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Call Drop Prediction Using Nonlinear Autoregressive with Exogenous Input(NARX) Model

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Abstract: *In the global system for mobile communication (GSM), call drop is one of the key parameters for performance indicator (KPI) as it affects customer satisfaction. This research presents a non-linear autoregressive exogenous (NARX) Neural Network model for predicting a call drop due to handover failure. The three handover failure parameters: handover failure due to no response from originating and destination side (HoF1), handover failure due to master switching centres (MSC) route selection failure (HoF2) and handover failure due to call release during handover (HoF3) were used to train and test the NARX Neural Network. Call drop target variable was also used. Four different input sizes (60, 120, 180 and 240) were used each to train the network; this was done to determine the appropriate size of input for training the network. The trained network with 120 inputs showed better performance in terms of means squared error (MSE) and a high coefficient of regression (R), hence it was adopted for predicting call drops for 20 hours ahead of the 120 hours used for training the network. The model was implemented using the time series Neural Network prediction in the MATLAB. The result shows a coefficient of regression value of 0.88653, prediction accuracy of approximately 89% with an MSE of 4.06697. The result will help telecommunication companies in improving the quality of service with the knowledge of call drops that are likely to occur in the future for a particular area, thereby improving customer satisfaction.*

Keywords: Call Drop; GSM Handover Failure; NARX Neural Network; Mean Square Error

INTRODUCTION

Call drop is the inability of a mobile user's call to connect through the network successfully. It is also the abrupt disconnection of a call after the allocation of a channel (M Ekpenyong & Isabona, 2014). Over the years, the number of subscribers has greatly improved the quality of service, as many subscribers were not happy with the services provided (Erunkulu et al., 2019). Drop call likelihood is one of the most important service quality indices for cellular network efficiency monitoring (Boggia et al., 2005, Tarkaa et al., 2011, Boggia et al., 2007). For this purpose, for many aspects of reducing cell phone operations, several optimization procedures are implemented. A call must be switched to the appropriate base station at the connection time to provide uninterrupted contact. The handover is known as this operation. In general, the failure of the method resulted in drop calls. It has been found that handover-based drop call likelihood models are only useful during the early stage of implementation of the mobile network. However, it has been discovered that call drop is mainly due to electromagnetic triggers in a well-established network; erratic user activity and abnormal network response. It is evident from these results that estimates of the probabilities of drop calls due to handover and the other variables could be implemented for performance analysis of the cellular network (Anioke et al., 2015).

Mobility represents a great advantage for user comfort while on the other hand, it could cause great degradation if not managed properly (Zhang & Dai, 2019, Ozturk et al., 2019). In a call drop process, the subscriber does not enter into a queue for potential assignments. In the global system for mobile communication (GSM), call drop is one of the key factors for performance indicator (KPI) as it affects customer satisfaction. Call drops are due to different reasons: electromagnetic causes, irregular user behaviour, abnormal response, hardware failure, transmission channel problem, intra-network and internetwork interface, coverage, handover failure and repeater problem (Sudhindra & Sridhar, 2012). Call drop is one of the major issues which affect the quality of service of the telecom network (Sankar, 2016). Call drops are annoying to the user; as the call drop incidence increases, it also increases customer dissatisfaction (Galadima et al., 2014). This can lead to changing of the network by the user. One of the key elements of a mobile cellular network system is that the system is divided into numerous small cells to provide good coverage and channel utilization. However, as the mobile user moves from one cell area to another, it should be possible to retain its communication connection (Galadima et al., 2014). Handoff or handover is an essential element of cellular communication as efficient handoff algorithms are a cost-effective way of enhancing the capacity and quality of service (QoS) of the cellular system (Umoren et al., 2014, Moses Ekpenyong et al., 2017). In wireless communication, networks handoff is used to provide communication everywhere to moving users. Handoff is a process of transferring an ongoing call from one channel to another without any interruption to user communication while maintaining the quality of service. Handoff is used to reduce the call drop rate. Handover provides and enhances the quality of service while the user moves from one point to another. Handover failure can lead to call drop or termination. Dropped calls are the calls that end due to the technical reason before the actual conversation finish; due to which performance goes down. The rate of these types of call is called the call drop rate (Aibinu et al., 2017). All over the world, cellular network operators are faced with the challenges of improving the quality of service (QoS) while increasing capacity and rolling out new services (Ozovehe et al., 2014). Therefore, there is a need for effective call drop prediction as a result of handover failure for better decision, planning and management to avoid deterioration of quality of service or call drop while a mobile user moves from one cell boundary to another during a call.

This research presents a model for hourly call drop prediction as a result of handover failure using a nonlinear autoregressive model with exogenous input (NARX). Globacom Nigeria Limited is used as a case study. Call drop due to handover failure is assumed, that the active user can change cell several times and during one of these transitions between cells, connectivity can be dropped. Call drop caused by handover failure depends on system characteristics as well as user behaviour. In this research, call drop due to handover failure such as Handover Failures due to no Response from Originating Side or Destination Side, Handover Failures due to MSC Route Selection or Bearer Operation Failures and Handover Failures due to Call Release during Handover are considered for the prediction. This research will help Telecommunication companies in improving the quality of service with the knowledge of all call drops that are likely to occur in the future for a particular area. The rest of this paper is organised into three sections.

MATERIAL AND METHODS

This section presents the procedures for realising the objectives of this research work. It explains the block diagram and all the steps involved in the development of the Call-drop prediction model using a Nonlinear Autoregressive exogenous (NARX) neural network. The research work adopts the method of NARX type of neural network to predict future hourly call drops for a GSM network using past values of Handover Failures (HoFs). An experiment was carried out using a variety of input sizes; 60, 120, 180 and

240. For each of the four sizes, the data was trained using the NARX neural network and their performance was evaluated in terms of Mean Square Error (MSE) and Correlation Coefficient (R). A dataset comprising of intra Master Switching Centre (MSC) handover times, start times, Objective instances, call drops and Hand over Failures (HoF) was collected. The network whose MSE is minimum and correlation coefficient value (R) is highest was selected and used to predict future 20 hours call drops. Fig. 1 presents the overall model block diagram for the work. The Figure shows different stages of the process involved in the development of the NARX Neural Network Model for Call Drop Prediction. They include A dataset, data pre-processing stage, NARX design, training and testing and finally performance evaluation. Table 1 presents the sample of the data used for the prediction.

Table- 1 A Sample of the Data used for Prediction

Object Instance	Start Time	Call Drop	HoF 1	HoF 2	HoF 3
(Handover Type--GSM to GSM handover(ho2g))	2018-01-05 00:00:00+01:00	0	21	3	5
(Handover Type--GSM to GSM handover(ho2g))	2018-01-05 01:00:00+01:00	0	8	11	0
(Handover Type--GSM to GSM handover(ho2g))	2018-01-05 02:00:00+01:00	0	9	3	0
(Handover Type--GSM to GSM handover(ho2g))	2018-01-05 03:00:00+01:00	0	8	0	2
(Handover Type--GSM to GSM handover(ho2g))	2018-01-05 04:00:00+01:00	0	3	0	1
(Handover Type--GSM to GSM handover(ho2g))	2018-01-05 05:00:00+01:00	1	5	0	0
(Handover Type--GSM to GSM handover(ho2g))	2018-01-05 06:00:00+01:00	2	27	8	5

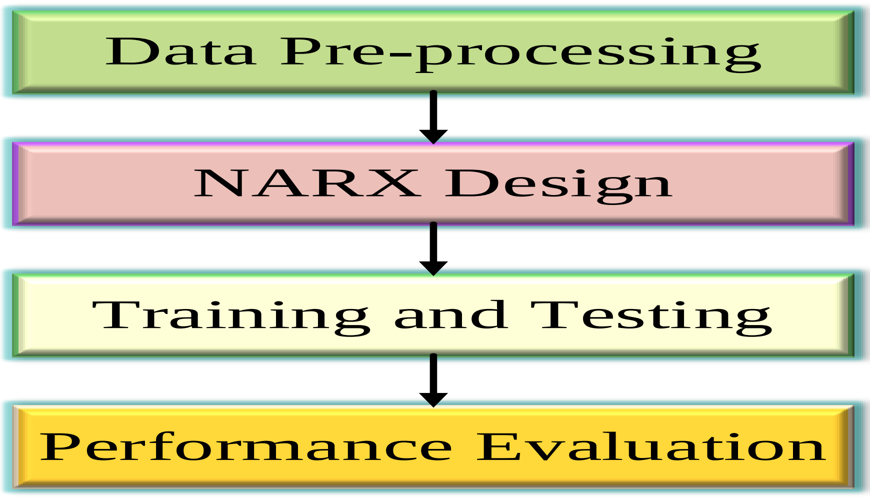

Fig 1. Overall Model Block Diagram

Three variables that affect call drop namely: First; Hand over Failure (HoF) due to no response from originating and destination side (HoF1), Second. HoF due to Master Switching Centre (MSC) route selection failure (HoF2) and third. HoF due to call release during handover (HoF3) were extracted from the dataset, the fourth variable 'call drop' were also extracted and used as the target. The aforementioned three features were formatted into a single cell (3 × 1 cell, 3 variables in one cell) and the call drop variable was also formatted into another single cell (1×1 cell, 1 variable in 1 cell). The data was then divided into four different sizes of 60 hours, 120 hours, 180 hours and 240 hours. Each dataset was used to train the network in other to determine the dataset size that is most appropriate for training the network. The Neural Network Architecture is shown in Fig 2.

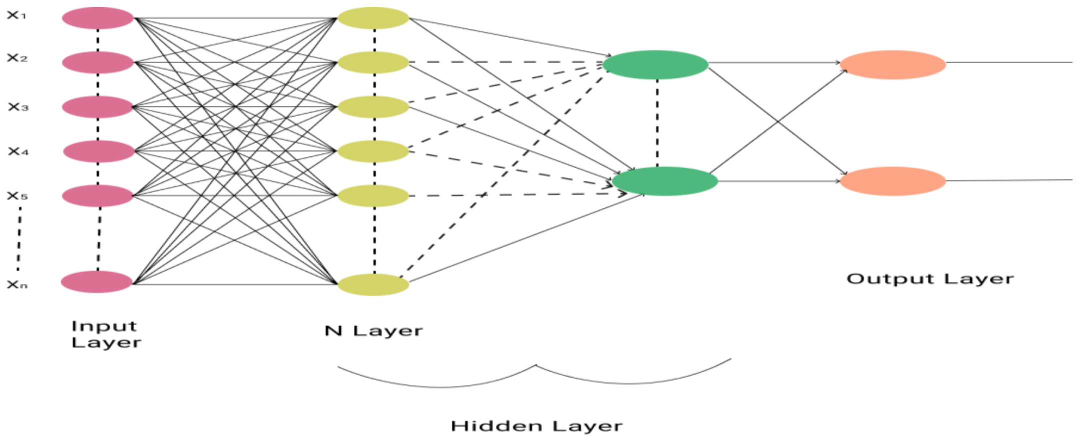

Fig. 2. Neural Network Architecture

2.1 Prediction Model Design

In designing the prediction model, the following were considered: The type of model: NARX was adopted as the model type because it performs better than the backpropagation neural network in time series prediction. The number of inputs: Three inputs were used HoF1, HoF2 and HoF3 which were selected from the pool of other data in the dataset because they directly result to call drops in any GSM network Number of neurons in the hidden layer: between 20 to 30 neurons were selected in trial-and-error basis, the number that gave the optimum performance was selected. The input time delay 'd' time delay of 3 was selected based on its success after several trials.

2.2 NARX Neural Network Training

For training, 65% of the data in the database for each of the input sizes described in table 1 were used to train the networks; while 20% goes to testing and 15% for validation. Hence, for 60 hours input size, the first 39 hours were used for training while 12 hours was used for testing, the remaining 9 hours was used for validating the network. Fig. 3 present the flowchart showing the NARX Neural Network training steps.

2.3 NARX Neural Network Testing

For each of the input sizes described in table 2.1, 20% was used for testing the network. The test data comprised samples whose call drops were known but not used in training. After the testing, the performance of each of the networks was evaluated. After selecting the best performing network, 20 hours' time-series call drop was predicted. The data input is the three handover errors while the output was compared to the call drop target to check the prediction accuracy.

2.4 Performance Evaluation

Mohammed *et al*., (2013) proposed three metrics for evaluating the hourly prediction model. The metrics are: coefficient of determination (R2), root mean squared error (RMSE) and mean bias error (MBE).

Khamis *et al.*, (2014) developed a model for Wheat price forecasting using backpropagation and NARX Neural Network. They measured the performance of their prediction using Mean Squared Error (MSE) and Correlation Coefficient (R). The correlation coefficient values measure the relationship between the output and target and it ranges between -1 and 1. Positive R values for example (1) indicate a direct relationship between two variables while negative R values indicate an inverse relationship. In this research, the performance of the model was evaluated using MSE and R performance metrics. The network, whose results showed minimum MSE with maximum R, is the best network that was adopted for the call drop prediction.

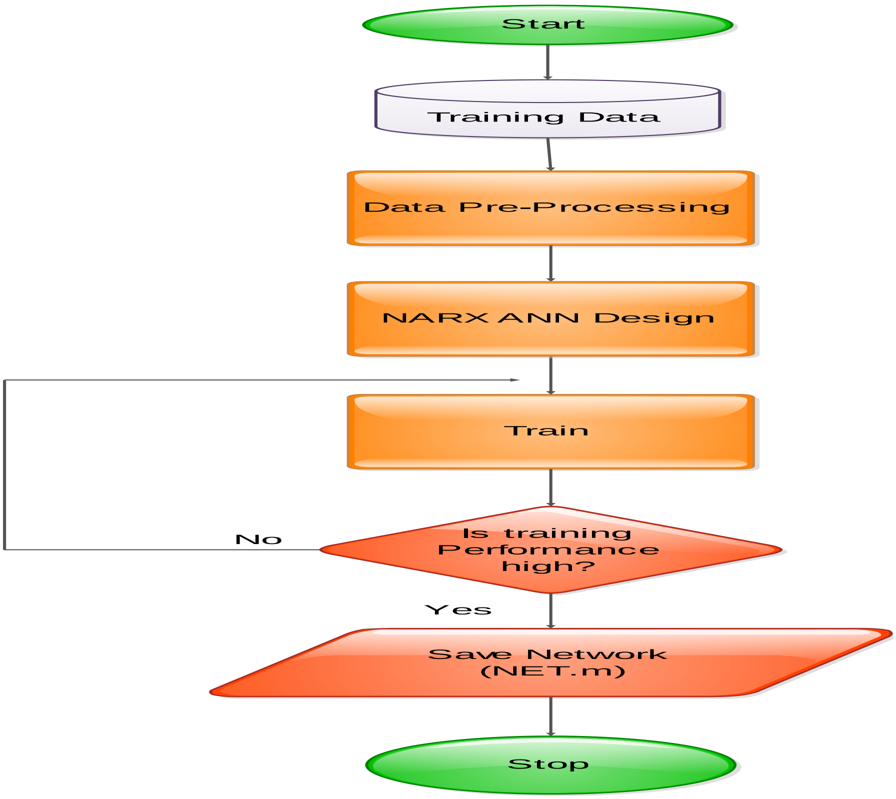

Fig. 3. NARX ANN Training Flow Chart

RESULTS AND DISCUSSION

This section presents the results obtained from the various stages of the development of the call drop prediction model using a Non-linear Autoregressive network with exogenous input (NARX) neural network. The model was trained and tested using the three input variables (HOF1, HOF2 and HOF3) and target variables (Call drop). The experiment was performed for four different input sizes (60, 120, 180 and 240) where 65% of the data was used for training, 20% for testing and 15% for validation. The network that produces the best result was adopted and used to predict call drop for the next 20 hours. In the NARX neural network analysis, the best model was selected to predict call drops based on the performances of the four networks trained with 60, 120, 180 and 240 input sizes.

The performance was measured in terms of the MSE and R values shows that the model trained with 120 input sizes performs better and was adopted for prediction of future call drops as shown in Fig. 3, 4, 5 and 6. Table 2 contain the illustration of data input used for the training, validation and testing of the network. Fig. 4 presents the trained performance (MSE) graph of the model trained with 60 inputs; the training stopped after 9 epochs because the validation error increased. The plots show the training, validation, and testing errors. The best validation performance (MSE) obtained is 17.8434 is obtained after the third epoch. Fig. 5. shows the trained performance (MSE) graph of the model trained with 120 inputs; the training stopped after 25 epochs because the validation error increased. The best validation performance (MSE) of 12.1827 is obtained after the 20th epoch.

The result shows a good network performance because the test set error and the validation set error have similar characteristics, and it doesn't appear that any significant overfitting has occurred. Fig. 6 shows the trained performance (MSE) graph of the model trained with 180 inputs; the training stopped after 11 epochs because the validation error increased. The best validation performance (MSE) of 17.5959 is obtained after the fifth epoch. The result shows a higher MSE value as compared to the model trained with 120 inputs.

Table -2 Illustration of the Input Data

S/N	Input	Training (65%)	Validation (20%)	Testing (15%)
1	60	39	12	9
2	120	78	24	18
3	180	117	36	27
4	240	156	48	36

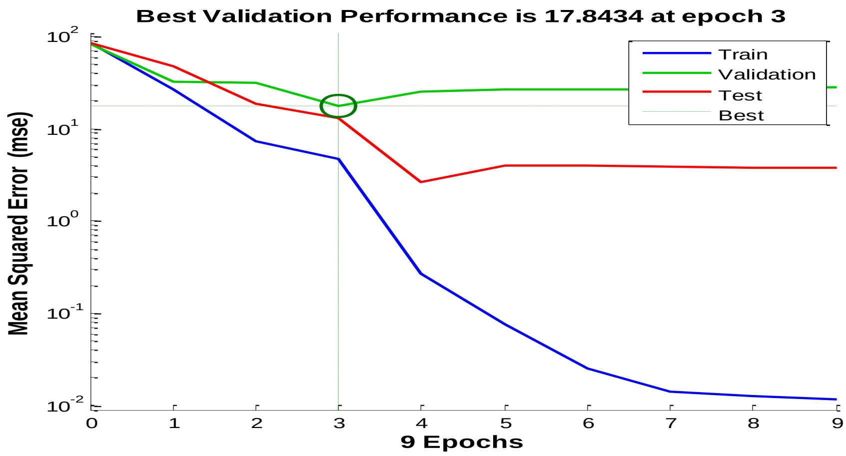

Fig. 4. NARX Network Training Performance for 60 Inputs.

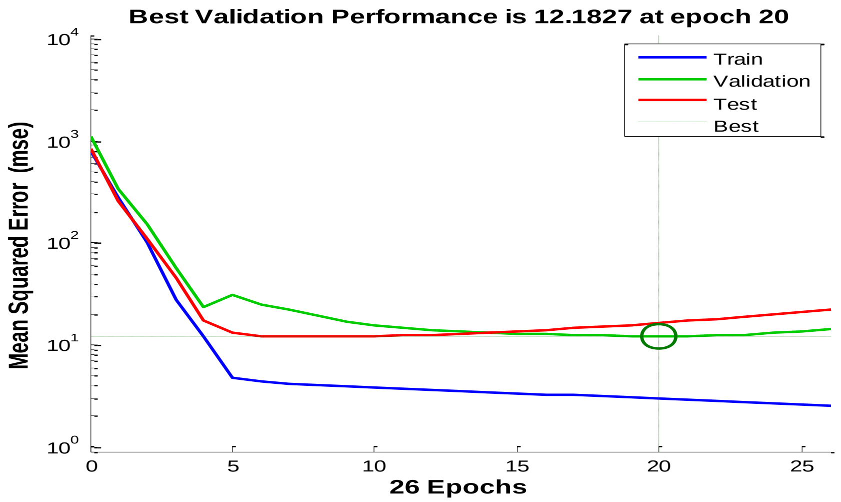

Fig. 5. NARX Network Training Performance for 120 Inputs

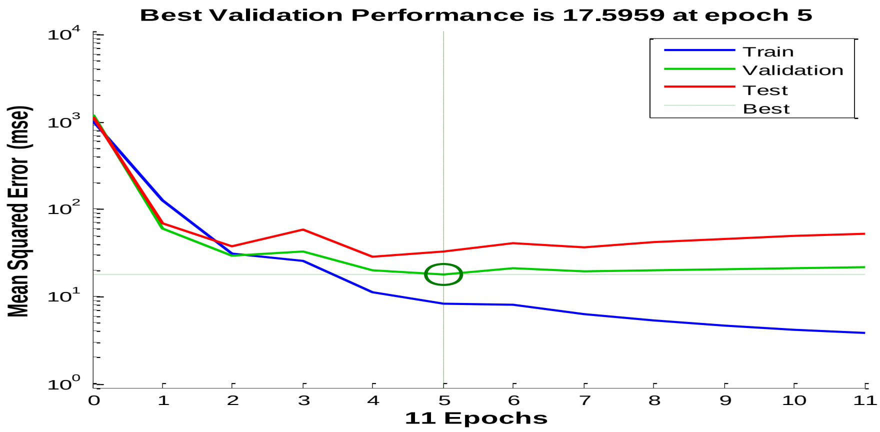

Fig. 6. NARX Network Training Performance for 180 Inputs

Fig. 7 shows the trained performance (MSE) graph of the model trained with 240 inputs; the training stopped after 9 epochs because the validation error increased. The best validation performance (MSE) of 20.2625 is obtained after the third epoch. The result shows a higher MSE value as compared to the model trained with 180 inputs.

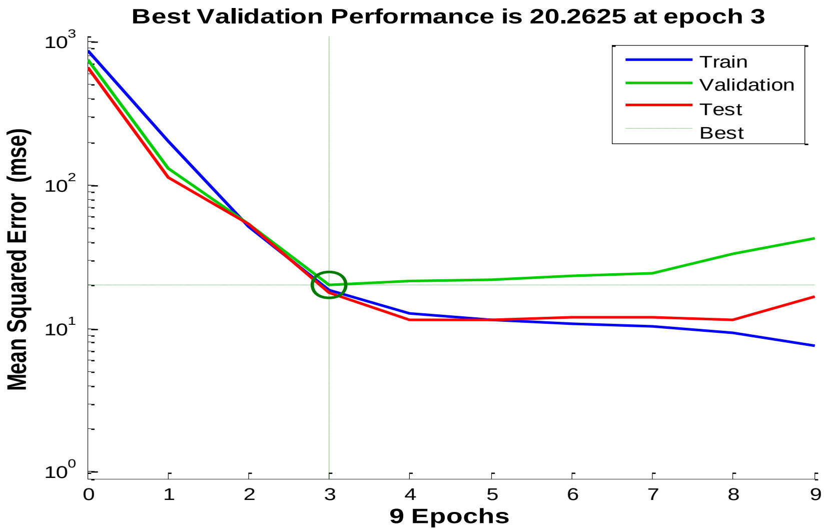

Fig. 7. NARX Network Training Performance for 240 Inputs

3.1 NARX Neural Network Correlation Analysis

The performance of Call drop prediction for the four NARX models trained with different input sizes was also analysed using correlation analysis. The correlation coefficient R was measured for each model. This was done to check which network size is appropriate for training the network and subsequent adoption. Fig. 8 shows the correlation plot for 60 input sizes. The value for *R* obtained *is* 0.89079 for training, 0.1037 for validation and 0.88985 for testing. From the result, the validation and overall R values are low, which means that the output produced by the network is not very similar to the target and that the model is not satisfactory. Fig. 9 presents the correlation plot for 120 input sizes. The value for *R* obtained is 0.96275 for training, 0.73847 for validation and 0.63829 for testing. From the result, the overall R values are high, which means that the output produced by the network is closely similar to the target and that the model is satisfactory. Fig. 10 shows the correlation plot for 180 input sizes. The value for *R* obtained is 0.86877 for training, 0.31489 for validation and 0.68329 for testing. From the result, the R values are lower than those obtained from the network trained with 120 inputs indicating not satisfactory performance. Fig. 11 shows the correlation plot for 240 input sizes. The value for *R* obtained was 0.73629 for training, 0.28942 for validation and 0.62638 for testing. From the result, the R values were lower than those obtained from the network trained with 180 inputs, which means the performance is not satisfactory.

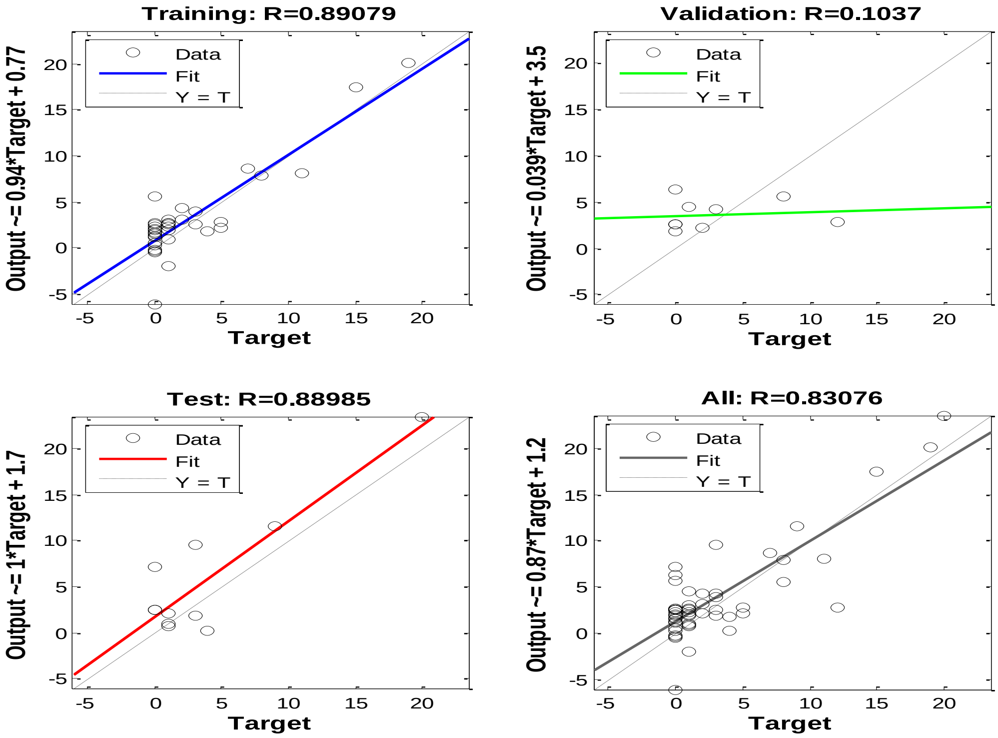

Fig. 8. Correlation Plot for 60 Input Size

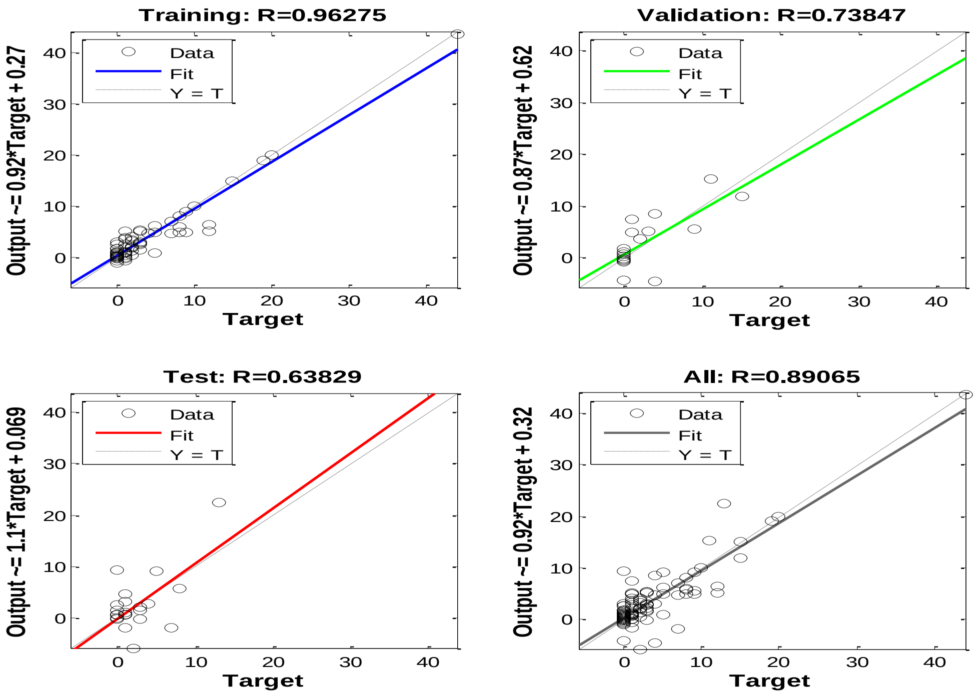

Fig. 9. Correlation Plot for 120 Input Size

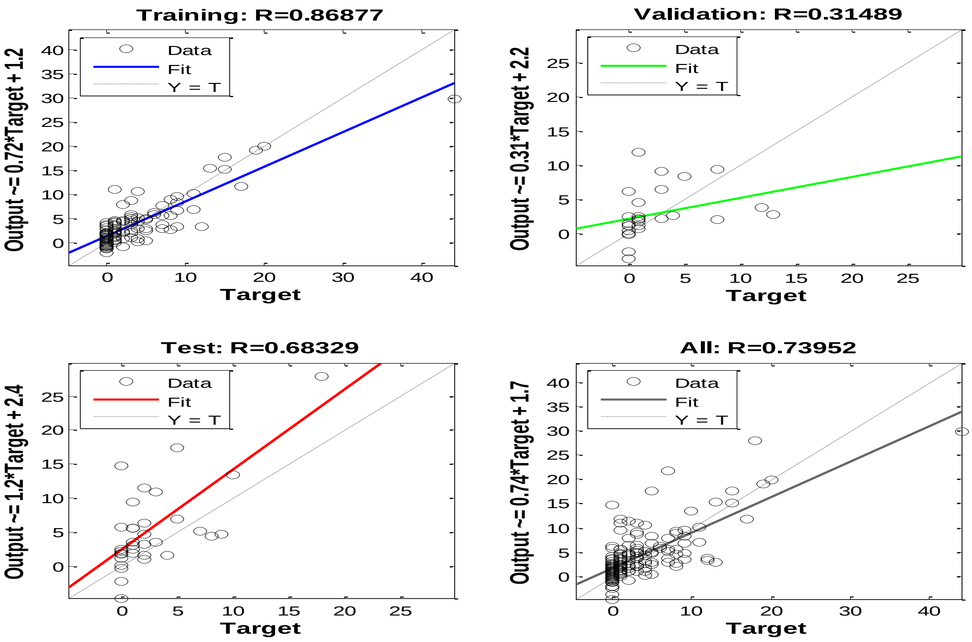

Fig. 10. Correlation Plot for 180 Input Size

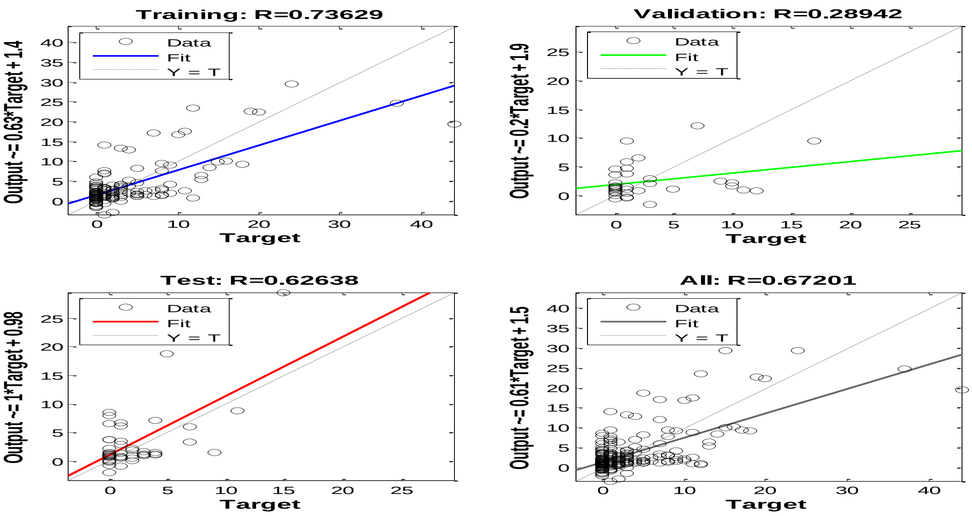

Fig. 11. Correlation Plot for 240 Input Size

3.2 Performance Comparison and Model Selection

From the analysis of the results, the best model was selected to predict future call drops based on its performance (MSE and R) values. As summarized in Table 3, the model trained with 120 inputs showed higher R values and lowest MSE value as compared to the models trained with 60, 180 and 240 inputs respectively. Hence, the model was selected and used to predict future 20 hours call drop ahead of the 120 hours that was used for training. Fig. 12 shows the correlation plot for the call drop prediction of the 20 test samples. The value for *R* obtained was 0.88653, which means that the predicted call drops are closely similar to the target call drops for the 20-hour time series being predicted. From the result, the MSE obtained is 4.0667 while the correlation coefficient value is 0.8865 which means the prediction accuracy is approximately 89% as shown in Fig. 12.

Table- 3. Training and Testing Performance Evaluation

TRAINING			TESTING		Prediction Accuracy
Input Size	**MSE**	**R**	**MSE**	**R**	
60 Input	4.7396	0.8908	12.8777	0.8899	83%
120 Input	1.8720	0.9628	38.3240	0.6383	89%
180 Input	8.2266	0.8688	32.2754	0.6833	73%
240 Input	18.400	0.7363	42.8268	0.6264	67%

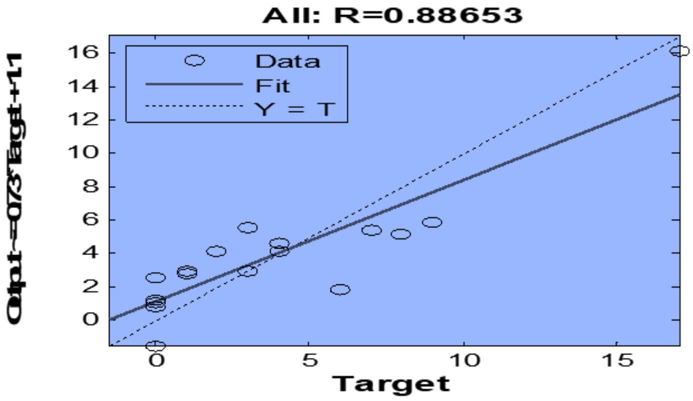

Fig. 12. Correlation Coefficient Plot for 20 Hours Calls Drop Predict

CONTRIBUTION TO KNOWLEDGE

A non-linear autoregressive exogenous (NARX) Neural Network model for predicting a call drop due to handover failure for predicting call drops for 20 hours ahead of the 120 hours was presented successfully. The result will help telecommunication companies in improving the quality of service with the knowledge of call drops that are likely to occur in the future for a particular area, thereby improving customer satisfaction.

CONCLUSION

The use of a Non-linear autoregressive exogenous (NARX) Neural Network for the prediction of time series call drops of a GSM (Globacom) network is presented. The best network was selected after four different networks were trained using four different input sizes which are 60, 120, 180 and 240 respectively. The network that was trained with 120 inputs showed better performance in terms of its MSE and R values, hence was adopted for predicting call drops for 20 hours ahead of the 120 hours used for training the network. The model was implemented in MATLAB using the Time series neural network prediction in the MATLAB environment. The performance of the system was evaluated using the coefficient of correlation R and mean squared error (MSE). The result shows a prediction accuracy of approximately 90% with an MSE of 4.06697.

CONFLICT OF INTEREST

There is no conflict of interest associated with this research work.

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