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Artificial Neural Network Based Prediction of Key Performance Indicators for Mobile Telecommunications

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Abstract

This paper presents comparative studies among artificial neural network neurons. Four key performance indicators were predicted using neural network. The key performance indicators and weather parameters for Osun State University, Osogbo, Nigeria were employed. MATLAB R2020a was employed to develop the neural network models. Three different neural network models were developed. Model A, Model B and Model C with ten neurons, fifteen neurons and twenty neurons respectively, the hidden layer of the models was Log-sigmoid activation function, and the linear activation was used at the output layer of the models. The three models were compared using mean absolute error and mean square error. The best performing model was Model B with fifteen neurons. Its mean absolute error and mean square error is 0.0909 and 0.0123 respectively. Model A with ten neurons was the least performing model with mean absolute error and mean square error of 0.0990 and 0.0148 respectively. The results show that for a model to be robust, several neurons should be tested to establish the most effective model.

1. Introduction

Modern day telecommunication between two or more people has greatly affected the socio-economic horizon of human race. Efficient, effective, and affordable telecommunication is a must for any society to develop. Key performance indicators are metrics put in place and are used to check and grade the quality of service delivered to subscribers on the network (Oje and Edeki, 2021). The telecommunication industry is witnessing a geometric increase in demand for services as well as application. To proffer solutions to the demand of users, technologies have evolved over the years: second generation (2G), third generation (3G), fourth generation (4G) and now fifth generation (5G) as well as future generation such as 6G networks and beyond. Interestingly, studies by Cisco show that there was 3.2 times increase in global internet traffic which was about 717 Tbps. It was also noted that in 2021 fixed access and Wi-Fi networks account for more than half of the total internet traffic and mobile networks with 4G and 5G accounting for 20.5% of the traffic. Telecommunication networks include thousands of connected user equipment (UEs) which generate and/or consume huge data. UEs are connected in emerging networking paradigm such as smart cities, smart road, Internet of Things (IoT). These connections range from near-field communication (NFC) to cellular networks to connect a virtually unlimited number of UEs (Shahraki *et al.*, 2018). It is expected that by 2025, the number of connected IoT devices will increase to 75 billion

(Horwitz, 2019; Shahraki *et al.*, 2020). To provide an efficient network infrastructure capable of managing such a huge amount of data requires an efficient network management system. Many techniques that have been introduced are targeted towards network faults, Quality of Service (QoS) and security.

Quality of Service (QoS) in cellular networks is about the provision of a satisfactory service in terms of good quality of voice signals, low call blocking and dropping rate, as well as high data rates for multimedia and data applications. QoS is determined by several factors which may include delay, throughput, packet loss and error rates and reliability (Balasubramanian, 2006). Monitoring these several parameters to ensure the best QoS makes it a huge and challenging task.

KPI of mobile telecommunication reveal the run time states of network system (Wang *et al.,* 2021). The KPIs can control the quality of provided services and achieved resource utilization. These indicators are categorized into the following subcategories: accessibility, retainability, mobility, integrity and availability (Krasniqi *et al.,* 2019). Maintaining the quality of service for mobile users has become a major challenge, given that several factors affect the transmitted signal. Factors such as the rate of mobility of users and the rate at which calls are made daily contribute to the drop in quality of service. These challenges require adequate and continuous monitoring of key performance indicators for early detection of areas with degraded service (Ekeocha *et al.,* 2021).

Eghonghon (2017) employed network statistics to investigate the QoS of a cellular network service provider. The results of the study show that the KPIs fall short of the recommended values by the Nigerian Communications Commission (NCC), especially during high traffic intensity. The paper concludes that the QoS still requires improvement to ensure better service delivery to subscribers. Atalaya (2020) evaluates the quality parameters of a 4G-LTE communications base station installed in a rural area of Peru. The study analyzes the signal level, signal-to-noise ratio (SRN), and signal quality of the base station, and establishes the level of relationship between these parameters. The results show that the base station complies with the KPI levels established by the International Telecommunications Union (ITU) and provides optimal mobile phone coverage in rural areas. The study concludes that the base station has accessibility to the entire mobile phone network nationwide. Krasniqi *et al.,* (2019) discuss the importance of key performance indicators (KPIs) in monitoring and optimizing the network performance of 4G/LTE technology. The study presents an analysis of KPI parameters on the level of cells or clusters, including E-UTRAN Cell Availability, Cell UL Maximum Throughput, and Inter-RAT Handover Success Rate (LTE to GERAN). The analysis is performed on a real network implemented by Telecom of Kosovo (TK), the main mobile operator in Kosovo. The paper also provides a literature review related to KPI performance analysis in 4G/LTE technology, general aspects, and the 4G/LTE network architecture. The study concludes that the number of handovers from 4G-to-4G network is significantly higher than the number of handovers from 3G to 4G network, which may indicate a better coverage and quality of 4G network in the cluster.

Oje and Edeki (2021) present a study on the quality of internet connectivity provided by various mobile network operators (MNOs) on the 4G network within the University of Ilorin. The study was conducted using a walk test methodology, and data was collected using TEMS Investigation 16.3.4 and analyzed using TEMS Discovery Device 10. The study focused on seven test areas within the university, and the results showed that MNO4 had the best overall quality and throughout, while MNO1 had the poorest service. The study also found that specific locations within the university had optimum 4G speed. The paper concludes by suggesting possible future studies, including expanding the study to other universities or public areas and investigating the reasons behind the differences in service quality and throughput between the MNOs. (Popoola and Areo, 2020) proposed an automatic artificial neural network (ANN) predictive QoS model for GSM networks in Nigeria. The model was developed using five KPIs data collected from a GSM operator and was found to be accurate and efficient compared to the manual approach currently being used by the Nigerian Communications Commission. The paper suggests that the developed ANN QoS prediction model could be adopted by GSM regulatory bodies in Nigeria and other parts of the world. Rattaro *et al.,* (2021) propose using graph-based machine learning methods to predict the channel state on a given link in wireless communications. They model the problem as a link-prediction one and consider two approaches: Random Dot Product Graphs and Graph Neural Networks. The methods consider the geometric structure underlying the data, enabling better generalization, and requiring less training data than classic methods. The authors evaluate their proposed methods using a dataset of RSSI measurements of real-world Wi-Fi operating networks and show that their methods outperform traditional methods.

Call Setup Success Rate (CSSR) measures the call setup success or reflects the probability of successful calls initiated by the mobile station (Galadanci and Abdullahi, 2018). This happens immediately after the traffic channel (TCH) assignment is done, regardless of whether the call is dropped later or not by either the calling or called party. The CSSR is a key counter in evaluating network performance. Dropped Call Rate (DCR) measures the network ability to retain call conversation when it has been established or setup. A dropped call is a call that is prematurely terminated before being released normally by either the caller or the callee (Ozovehe and Usman, 2015). Standalone Dedicated Control Channel Congestion rate (SDCCH) is used for providing signaling required

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by the user (Aderinkola *et al.*, 2018). It carries signaling data following the connection of the mobile station (Phone) with the base station and just before a TCH (Traffic Channel) assignment is issued by the base station. The SDCCH maintains connection between the mobile station and the base station. Traffic Channel Congestion Rate (TCH) is accessed after a successful SDCCH seizure. TCH is used to either carry voice or data traffic. TCH congestion ratio measure how difficult it is setting up a call due to busy TCHs or indicates the ratio of the number of failed TCH seizures due to busy TCHs to the number of TCH seizure requests (Abdulkareem *et al.*, 2019).

The aim of the study is to predict KPIs for mobile telecom companies in Osun State University, Osogbo using Artificial Neural Network. The specific objectives of the studies are to design the ANN models using MATLAB R2020a software with different number of neurons and to also evaluate and compare the ANN models' prediction strength using mean absolute error and mean square error.

2. Materials and Methods

Monthly data of water vapor, air temperature, air pressure and relative-humidity were collected from the Nigerian Meteorological Agency (NIMET) in comma-separated values (CSV) using Modern Era Retrospective Analysis for Research and Applications version 2 (MERRA – 2). The data collection of seven years will span from January 1, 2016 to December 31, 2022. Also, the database of Nigerian Communications Commission (NCC), an independent National Regulatory Authority for the telecommunications industry in Nigeria, contains key performance indicators (KPIs) of all telecommunication service providers. KPI dataset was obtained from this database.

Key performance indicator of MTN shall be investigated and predicted in this study. The scope of this paper shall be limited to Osun State University, Osogbo, Osun State Nigeria. Osogbo is the Capital of Osun State, Nigeria. It lies on coordinate 7.778 North and 4.553 East (Google Map, 2023). These KPIs include Call Setup Success Rate (CSSR), Dropped Call Rate (DCR), Standalone Dedicated Control Channel (SDCCH) congestion rate, Traffic Channel (TCH) congestion rate. MATLAB R2020a Software programming language tool was employed for model development in this study.

The neural network architectures were developed using MATLAB R2020a. The neural networks had two layers with seven inputs and four outputs. The hidden layer had ten neurons, fifteen neurons and twenty neurons as shown in Figures 1, 2 and 3 respectively. The neural networks with different number of neurons were compared using the mean absolute error and mean square error. Log-sigmoid activation was employed in this study.

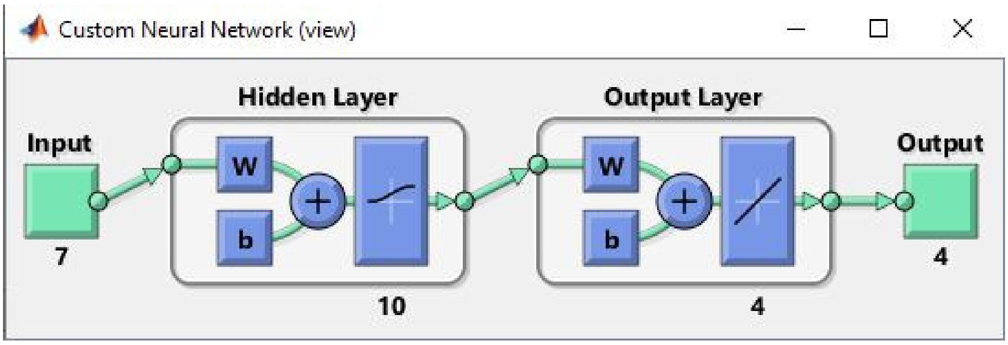

Fig. 1 *Neural network with 10 neurons*

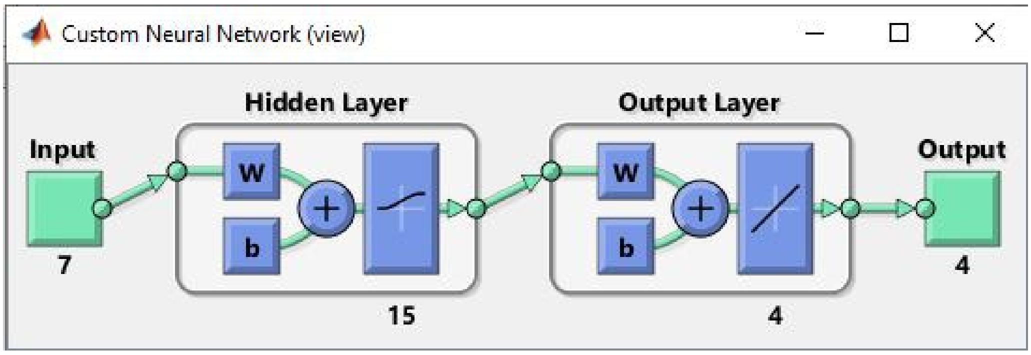

Fig. 2 *Neural network with 15 neurons*

Penerbit UTHM

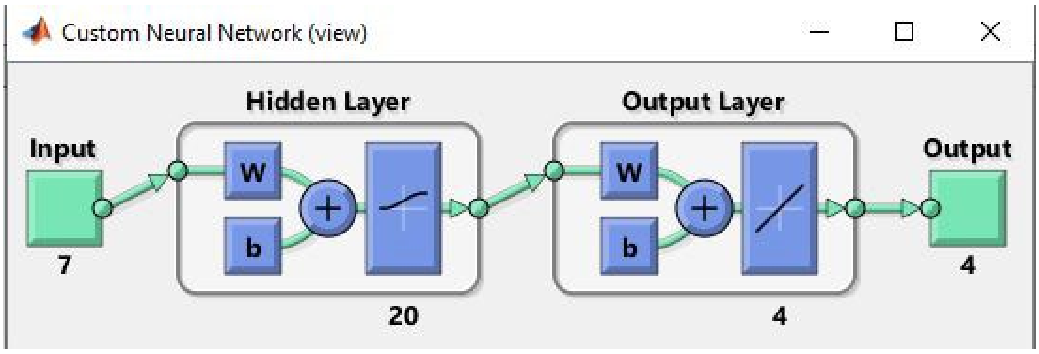

Fig. 3 *Neural network with 20 neurons*

3. Results and Discussion

Figures 4-7 show the prediction of the key performance indicators (KPIs) with 10 neurons in the hidden layer of the neural network. CSSR had a maximum error of 0.248, a minimum error of -0.308 and an average error of -0.045. The average, maximum and minimum errors for DCR are - 0.042, 0.093 and -0.212 respectively. -0.075, -0.013 and -0.171 are errors for average, maximum and minimum for SDCCH respectively. The average, maximum and minimum errors for TCH are -0.126, 0.038 and -0.239 respectively. The model with 10 neurons has good performance in predicting the KPIs with minimum errors recorded.

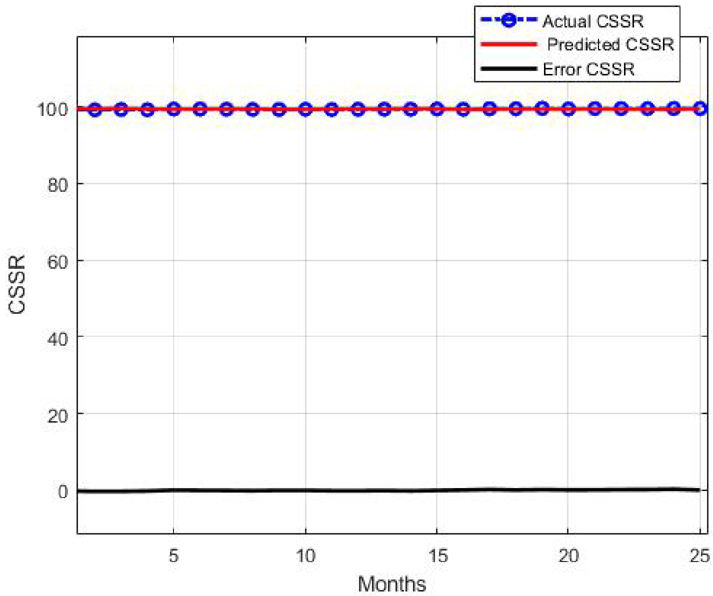

Fig. 4 *CSSR prediction with 10 neurons*

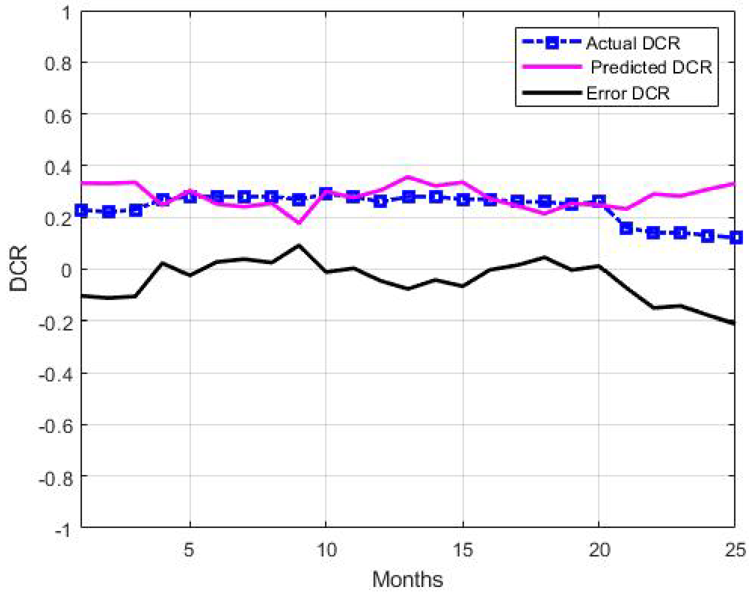

Fig. 5 *DCR prediction with 10 neurons*

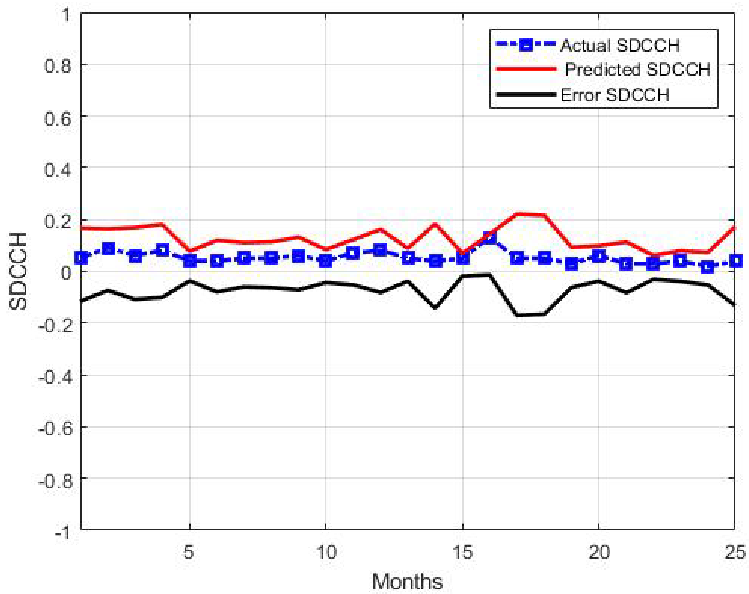

Fig. 6 *SDCCH prediction with 10 neurons*

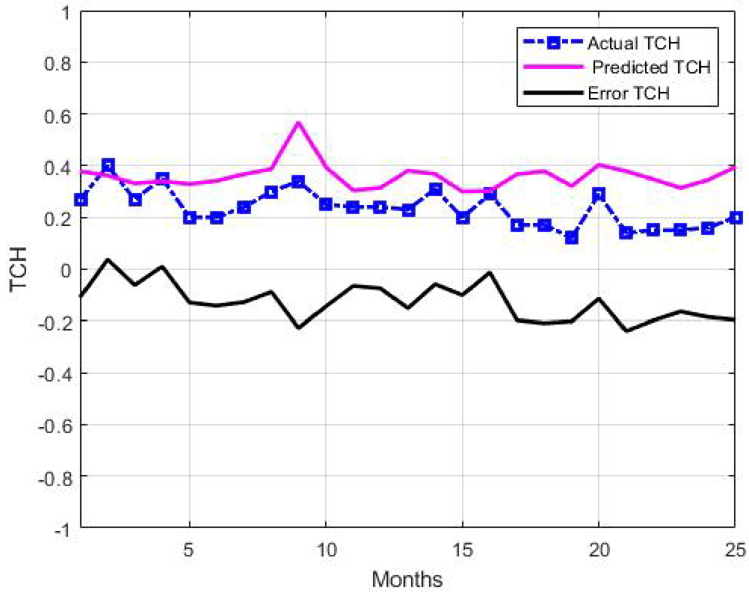

Fig. 7 *TCH prediction with 10 neurons*

Figures 8-11 show the prediction with fifteen neurons. The model with fifteen neurons in the hidden layer shows a considerably improvement viz-a-viz the previous model with ten neurons in the hidden layer. The average, maximum and minimum errors for CSSR are -0.045, 0.176 and -0.241 respectively. For DCR, -0.019, 0.104 and -0.144 are errors of the average, maximum and minimum respectively. The average, maximum and minimum errors for SDCCH are -1.753, 0.103 and -1.753 respectively. It is noteworthy that the model with ten neurons predicted SDCCH better than the model with fifteen neurons in the hidden layer. The average, maximum and minimum errors for TCH are -0.079, 0.202 and -0.232 respectively. The model with fifteen neurons did better than the model with ten neurons in the hidden layer.

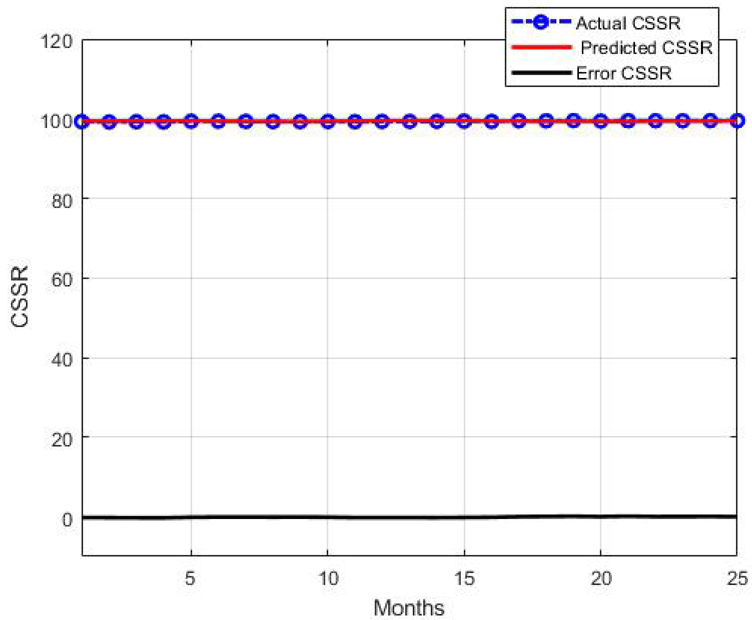

Fig. 8 *CSSR prediction with 15 neurons*

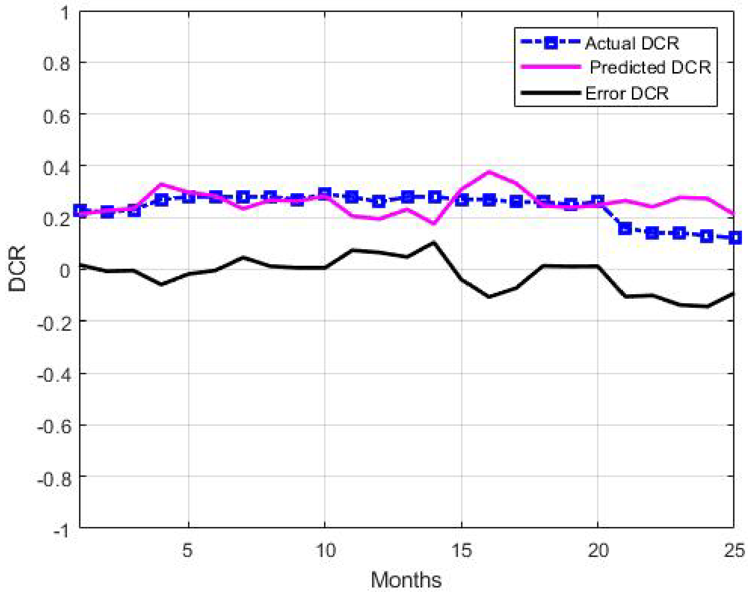

Fig. 9 *DCR prediction with 15 neurons*

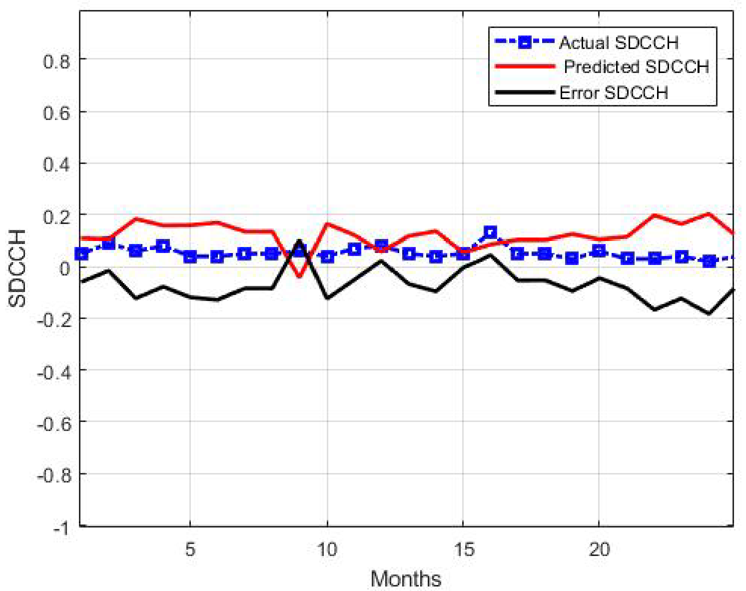

Fig. 10 *SDCCH prediction with 15 neurons*

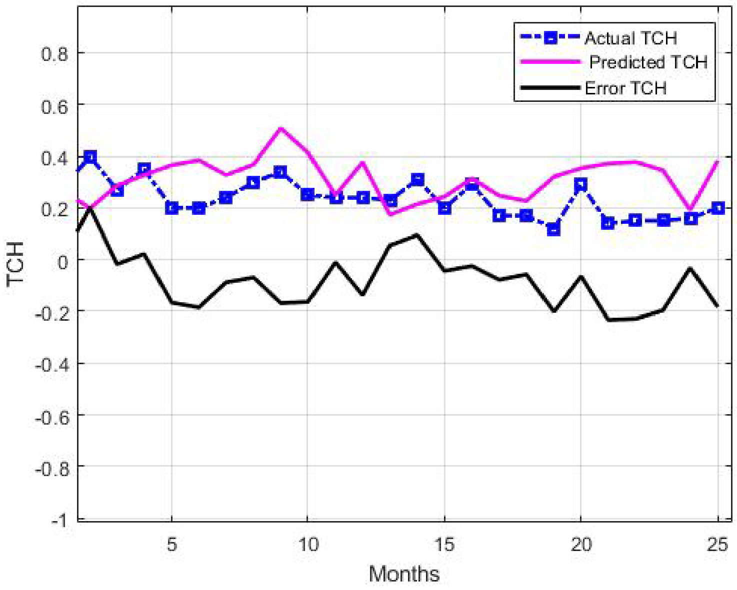

Fig. 11 *TCH prediction with 15 neurons*

Figures 12-15 show the prediction of the key performance indicators (KPIs) with 20 neurons in the hidden layer of the neural network. CSSR had a maximum error of 0.149, a minimum error of -0.297 and an average error of -0.039. The average, maximum and minimum errors for DCR are - 0.937, 0.049 and -0.127 respectively. -0.076, 0.129 and -0.324 are errors for average, maximum and minimum for SDCCH respectively. The average, maximum and minimum errors for TCH are -0.097, 0.148 and -0.257 respectively. The model with 20 neurons had the overall least performance model.

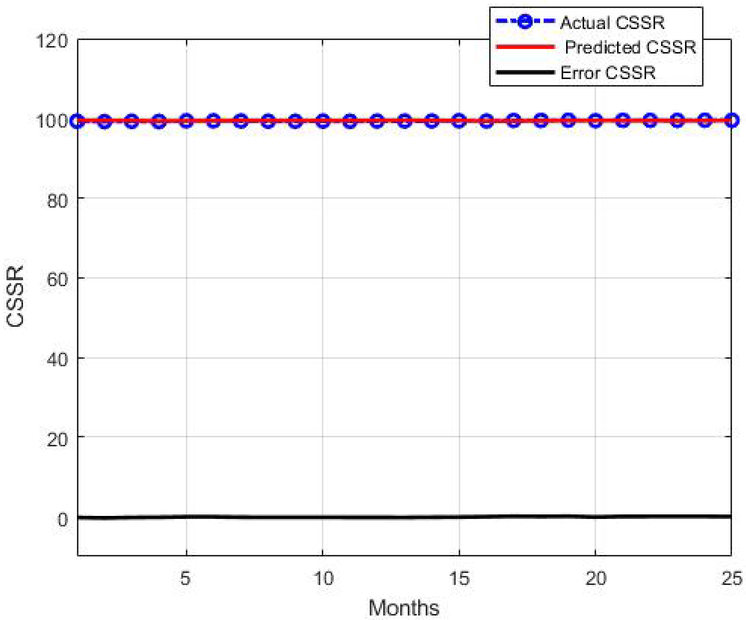

Fig. 12 *CSSR prediction with 20 neurons*

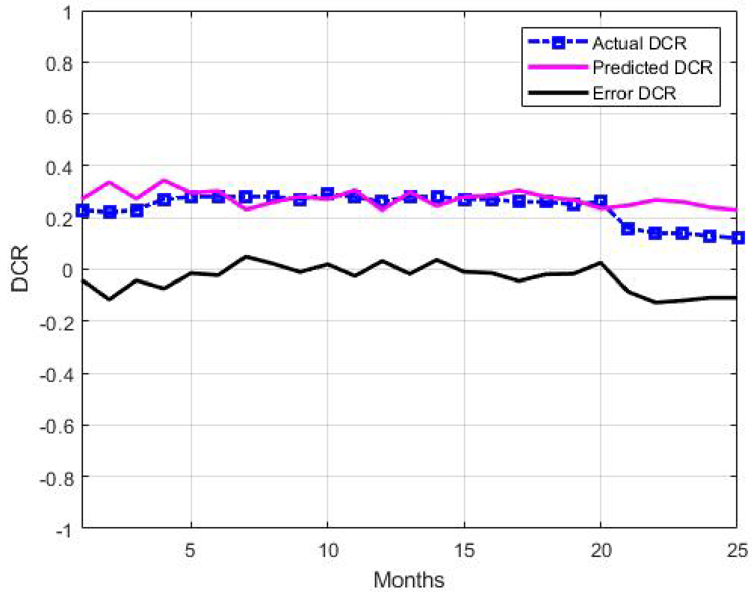

Fig. 13 *DCR prediction with 20 neurons*

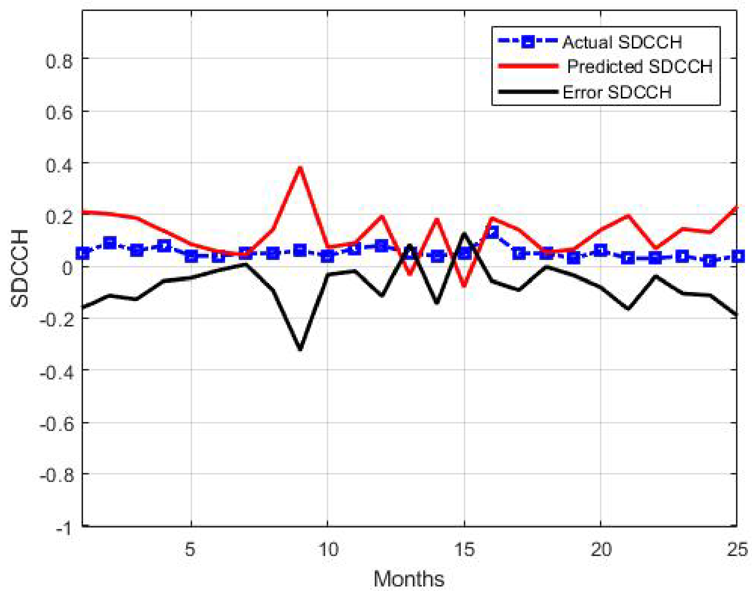

Fig. 14 *SDCCH prediction with 15 neurons*

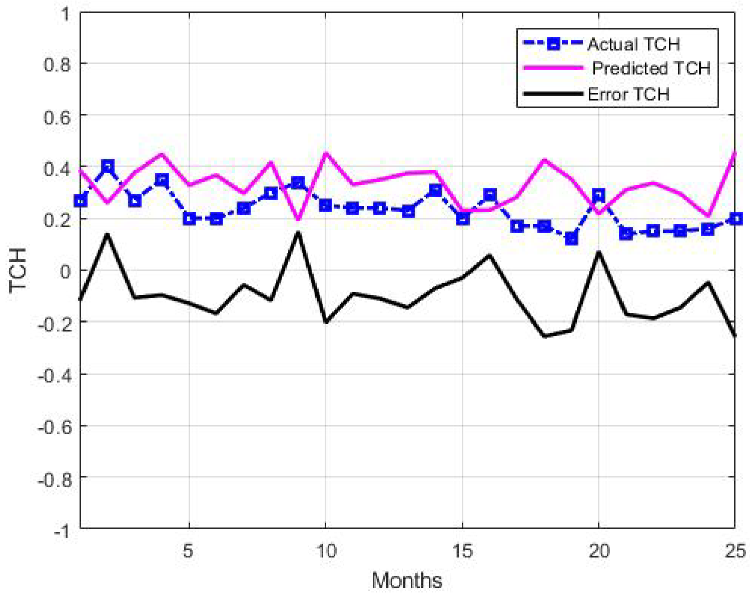

Fig. 15 *TCH prediction with 15 neurons*

Table 1 *The performance evaluation of the three neural network models*

Models	Hidden Layers Neurons	MAE	MSE
A	10	0.0990	0.0148
B	15	0.0909	0.0123
C	20	0.0960	0.0135

Table 1 represents the performance metric of the neural network models with three different neurons in the hidden layer. The Model B with 15 neurons shows the best performance. The Mean Absolute Error and Mean Square Error of Model B is 0.0909 and 0.0123 respectively. Model A with 10 neurons displays the least performance for the prediction of the KPIs. So, Model B, with fifteen hidden neurons was subsequently implemented for the prediction of the KPIs. The results show the effect of the hyperparameter that is, the number of neurons, on the performance of the models. In this study, differences in the number of hidden neurons change the evaluation metric of the models. There are other neural network hyperparameters, like number of layers and activation functions, that could be investigated in further studies.

4. Conclusion

The research was able to show that, for a neural network to predict accurately, more than one model should be developed and evaluated against the available datasets. Also, the study proved that the number of neurons in the hidden layer has impact on the performance of the model. The ANN models in this study were designed using MATLAB R2020a. The models were evaluated with MAE and MSE. The datasets employed were the meteorology data and the KPIs of Osun State University, Osogbo. The ANN model with fifteen neurons outperformed the ANN models with ten and twenty neurons. The findings in this research could assist the telecom companies to take inform decision to better the service delivery of the region under consideration in this research. Future research could also examine the effect of activation functions on the performances of the neural network models. Furthermore, different machine learning models like support vector machine model and random forest could be investigated.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

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