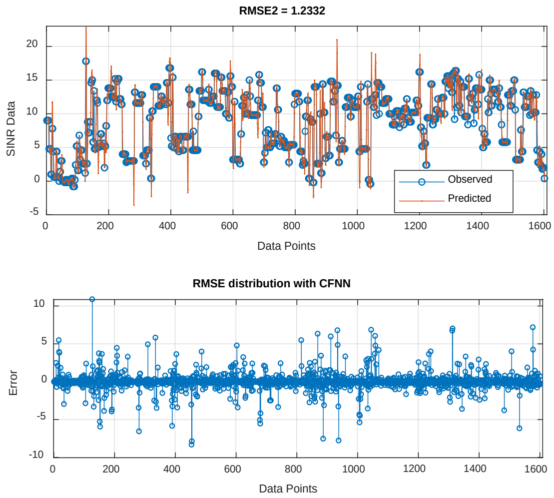

Fig.9. RMSE Performance with CFNN model in Conference Hall (Outdoor)

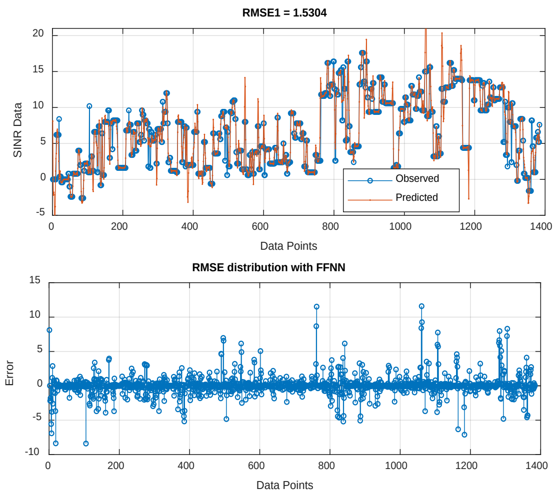

Fig.10. RMSE Performance with CFNN model in Conference Hall (Indoor)

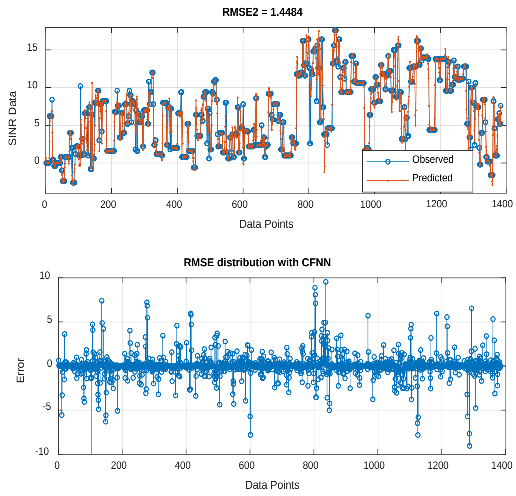

Fig.11. RMSE Performance with CFNN model in Conference Hall (Indoor)

The graphs in Figs. 12 to 15 are displayed to reveal the correlation coefficient (R) fit performance distribution plots for both outdoor and indoor locations in Physics laboratory and Conference Hall using CFNN and FFNN models.

From the graphs, the results indicate 0.9311; 0.9900 Rs for outdoor locations and 0.9624; 0.9520 Rs for indoor locations with CFNN model compared to FFNN model which attained 0.9131; 0.9844 Rs for outdoor locations and 0.9531; 0.9483 Rs for indoor locations, respectively. It also clears from the Rs plots that the proposed CFNN model fits into the measured stochastic SINR data better than the benchmark FFNN model in both studied outdoor and indoor locations of Physics laboratory and Conference hall of federal university, Lokoja, Adamkolo campus.

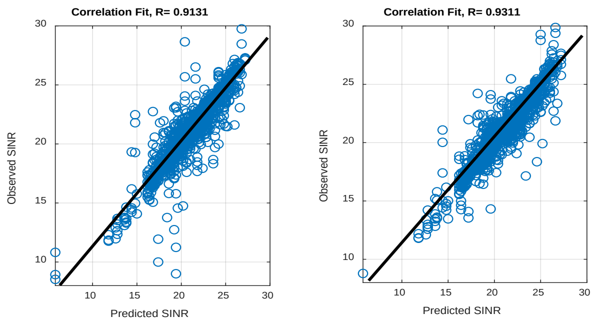

Fig.12. Correlation fit with FFNN and CFNN models to SINR Data in Physics Lab (Outdoor)

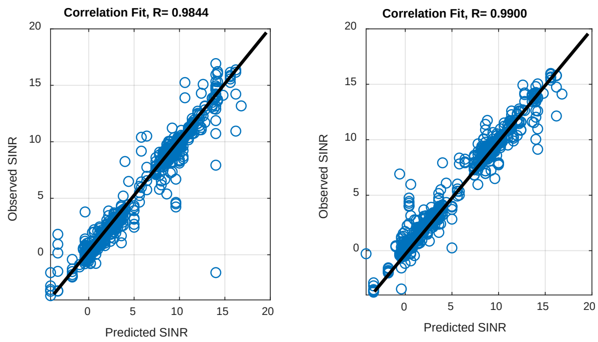

Fig.13. Correlation fit with FFNN and CFNN models to SINR Data in Physics Lab (Indoor)

The displayed graphs of Figs. 16 to 19 are mean error performance results with normal distribution fit for both outdoor and indoor locations in Physics laboratory and Conference Hall using CFNN and FFNN models.

In terms of MAE, the results indicate that the CFNN model attained 0.5210; 0.5959 values for outdoor locations and 0.2426; 0.6949 values for indoor locations compared to FFNN model which attained 0.5568; 0.6275 values for outdoor locations and 0.2507; 0.7563 values for indoor locations, respectively. It also clears from the mean error distribution results that the proposed CFNN model outperform the benchmark FFNN model in both studied outdoor and indoor locations.

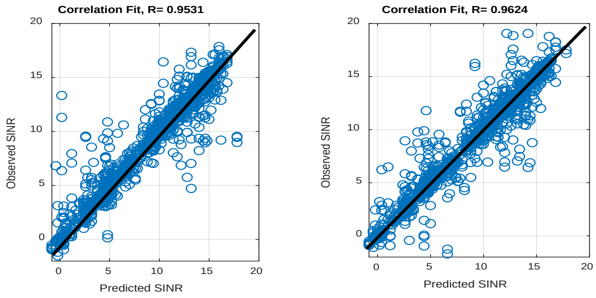

Fig.14. Correlation fit with FFNN and CFNN models to SINR Data in Conference Hall (Outdoor)

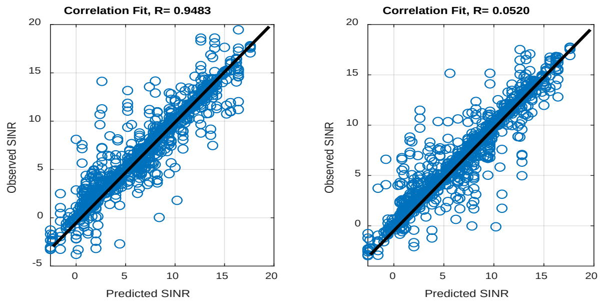

Fig.15. Correlation fit with FFNN and CFNN models to SINR Data in Conference Hall (Indoor)

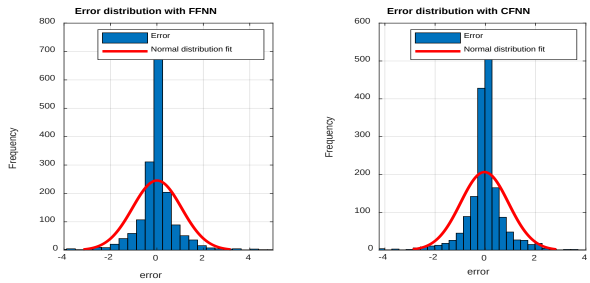

Fig.16. Mean Error with FFNN and CFNN models performance in Physics Lab (Outdoor)

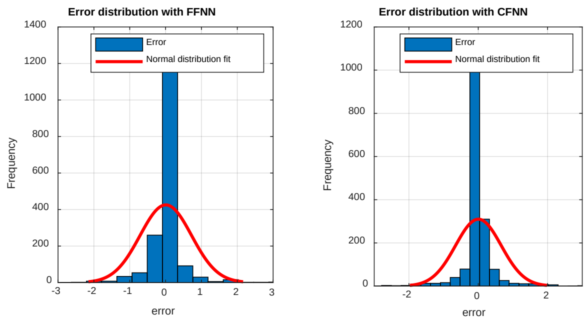

Fig.17. Mean Error with FFNN and CFNN models performance in Physics Lab (Indoor)

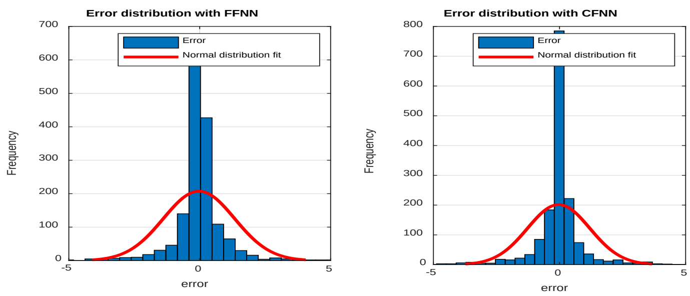

Fig.18. Mean Error with FFNN and CFNN models performance in Conference Hall (Outdoor)

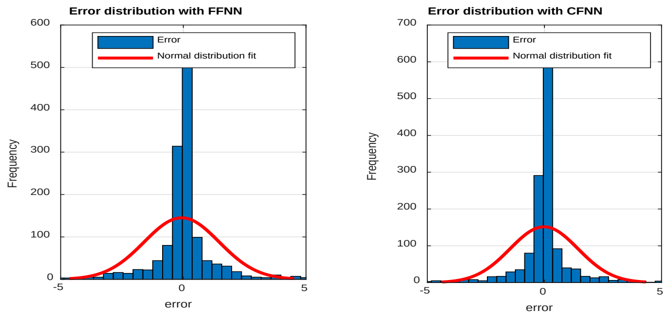

Fig.19. Mean Error with FFNN and CFNN models performance in Conference Hall (Indoor)

4. Conclusion

The study of stochastic SINR data phenomenon obtained from an operating commercial LTE Broadband Networks have been carried out in this work, using adaptive learning ability of cascade forward neural network (CFNN) and feedforward neural network (FNN) model algorithms. The performances of the two adaptive CFNN and FNN models were subjected to a number of measured stochastic SINR datasets obtained at two different locations. The results showed that CFNN model provided the best adaptive learning performance (0.9310 RMSE; 0.8669 MSE; 0.5210 MAE; 0.9311 *R*), compared to the benchmark FFNN model (1.0566 RMSE; 1.1164 MSE; 0.5568 MAE; 0.9131 *R*) in the first studied outdoor location. Similar robust performance was attained for the proposed CFNN model in other locations, thus indicating that it is superior to FFNN model for adaptive learning of real-time stochastic phenomenon.

References

[1] J. Isabona, and C.C. Konyeha., ‘‘Urban Area Path loss Propagation Prediction and Optimisation Using Hata Model at 800MHz’’, *IOSR Journal of Applied Physics (IOSR-JAP)*, vol.3, (4), pp.8-18, 2013.

[2] J. Isabona, and D.O Ojuh, Adaptation of Propagation Model Parameters toward Efficient Cellular Network Planning using Robust LAD Algorithm *I.J. Wireless and Microwave Technologies*, 2020, 5, pp.13-24.

[3] J. Isabona, C.C. Konyeha, C.B.Chinule, and P.G. Isaiah, ‘‘Radio Field Strength Propagation Data and Pathloss calculation Methods in UMTS Network’’, *Advances in Physics Theories and Applications*, vol.21,pp. 54-68, 2013.

[4] S.R. Devi, P. Arulmozhivarman, C. Venkatesh, and P. Agarwal, ‘‘Performance Comparison of Artificial Neural Network Models for Daily Rainfall Prediction’’, *International Journal of Automation and Computing vol.*13 (5), pp.417-427, October 2016.

[5] W. Budi, S. Rukun S, Suparti, and Y. Hasbi**,** Cascade Forward Neural Network for Time Series Prediction, *Journal of Physics: Conf. Series* vol.1025 (2018). doi :10.1088/1742-6596/1025/1/012097

[6] T. Bolanca, S.C. Stefanovic, S. Uki, and M. Rogosic, Development of Temperature Dependent Retention Models in Ion Chromatography by the Cascade Forward and Back Propagation Artificial Neural Networks, *Journal of Chromatography and Related Technologies*, vol.32, pp.2765–2778, 2009.

[7] A. Hedayat, H. Davilu, A.A. Barfrosh, and S. Sepanloo, Estimation of research reactor core parameters using cascade feed forward artificial neural networks, *Progress in Nuclear Energy, vol.51*, 709–718, 2009.

[8] Y. Karaca, Case Study on Artificial Neural Networks and Applications, Applied Mathematical Sciences, vol.10, 45, pp. 2225 – 2237, 2016.

[9] N. Kumar, A. Middey and P.S. Rao, Prediction and examination of seasonal variation of ozone with meteorological parameter through artificial neural network at NEERI, Nagpur, India, *Urban Climate*, vol.20, pp. 148-167, 2017.

[10] D.C.Montgomery, C.L. Jennings and M. Kulahci, Introduction to Time Series Analysis and Forecasting, *John Wiley & Sons, Inc.*, 2015.

[11] S. Narad, and P. Chavan, ‘‘Cascade Forward Back-propagation Neural Network Based Group Authentication Using (n, n) Secret Sharing Scheme’’, *Procedia Computer Science*, vol.78, pp.185 – 191, 2016.

[12] A. Pwasong and S. Sathasivam, A new hybrid quadratic regression and cascade forward backpropagation neural network, *Neurocomputing vol*. 182, pp.197-209, 2016.

[13] S. Tengeleng and N. Armand. ‘‘Performance of Using Cascade Forward Back Propagation Neural Networks for Estimating Rain Parameters with Rain Drop Size Distribution’’, *Atmosphere vol.***5**, pp.454-472, 2014.

[14] J.P. Zhang and M. Qi, ‘‘Neural network forecasting for seasonal and trend time series’’, *European Journal of Operational Research*, 160, 501–514, 2005.

[15] S. Ayub and J.P. Saini, ECG classification and abnormality detection using cascade forward neural network, *International Journal of Engineering, Science and Technology*, vol. 3, No. 3, pp. 41-46, 2011.

[16] V. Schetinin, ‘‘A Learning Algorithm for Evolving Cascade Neural Networks’’ *Neural Processing Letter* vol.17, pp.21-31, 2003. Kluwer

[17] M. L. Iuzzolino, M.C. Mozer, and S. Bengio, Improving Anytime Prediction with Parallel Cascaded Networks and a Temporal-Difference Loss, Advances in Neural Information Processing Systems. 2021 Dec 6;34.

[18] Qifei Zhang, Lingjian Fu, Linyue Gu, "A Cascaded Convolutional Neural Network for Assessing Signal Quality of Dynamic

ECG", Computational and Mathematical Methods in Medicine, vol. 2019, 2019. https://doi.org/10.1155/2019/7095137
[19] L.B. Nigrini LB, ‘‘Developing a Neural Network Model to Predict the Electrical Load Demand in the Mangaung Municipal Area, *thesis in the School of Electrical and Computer Systems Engineering*, Faculty of Engineering and Information Technology, Central University of Technology, Free State.
[20] Divine O. Ojuh, Joseph Isabona," Empirical and Statistical Determination of Optimal Distribution Model for Radio Frequency Mobile Networks Using Realistic Weekly Block Call Rates Indicator ", International Journal of Mathematical Sciences and Computing, Vol.7, No.3, pp. 12-23, 2021.
[21] Joseph Isabona, Divine O. Ojuh, "Application of Levenberg-Marguardt Algorithm for Prime Radio Propagation Wave Attenuation Modelling in Typical Urban, Suburban and Rural Terrains", International Journal of Intelligent Systems and Applications, Vol.13, No.3, pp.35-42, 2021.
[22] 3GPP TS 36.214 version 11.1.0 Release 11 (2013), "LTE; Evolved Universal Terrestrial Radio Access (E-UTRA); Physical layer; Measurements". ETSI TS 136 214 V11.1.0 (2013-02), pp.1-15.
[23] J. Isabona, and D.O Ojuh, ‘‘Modelling based Quantitative Assessment of Operational LTE Mobile Broadband Networks Reliability: a Case Study of University Campus Environ’’, *IOSR Journal of Electronics and Communication Engineering (IOSR-JECE)*, vol. 15(1). pp. 22-31,2020
[24] Marquardt, D., "An algorithm for least-squares estimation of nonlinear parameters," *SIAM Journal on Applied Mathematics*, Vol. 11, No. 2, 431–441, DIO:10.1137/0111030, 1963.
[25] V, C. Ebhota, J. Isabona and V.M. Srivastava, V.M. ‘‘Environment-Adaptation Based Hybrid Neural Network Predictor for Signal Propagation Loss, Prediction in Cluttered and Open Urban Microcells’’, *Wireless Personal Communications*, Vol. 104 (3), pp. 935–948.
[26] J. Isabona Wavelet Generalized Regression Neural Network Approach for Robust Field Strength Prediction. *Wireless Pers Commun*, *vol* 114**,** pp. 3635–3653 (2020). https://doi.org/10.1007/s11277-020-07550-55.

Authors' Profiles

Joseph Isabona (Associate Professor), Ph.D, received Ph.D. and M.Sc. degrees in Communication Electronics, 2013 and 2007 respectively, and a B.Sc in Applied Physics in 2003. He is the author of more than 100 scientific contributions including articles in international refereed Journals and Conferences in the area of Wireless Mobile communications. The Author is a Postdoctoral Research Fellow of the Department of Electronic Engineering, Howard College, University of KwaZulu-Natal, Durban, South Africa. His area of interest includes Signal Processing, RF Propagation Modelling and Radio Resource Management in Radio Telecommunication Networks. He can been reached with joseph.isabona@fulokoja.edu.ng.

Dr. Ituabhor Odesanya is a lecturer in the Department of Physics, Federal University, Lokoja, K ogi State, Nigeria. She obtained her B.Sc in Applied Physics from Ambrose Ali University, Ekpoma and her M.Sc and PhD in Physics Electronics from the University of Benin, Edo State, Nigeria. Her area of interest is in artificial Intelligence and Telecommunications. ituabhor.odesanya@fulokoja.edu.ng

Jangfa Timothy Zhimwang is a Lecturer with Department of Physics, Federal University Lokoja, Nigeria. He holds a BSc in Physics Electronics Technology, MSc in Physics (Electronics & Communication Tech.), PGD in mathematics Education, HND. Pest Management Technology and presently a PhD candidate. He has previously worked under a research team sponsored by the Tertiary Education Trust Fund (TETFund) through the Department of Physics, University of Jos and productively written and published renowned articles in the field of Physics Electronics and Communication Technology.

Ikechi Risi is lecturer at Rivers State University, Nigeria in Physics Department where he lectures physics. He obtained his B.Sc and M.Sc in Solid State Physics at the university in 2013 and 2019 respectively and currently pursuing his Ph.D at Ignatius Ajuru University of Education, Port-Harcourt. His interest areas are electronic circuit design/construction, embedded system, and radio signal propagation engineering. He can be contacted through ikechi.risi@ust.edu.ng

How to cite this paper: Odesanya Ituabhor, Joseph Isabona, Jangfa T. zhimwang, Ikechi Risi, "Cascade Forward Neural Networks-based Adaptive Model for Real-time Adaptive Learning of Stochastic Signal Power Datasets", International Journal of Computer Network and Information Security(IJCNIS), Vol.14, No.3, pp.63-74, 2022. DOI: 10.5815/ijcnis.2022.03.05