International Journal of Science and Research Archive

eISSN: 2582-8185

Cross Ref DOI: 10.30574/ijsra

Journal homepage: https://ijsra.net/

(Research Article)

Forecast analysis of call setup success rate in mobile networks: A hybrid approach

Enoima Essien Umoh [1,*], Atte Enyenihi Okwong [1] and C. Emeruwa [2]

[1] *Department of Computer Science, University of Cross River State, Calabar, Nigeria.*

[2] *Department of Physics, Federal University, Otuoke, Nigeria.*

International Journal of Science and Research Archive, 2025, 16(02), 997-1006

Publication history: Received on 10 July 2025; revised on 17 August 2025; accepted on 19 August 2025

Article DOI: https://doi.org/10.30574/ijsra.2025.16.2.2373

Abstract

This study employs a hybrid forecasting approach, combining a statistical model and a machine learning model, to predict the monthly Call Setup Success Rate (CSSR) for Nigeria's four major cellular networks using the CSSR dataset sourced from the Nigerian Communications Commission. The mobile networks studied were MTN, Airtel, Glo, and 9mobile. The machine learning model applied in this study was the Random Forest algorithm, while the statistical model used is the Autoregressive Integrated Moving Average (ARIMA) model. Model performance was evaluated using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE), with forecasts validated against actual 2024 data. Results reveal consistently high CSSR values for most networks, with all operators frequently exceeding the Nigerian Communications Commission (NCC) benchmark. In this study, Random Forest generally outperformed ARIMA for datasets with pronounced non-linear fluctuations, while ARIMA performed better where trends were smooth and stable. Both models achieved exceptionally low forecast errors, with MAPE values below 0.5% for Airtel, Glo, and MTN, and below 3% for 9mobile using Random Forest. The findings demonstrate the viability of combining statistical and machine learning models for accurate KPI forecasting, supporting proactive network optimisation, regulatory compliance, and customer satisfaction strategies.

Keywords: CSSR; Machine Learning; Random Forest; ARIMA; GSM Networks

1. Introduction

The Call Setup Success Rate (CSSR) is a key performance indicator (KPI) used to evaluate mobile network performance and reflect a network's accessibility. It measures the percentage of call attempts that are successful, directly indicating the network's accessibility [1-3], signaling efficiency, and service reliability [1,4-5]. A high CSSR indicates a robust infrastructure and efficient resource utilization. At the same time, a low CSSR often signals problems such as radio link failure, limited tower coverage, high traffic congestion, or core network issues [1-3,5-6]. Given the increasing reliance on mobile communication for business, education, governance, and social interaction, ensuring consistent and reliable call connectivity is more important than ever [6-7]. As mobile networks evolve with growing subscriber bases and rising demand for seamless voice services, continuous monitoring of call setup performance becomes essential for identifying underlying network weaknesses and guiding infrastructure development [6-7].

In Nigeria, several studies have examined the CSSR across various GSM networks, often with a focus on specific regions or limited measurements [8-38]. While these studies have provided valuable insights into network accessibility, they fall short of offering a comprehensive, nationwide perspective based on an extended longitudinal dataset [39-40]. Furthermore, only a limited number of investigations have employed predictive modelling techniques to forecast future performance of mobile networks [41-48] or systematically compare model accuracies [49-50]. These methodological and scope-related gaps constrain the ability of stakeholders to anticipate potential performance challenges and to implement proactive strategies for service optimization [48,51]. Addressing these limitations is therefore essential to

* Corresponding author: Enoima Essien Umoh

enhance the understanding of network performance dynamics and to support evidence-based decision-making in the Nigerian telecommunications sector.

This study applies predictive modelling techniques, specifically the Autoregressive Integrated Moving Average (ARIMA) model and the Random Forest algorithm, to forecast future CSSR values. Model accuracy was evaluated using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). By integrating statistical and machine learning approaches within a longitudinal analysis framework, the research provides deeper insights into network accessibility patterns across Nigeria. The findings support the development of more robust and intelligent forecasting methods, offering a valuable decision support tool for regulatory bodies and Mobile Network Operators (MNOs) to enhance service monitoring, optimise network performance, and maintain high-quality telecommunications services nationwide.

2. Methodology

This section employed a three-phase approach: data acquisition, predictive modeling, and validation of the prediction models.

2.1. Data Acquisition

Monthly CSSR data for the four major GSM Networks across Nigeria were obtained from the Nigerian Communications Commission (NCC), spanning January 2014 to November 2024. This data was obtained by NCC using specialized counters from the Network Operation Centers (NOCs) of the respective MNOs. The dataset captures variations in successful call setups across the networks. The networks are MTN, Airtel, Globacom, and 9mobile.

2.2. Historical Trend and Predictive Modeling

For each network investigated, graphs were plotted to understand the trend in the networks from January 2014 to November 2024. The historical data from January 2014 to December 2023 was then used to train the forecast models. Forecasts were generated from January 2024 to December 2024 using the statistical and machine learning models. The statistical approach involved using the ARIMA model, a classical method for forecasting time series. The machine learning model used was the random forest, an ensemble machine learning model, which was employed in this study due to its robustness and generalization capabilities. Each of the models used in this study had its uniqueness.

2.2.1. Autoregressive Integrated Moving Average (ARIMA)

The ARIMA model is a statistical method for analysing and forecasting time series data. It combines three components: Autoregressive (AR), Integrated (I) and Moving Average (MA).

The Autoregressive component uses the relationship between a current observation and several past observations. It is controlled by parameter p (the number of lag observations used). The integrated component involves differencing the data to remove trends and seasonality, making the data stationary. The integrated component is controlled by parameter d, which is the number of differences taken. The last component is the moving average, which utilizes the relationship between the observation and the residual errors from a moving average model applied to lagged observations. The moving average model is controlled by parameter q, which is the size of the moving average window. A summation of the components gives the general form of ARIMA as ARIMA (p, d, q) [52].

While the ARIMA works well for short-term forecasting and is flexible for non-seasonal and seasonal data, however, the limitations of the model are that it requires stationary data and is not ideal for highly volatile or non-linear series.

2.2.2. Random Forest

Random forest is a machine learning approach widely applied in both classification and prediction tasks [53]. It operates on the principle of decision trees by building an ensemble of multiple trees and combining their results to produce a final prediction. Each decision tree in the forest is generated from a random subset of the dataset, with training carried out on only a fraction of the entire data. The predictions from all trees are then aggregated to form the overall output [54]. A key strength of random forests lies in their ability to manage imbalanced datasets and handle variables with missing values. They also reduce the bias associated with arbitrary variable selection, which can occur in some other models. By training multiple trees on randomly selected subsets of data, random forests effectively minimise overfitting and improve generalisation to unseen data. Recognised as one of the most powerful and efficient machine learning methods, random forests are extensively employed in areas such as automated classification, predictive analytics, and supervised learning [55].

2.3. Performance Metrics

To evaluate the performance (accuracy and reliability) of the forecast models, error metrics were deployed. Error metrics used in this study were the RMSE, MAE, and MAPE. The best-performing model for each network was selected based on the lowest error values, as the model with the lowest error values was seen to have the highest predictive accuracy.

2.4. Software Used

Python was employed as the primary software tool for data analysis and modeling in this study. Its flexibility, extensive library support, and strong data handling capabilities made it an ideal choice for conducting both statistical and machine learning tasks. Specifically, the following Python libraries were utilized: Pandas was used for data cleaning, manipulation, and time-series structuring. Matplotlib and Seaborn were used for generating trend plots and comparative graphs across networks. SciPy was used for statistical analysis. Statsmodels was used for ARIMA modeling, while Scikit-learn was used for the machine learning application (Random Forest)

3. Results and Discussion

The historical analysis of the CSSR performance across Nigeria, forecasting of CSSR for mobile networks, and performance evaluation of the forecast models have been completed. The results are being displayed in this section in the form of graphs and tables, each of which is been discussed in detail.

3.1. Analysis of Historical Trend

In this section, historical graphs are plotted for the mobile networks under study. The historical graphs describe CSSR data from January 2014 to November 2024, for each network.

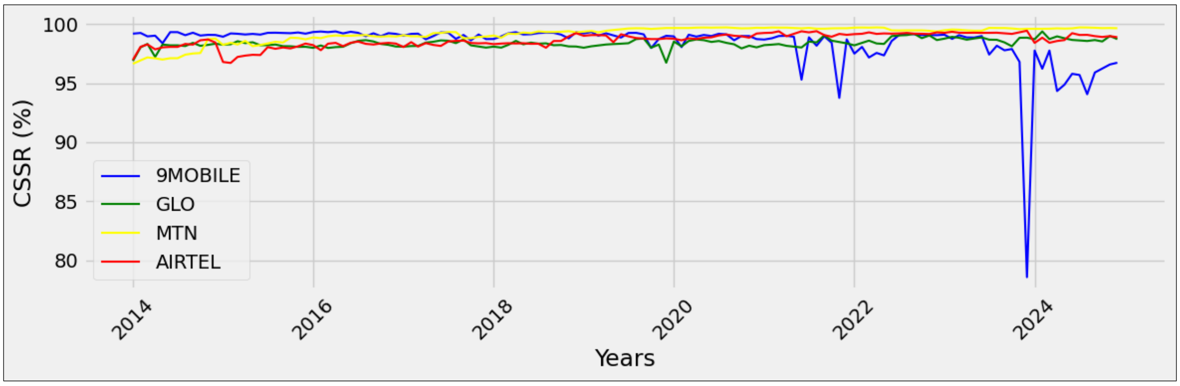

Figure 1 Graph of CSSR from January 2014 to December 2024

Figure 1 presents the monthly trends of CSSR from January 2014 to December 2024. The plot uses colour-coded lines to represent each network: red for Airtel, blue for 9mobile, green for Globacom, and yellow for MTN. Using the NCC benchmark of 98% for CSSR, the performance of the four networks over a 132-month study period is summarized as follows:

Airtel achieved CSSR values equal to or above the 98% benchmark in 121 out of 132 months, representing approximately 91.7% of the study period. Only 11 months recorded CSSR values below the benchmark. The minimum CSSR observed for Airtel was 96.72%, while the maximum reached 99.45%.

9mobile recorded CSSR values at or above the benchmark in 107 months, which accounts for approximately 81.1% of the total period. CSSR values fell below 98% in 25 months. The network's CSSR ranged from a minimum of 78.57% to a maximum of 99.39%.

Glo attained CSSR values of 98% or higher in 127 months, representing approximately 96.2% of the study duration. Only 5 months fell below the benchmark. Glo's CSSR spanned from 96.74% at its lowest to 99.18% at its highest.

MTN CSSR values met the benchmark in 122 months, approximately 92.4% of the study period. It recorded values below 98% in only 10 months. During this period of study, the minimum CSSR for MTN was 96.65%, while the maximum reached 99.73%.

3.2. Analysis of Forecast Models

In this section, the historical CSSR data from January 2015 to December 2023, for the four mobile networks, were used to generate monthly CSSR forecasts from January 2024 to December 2024 using two forecasting models: ARIMA and Random Forest. The results are discussed on a per-network basis, as each mobile network employed a different ARIMA model for forecasting due to the nature of the various networks' data.

3.2.1. Forecast Description for Airtel Network

For the Airtel network, the dataset comprised monthly CSSR values from January 2014 to December 2023 (120 observations). The data series was indexed monthly to ensure temporal ordering in Python, stored as a panda's series object for processing. Visual inspection and Augmented Dickey–Fuller (ADF) testing suggested slight non-stationarity in the mean. First-order differencing (d=1) was applied to stabilise the series. A grid search was conducted over p = 0 to 3, d = 0 to 2, and q = 0 to 3. The Akaike Information Criterion (AIC) guided parameter selection, with the lowest AIC corresponding to the ARIMA (2,1,2) configuration. The ARIMA (2,1,2) model was fitted to the historical data using Maximum Likelihood Estimation (MLE). This process optimised the autoregressive and moving average coefficients to minimise in-sample forecast errors. The fitted model was used to forecast CSSR values from January 2024 to December 2024.

For Random Forest, the raw monthly CSSR values were transformed into a supervised learning dataset suitable for machine learning regression. For each forecast target month, twelve lag features were generated to represent CSSR values from the preceding twelve months, capturing temporal dependencies in call setup patterns. Month-of-year dummy variables were added to account for seasonal variations. For example, to predict January 2024, the input vector contained CSSR values from January–December 2023 and a binary indicator representing January. This model was trained using the prepared dataset covering January 2016 to December 2023 (the first twelve months were reserved for lag generation). Hereafter, the Random Forest model constructed multiple decision trees using bootstrap sampling. At each node split, a random subset of features was selected, encouraging diversity among trees and reducing correlation between them. The final prediction was obtained by averaging the outputs of all trees, which improves generalisation and reduces the likelihood of overfitting.

A recursive forecasting approach was adopted for the 2024 period. First, the RFR predicted the TCCH value for January 2024 using the most recent twelve months of lag features. This predicted value was appended to the historical dataset and used as one of the lag inputs for forecasting February 2024. The process was repeated sequentially until forecasts were generated for all twelve months of 2024.

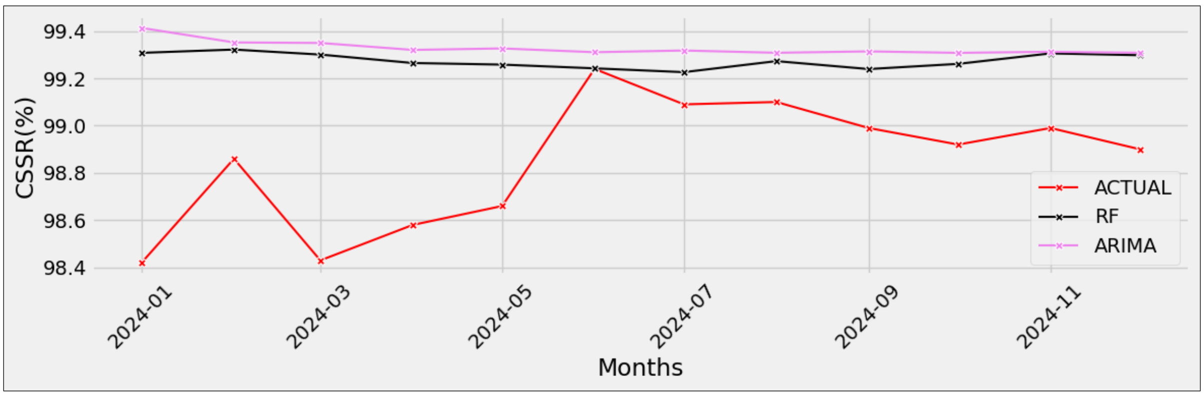

Figure 2 Actual and Forecast CSSR Plot for Airtel Network

The actual CSSR values and the forecasted values for Airtel network are presented in Figure 2. Again, colour-coded lines were used to represent the plots. Red for the actual value, black for the Random Forest and violet for the ARIMA plot. As depicted in the graph, both models accurately reproduced the stable trajectory of Airtel's CSSR over the 2024 forecast horizon. While ARIMA effectively captured the long-term stability, Random Forest provided slightly closer alignment to the actual monthly variations. This was evident in the finer tracking of small fluctuations between months, as visualised in the forecast plot.

The forecast plot also indicated that Airtel's CSSR remained consistently above the NCC benchmark, usually ≥ 98%, throughout the forecast period. The minimal forecast deviations in both models underscore a high level of operational stability, suggesting that network accessibility was both strong and resilient during the study period. Finally, performance evaluation of the forecast models was assessed using the MAE, RMSE, and MAPE. This was done to ensure comparability between the two models as presented in Table 1.

Table 1 Performance Evaluation Metrics for Airtel Network

Model	MAE	RMSE	MAPE (%)
ARIMA	0.48	0.55	0.49
Random Forest	0.43	0.51	0.43

From the table, it can be deduced that the Random Forest model demonstrated marginally superior predictive accuracy compared to ARIMA. However, both models achieved errors below 0.5% MAPE, signifying exceptionally high reliability in forecasting monthly CSSR values for Airtel network.

3.2.2. Forecast Description for 9mobile Network

Here, monthly CSSR data for 9mobile, covering January 2014 to December 2023, were used. The dataset was complete, with no missing values, and represented in percentage form (%). The Random Forest procedure was the same as described in section 3.2.1. However, there was a slight deviation in the ARIMA model.

In the ARIMA model, a visual inspection of the time series suggested minor trends in the mean, indicating near-stationarity. First-order differencing (d = 1) was applied to stabilise the series. The differenced series exhibited constant mean and variance, fulfilling the stationarity requirement.

A grid search over p = 0 to 3, d = 0 to 2, and q = 0 to 3 was performed. For each parameter combination, the model was fitted, and the AIC was computed. The combination with the lowest AIC was selected. This resulted in the optimal configuration: ARIMA (2,1,2). The ARIMA (2,1,2) model was then fitted using the MLE method implemented in Python's statsmodels package. This process estimated the coefficients of the AR and MA components along with the model intercept. The actual CSSR values and the forecasted models are presented in Figure 3.

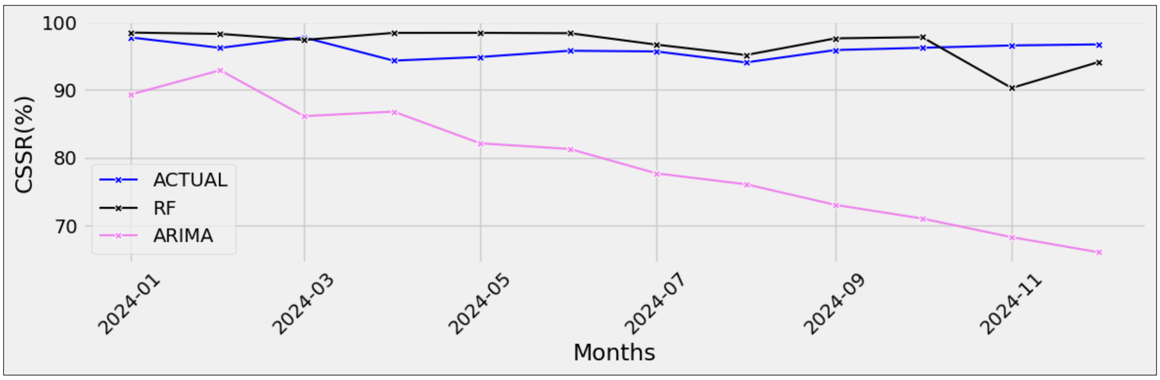

Figure 3 Actual and Forecast CSSR Plot for 9mobile Network

As seen in the graph, actual CSSR (blue line) remained relatively stable, fluctuating between 94.07% and 97.77% over the year. However, ARIMA (1,2,3**)** (violet line) consistently underestimated performance, beginning around 89% in January and declining sharply to about 66% by December, failing to capture the actual stability of the network. At a close look, Random Forest (black line) closely tracked the actual CSSR, remaining within 1 to 3 % of the true values and accurately representing both peaks and dips.

In terms of NCC's benchmark for CSSR, ARIMA's forecasts indicated severe non-compliance for 2024, while Random Forest provided a realistic forecast that was closer to actual compliance performance. Again, the performance evaluation of both forecast models was evaluated using the actual CSSR values for January to December 2024. The accuracy metrics used were MAE, RMSE, and MAPE, as presented in Table 2.

Table 2 Performance Evaluation Metrics for 9mobile Network

Model	MAE	RMSE	MAPE (%)
ARIMA	16.79	18.73	17.48
Random Forest	2.31	2.82	2.41

The results show that Random Forest achieved significantly lower errors across all metrics, with a MAPE of 2.41%, compared to ARIMA's 17.48%. This indicates that Random Forest tracked the actual CSSR values far more accurately. Also, Random Forest proved more suitable for this dataset, capturing non-linear patterns and recent performance trends more effectively than ARIMA. Hence, using ARIMA for operational planning will result in false alarms and misallocation of network resources.

3.2.3. Forecast Description for Glo Network

The monthly CSSR dataset for Glo, covering January 2014 to December 2023, was first arranged in chronological order. Each data point represented the average (CSSR) for a given month. For the Glo dataset, the forecast using Random Forest followed the same process. Also, for the ARIMA model, the same process was followed; however, to determine the optimal values, grid search was carried out over a range of p = 0 to 4, d = 0 to 2, and q = 0 to 4. Each combination was fitted using the AIC for model selection. The model with the lowest AIC was ARIMA (3,1,3). This ARIMA (3,1,3) model implies that the model used the previous 3 months' CSSR values to predict the current month, worked with the first differences of the data to achieve stationarity, and used the previous 3 months' forecast errors in the prediction process. The selected ARIMA (3,1,3) was fitted to the entire 2014–2023 dataset using the MLE method. Using this fitted model, a 12-step ahead forecast was generated for January to December 2024. The actual values and the forecast models are shown in Figure 4.

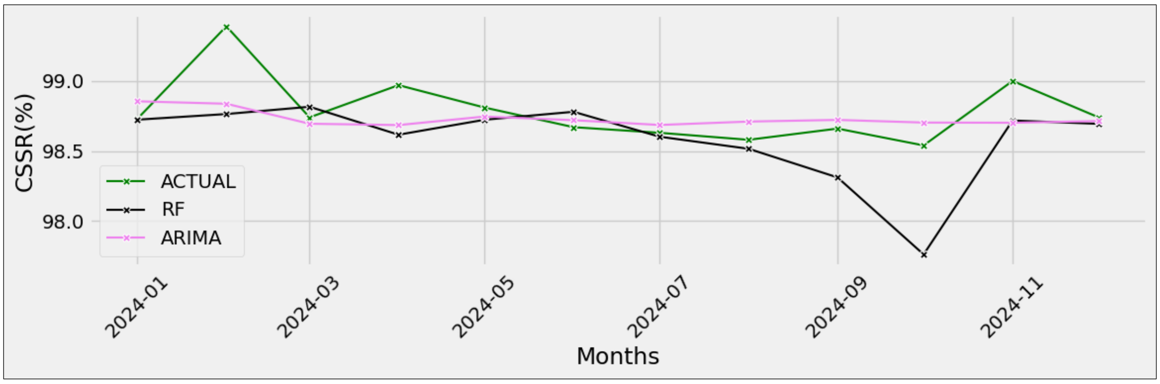

Figure 4 Actual and Forecast CSSR Plot for Glo Network

From the graph, actual CSSR (green line) was fluctuating between 98.54% and 99.39% over the year. The ARIMA (3,1,3**)** (violet line) and Random Forest (black line) exhibited patterns that closely tracked the actual CSSR, showing short-term fluctuations. Again, the performance accuracy of both forecast models was evaluated using the actual CSSR values for January to December 2024. The accuracy metrics used were MAE, RMSE and MAPE as displayed in Table 3.

Table 3 Performance Evaluation Metrics for Glo Network

Model	MAE	RMSE	MAPE (%)
ARIMA	0.15	0.21	0.16
Random Forest	0.23	0.34	0.24

Results show that ARIMA (3,1,3) slightly outperformed Random Forest in tracking monthly variations for Glo network. This was visible as observed in its lower MAE, RMSE, and MAPE values than Random Forest. However, both models achieved very high accuracy (MAPE < 0.3%), implying that they were extremely close to the actual values and their forecasts reflected the underlying patterns in the historical data while accounting for short-term fluctuations.

3.2.4. Forecast Description for MTN Network

The monthly Call Setup Success Rate (CSSR) dataset for MTN, covering January 2014 to December 2023 was used. The ARIMA process was chronologically followed. The second-order differencing resulted in a stationary series with constant mean and variance over time. The parameter selection was performed over a range of values: p = 0 to 4, d = 0 to 2, and q = 0 to 4. The model with the lowest AIC was ARIMA (1,2,2). This means that the model used one lagged value of the differenced series for prediction, worked on the second differences to achieve stationarity, and used two lagged forecast errors in making predictions. The ARIMA (1,2,2) model was fitted to the training dataset (January 2014 to December 2023) using the MLE approach. The fitted model was used to generate 12-month-ahead forecasts for January to December 2024. These forecasts captured the underlying trend of MTN's CSSR while accounting for short-term fluctuations. For the MTN dataset, the forecast using Random Forest followed the same process as described in section 3.2.1. The actual values and the forecast values of both models are presented in Figure 5.

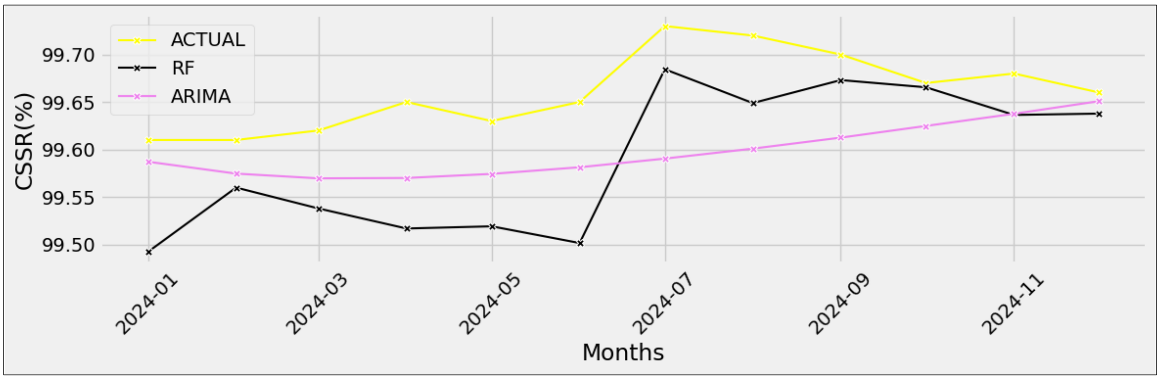

Figure 5 Actual and Forecast CSSR Plot for MTN Network

To evaluate the accuracy of the forecast models, MAE, RMSE, and MAPE were calculated and presented in Table 4.

Table 4 Performance Evaluation Metrics for MTN Network

Model	MAE	RMSE	MAPE (%)
ARIMA	0.15	0.21	0.16
Random Forest	0.23	0.34	0.24

It is deduced from the table that both models achieved extremely high accuracy (MAPE < 0.1%), though ARIMA (1,2,2) performed slightly better than Random Forest in all three metrics, meaning it tracked MTN's 2024 CSSR pattern more closely. This indicates ARIMA is more reliable for short-term CSSR forecasting when the data has a smooth, stable trend like that of MTN.

4. Conclusion

This study analysed the Call Setup Success Rate (CSSR) performance of Nigeria's four major GSM networks (MTN, Airtel, Globacom, and 9mobile) from January 2014 to December 2024 and produced forecasts for January 2024 to December 2024 using ARIMA and Random Forest models. Model accuracy was assessed using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE), with forecasts validated against actual 2024 CSSR values.

The results show that MTN, Airtel, and Globacom consistently maintained CSSR values above the Nigerian Communications Commission (NCC) threshold of 98%, indicating stable and reliable network accessibility. Airtel and MTN recorded minimal deviations from the benchmark, reflecting robust infrastructure and efficient resource utilisation. Globacom exhibited moderate fluctuations but generally met the benchmark. Conversely, 9mobile displayed lower CSSR values and higher variability, suggesting operational challenges and the need for targeted improvements.

In terms of modelling, Random Forest outperformed ARIMA in capturing short-term fluctuations and non-linear patterns, particularly for networks with high variability such as 9mobile and Globacom. The ARIMA model performed comparably well for more stable networks, such as Airtel and MTN, offering a simpler and more interpretable forecasting option. Both models achieved high predictive accuracy, with MAPE values below 0.5% for most networks when using Random Forest, and below 3% for 9mobile, confirming their suitability for KPI monitoring.

These findings have important implications for network operators, regulators, and policymakers. Accurate CSSR forecasting supports proactive network optimisation, early identification of performance issues, and data-driven investment planning. For the NCC, the results provide a solid basis for regulatory compliance monitoring. Maintaining high CSSR levels also enhances customer satisfaction, reduces churn, and strengthens competitive advantage in Nigeria's telecommunications market.

Future researchers should extend this study by incorporating additional Quality of Service (QoS) indicators and should also explore advanced hybrid deep learning models to further improve predictive performance.

Compliance with ethical standards

Acknowledgments

The authors sincerely acknowledge the Nigerian Communications Commission (NCC) for providing the Call Setup Success Rate (CSSR) data utilised in this research.

Disclosure of conflict of interest

No conflict-of-interest to be disclosed.

References

[1] Ajayi OT, Onidare SO, Ayeni AA, Adebowale QR, Yusuf SO, Ogundele A. Performance Evaluation of GSM and WCDMA Networks: A Case Study of the University of Ilorin. International Journal on Electrical Engineering and Informatics. March 2021; 13(1): 87-106

[2] Kollar M. Evaluation of real call set up success rate in GSM. Actaelectrotechnica et informatica. Feb 2008; 8(3): 54-56

[3] Ozovehe A, Usman AU. Performance analysis of GSM networks in Minna Metropolis of Nigeria. Nigerian Journal of Technology. 2015 Mar 31;34(2):359-67.

[4] Ekah UJ, Onuu MU. Tropospheric influence on call setup in mobile networks. J Eng Res Rep. 2022;22(2):14-26.

[5] Ekah UJ, Emeruwa C. Guaging of key performance indicators for 2G mobile networks in Calabar, Nigeria. World J Adv Res Rev. 2021;12(2):157-63

[6] Tekanyi AMS, Abdulkareem HA, Muhammad ZZ. Analysis of GSM network quality of service using call setup failure rate and handover failure rate indices. Telecommunications and radio engineering. 2019; 78(16): 1471-1481

[7] Abdulkareem HA, Tekanyi AMS, Kassim AY, Muhammad ZZ, Almustapha MD, Abdu-Aguye UF, Adamu H. Analysis of a GSM network quality of service using call drop rate and call setup success rate as performance indicators. Zaria journal of electrical engineering technology. Mar 2020; 9(1): 113-21.

[8] Adediran AA, Oni J, Musa A. Congestion and service quality improvement of mobile telephone networks in Nigeria: A review. Technoscience Journal for Community Development in Africa. 2024 Dec 30;3:83-90.

[9] Ekah UJ, Adebayo AO, Shogo OE. Spatial distribution of frequency modulated signals in Uyo, Nigeria. World J Adv Eng Technol Sci. 2022;5(1):39-46.

[10] Obiyemi OO, Lasisi HO, Oladepo O, Awofolaju TT, Ibrahim MA. A Performance Evaluation of Cellular Mobile Networks: A Case Study of Osun State University. Adeleke University Journal of Engineering and Technology. 2022 Jun 25;5(1):16-24.

[11] Ekah UJ, Emeruwa C. Penetration depth analysis of UMTS networks using received signal code power. J Eng Res Rep. 2022;23(7):16-25.

[12] Odo GO, Ezeonye CS. Analysis and Evaluation of Intercell Vertical Handoff for 4G Networks using NCC Key Performance Indicators. UNIZIK Journal of Engineering and Applied Sciences. 2022 Jun 1;20(1):767-74.

[13] Iloke J, Ekah UJ, Ewona I. Tropospheric influence on ultra-high frequency (UHF) radio waves. Asian J Res Rev Phys. 2022;6(3):48-57.

[14] Saragih Y, Hadikusuma RS. Evaluation of cellular network performance involving the LTE 1800 band and LTE 2100 band using the drive test method. Jurnal Infotel. 2022 Nov 4;14(4):294-300.

[15] Ekah UJ, Obi E, Ewona I. Tropospheric influence on low-band very high frequency (VHF) radio waves. Asian J Adv Res Rep. 2022;16(11):25-36.

[16] Asiegbu BC, Ohuabunwa AE, Nwakanma IC, Ezeh GN. Assessment of factors affecting quality of service of cellular mobile network operators in Nigeria for the period 2010 to 2014. International Journal of Engineering and Modern Technology. 2015;1(8):2504-8848.

[17] Iloke J, Ekah UJ, Uduobuk EJ, Ewona I, Obi E. Quality of service reliability: A study of received signal quality in GSM networks. Asian J Phys Chem Sci. 2022;10(3):25-34.

[18] Kehinde AI, Adunola SL, Fatai O, Isaac AI. GSM quality of service performance in Abuja, Nigeria. International Journal of Computer Science, Engineering and Applications (IJCSEA) Vol. 2017;7(3/4)

[19] Ewona I, Ekah UJ, Ikoi AO, Obi E. Measurement and performance assessment of GSM networks using received signal level. J Contemp Res. 2022;1(1):88-98.

[20] Ozovehe A, Okereke OU, Anene EC. Literature survey of traffic analysis and congestion modeling in mobile network. IOSR Journal of Electronics and Communication Engineering Volume. 2015 Nov;10(6):31-5.

[21] Ekah UJ, Iloke J, Ewona I, Obi E. Measurement and performance analysis of signal-to-interference ratio in wireless networks. Asian J Adv Res Rep. 2022;16(3):22-31.

[22] Kadiri KO, Lawal SO, Adejuwon AA. Analysis of congestion of mobile network in Offa. J. Sci. Res. Rep. 2019;22(6):1-8.

[23] Ekah BJ, Iloke J, Ekah UJ. Tropospheric influence on dropped calls. Glob J Eng Technol Adv. 2022;10(2):83-93.

[24] Adikpe AO, Iyobhebhe M, Amlabu CA, Bashayi JG. Congestion analysis of a GSM network in Kaduna State Nigeria. International Journal of Advanced Natural Sciences and Engineering Researches. 2021;5(1):1-6.

[25] Ekah UJ, Iloke J. Performance evaluation of UMTS key performance indicators in Calabar, Nigeria. GSC J Adv Res Rev. 2022;10(1):47-52.

[26] Ozovehe A, Okereke OU, Chibuzo AE, Usman AU. Comparative analysis of traffic congestion prediction models for cellular mobile macrocells. Eur J Eng Res Sci. 2018;3(6):32-38.

[27] Ekah UJ, Emeruwa C. A comparative assessment of GSM and UMTS networks. World J Adv Res Rev. 2022;13(1):187-96.

[28] Ozovehe A, Okereke OU, Anene E, Usman AU. Traffic congestion analysis in mobile macrocells. InProceedings of the International Conference on Information and Communication Technology and Its Applications (ICTA 2016) Federal University of Technology, Minna, Nigeria 2016 Nov 28 (pp. 28-30).

[29] Ewona I, Ekah U. Influence of tropospheric variables on signal strengths of mobile networks in Calabar, Nigeria. J Sci Eng Res. 2021;8(9):137-45.

[30] Ajala AT. Analysis of traffic congestion on major urban roads in Nigeria. Journal of Digital Innovations and Contemporary Research in Science, Engineering and Technology. 2019;7(3):1-10.

[31] Obi E, Ekah U, Ewona I. Real-time assessment of cellular network signal strengths in Calabar. Int J Eng Sci Res Technol. 2021;10(7):47-57.

[32] Adelakun AO, Lawal BY, Adekoya MA, Ukhurebo KE. Chaotic assessment of the key performance indicators for a GSM Network congestion in an election period in Nigeria. Nigeria Journal of Pure and Applied Physics. 2019;9(1):28-33.

[33] Iloke J, Utoda R, Ekah U. Evaluation of radio wave propagation through foliage in parts of Calabar, Nigeria. Int J Sci Eng Res. 2018;9(11):244-9.

[34] Galadanci GS, Abdullahi SB, Usman AU. Modeling the Traffic Load of Selected Key Parameters for GSM Networks in Nigeria. International Journal of Digital Information and Wireless Communications. 2019 Jan 1;9(1):22-33.

[35] Emeruwa C, Ekah UJ. Pathloss model evaluation for long term evolution in Owerri. Int J Innov Sci Res Technol. 2018;3(11):491-6.

[36] Mebawondu OJ, Dahunsi FM, Adewale SO, Alese BK. Radio access evaluation of cellular network in Akure metropolis, Nigeria. Nigerian Journal of Technology. 2018;37(3):703-19.

[37] Emeruwa C, Ekah UJ. Investigation of the variability of signal strength of wireless services in Umuahia, Eastern Nigeria. IOSR J Appl Phys. 2018;10(3):11-7.

[38] Ukhurebor KE, Awodu OM, Abiodun IC, Azi SO. A Comparative Study of the Quality of Service of GSM Network during Crowd Upsurge in University of Benin Nigeria. International Journal of Scientific and Engineering Research. 2015;6(10):1484-97.

[39] Imoize AL, Orolu K, Atayero AA. Analysis of key performance indicators of a 4G LTE network based on experimental data obtained from a densely populated smart city. Data in brief. 2020 Apr 1;29:105304.

[40] Popoola SI, Atayero AA, Faruk N, Badejo JA. Data on the key performance indicators for quality of service of GSM networks in Nigeria. Data in brief. 2018 Feb 1;16:914-28.

[41] Aouedi O, Le VA, Piamrat K, Ji Y. Deep learning on network traffic prediction: Recent advances, analysis, and future directions. ACM Computing Surveys. 2025;10;57(6):1-37.

[42] Rohini G, Singh N, Patil VR. Autonomous forecasting of traffic in cellular networks based on long-short term memory recurrent neural network. Cybernetics and Systems. 2025;56(1): 33-45

[43] Ahmad Fauzi MF, Nordin R, Abdullah NF, Alobaidy HAH. Mobile network coverage prediction based on supervised machine learning algorithms. IEEE Access. 2022;(10)55782-93.

[44] Gebrie H, Farooq H, Imran A. What machine learning predictor performs best for mobility prediction in cellular networks? In2019 IEEE International Conference on Communications Workshops (ICC Workshops) 2019 May 20 (pp. 1-6). IEEE.

[45] Mohammadjafari S, Roginsky S, Kavurmacioglu E, Cevik M, Ethier J, Bener AB. Machine learning-based radio coverage prediction in urban environments. IEEE Transactions on Network and Service Management. 2020 Nov 3;17(4):2117-30.

[46] Alekseeva D, Stepanov N, Veprev A, Sharapova A, Lohan ES, Ometov A. Comparison of machine learning techniques applied to traffic prediction of real wireless network. IEEE access. 2021 Nov 22;9:159495-514.

[47] Minovski D, Ögren N, Mitra K, Åhlund C. Throughput prediction using machine learning in LTE and 5G networks. IEEE Transactions on Mobile Computing. 2021 Jul 26;22(3):1825-40.

[48] Gehlot A, Ansari BK, Arora D, Anandaram H, Singh B, Arias-Gonzáles JL. Application of neural network in the prediction models of machine learning based design. In2022 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES) 2022 Jul 15 (pp. 1-6). IEEE.

[49] Abubakar MM, Danladi A, Salim A. Machine learning approach for coverage prediction in wireless networks. Adv J Sci Eng Tech. 2025;10(1):62-78

[50] Rahmayanti D. Predicting Quality of Service on Cellular Networks Using Artificial Intelligence. J Eng Electr Inform. 2025;5(2):28-35.

[51] Riihijärvi J, Mähönen P. Machine learning for performance prediction in mobile cellular networks. IEEE Comput Intell Mag. 2018;13(1):51-60.

[52] Al-Chalabi H, Al-Douri YK, Lundberg J. Time series forecasting using ARIMA model: A case study of mining face drilling rig. In12th International Conference on Advanced Engineering Computing and Applications in Sciences (ADVCOMP 2018), Athens, Greece, November 18-22, 2018 2018 (pp. 1-3). International Academy, Research and Industry Association (IARIA).

[53] Rushall YK, Sinha PK. Random Forest classifiers: a survey and future research directions. Int J Adv Comput. 2013; 36(1): 1144-115

[54] Breiman L. Random forests. Mach Learn. 2001; 45:5-32.

[55] Salman HA, Kalakech A, Steiti A. Random Forest Algorithm Overview. 2024. Babylonian Journal of Machine Learning. 2024:69-79.