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(Research Article)

Prediction Modelling for Forecast of Standalone Dedicated Control Channel Congestion using Machine Learning

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Abstract

Standalone Dedicated Control Channel (SDCCH) congestion remains a persistent challenge in mobile networks, often resulting in failed call setups, delayed SMS delivery, and degraded user experience. To address this, the present study applied machine learning techniques to forecast SDCCH congestion in four major Nigerian mobile networks (MTN, Airtel, Globacom, and 9mobile} using monthly data obtained from the Network Operations Centres (NOCs) of the Mobile Network Operators (MNOs), spanning January 2015 to December 2024. Two regression algorithms, Random Forest (RF) and Extreme Gradient Boosting (XGBoost), were employed within a supervised learning framework that incorporated lag features and seasonal dummy variables. Forecasts for January to December 2024 were generated through recursive multi-step prediction, and model performance was evaluated using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The results showed that both models were able to capture short-term variations but struggled with large fluctuations and nonlinear spikes in actual congestion values. RF slightly outperformed XGBoost for Airtel, while XGBoost yielded better results for MTN, Glo, and 9mobile. However, both models exhibited relatively high percentage errors and a tendency to either flatten variability or underestimate peak congestion levels, limiting their suitability for direct operational deployment. The study concludes that although machine learning holds promise for forecasting SDCCH congestion and supporting proactive capacity planning, further refinement is required. Incorporating larger datasets, additional lag features, and exogenous variables such as traffic load and time-of-day effects could improve predictive accuracy. Overall, XGBoost demonstrated marginally greater reliability than RF, but both models need optimisation before being used for real-time network decision-making.

Keywords: SDCCH Congestion; Machine Learning Forecasting; Random Forest Regressor; Extreme Gradient Boosting; Predictive Modelling; Key Performance Indicators

1. Introduction

Mobile subscribers in Nigeria often experience call setup failures and delays in Short Message Service (SMS) delivery, particularly during peak usage hours. These challenges are largely due to congestion in the Standalone Dedicated Control Channel (SDCCH) [1], which is a critical signaling channel in mobile networks responsible for managing call setup, SMS transmission, and location updates [2]. When the number of available SDCCH channels is insufficient to handle signaling requests, congestion occurs, resulting in failed calls, delayed message delivery, and difficulties with network registration [3].

The SDCCH Congestion Rate is a key performance indicator used to assess a network's ability to process signaling traffic effectively [4]. Recognising the importance of this metric, the Nigerian Communications Commission (NCC) has set a benchmark stipulating that the SDCCH Congestion Rate must not exceed one percent [5]. Despite this regulation,

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persistent congestion continues to degrade service quality and negatively impact user experience in several networks [6-7].

Previous research on SDCCH performance in Nigerian mobile network operators (MNOs) has often relied on drive test data [8-37]. Although useful, such tests are geographically restricted and provide only short term snapshots of network performance, making it challenging to obtain a comprehensive and continuous nationwide assessment [38-39]. In contrast, this study utilises data from the Network Operations Centre (NOC), enabling extensive, long term monitoring of network performance.

This research applies machine learning models to predict SDCCH congestion for the period January to December 2024 for four mobile networks in Nigeria. The outcomes are intended to provide operators with actionable insights for capacity planning, performance optimisation, and sustained regulatory compliance. By integrating large-scale operational data with predictive modeling, this work offers a comprehensive understanding of SDCCH congestion patterns and proposes practical measures to enhance mobile network quality in Nigeria.

1.1. The Random Forest Regressor

A Random Forest Regressor is a powerful machine learning algorithm that uses an ensemble of decision trees to predict a continuous value. Developed by Leo Breiman, the method improves upon single decision trees by combining the principles of bagging and random feature selection to create a more robust and accurate model [40]. The algorithm's core strength lies in its ability to introduce randomness at key stages to ensure a diverse and generalized model. First, each tree in the forest is trained on a random subset of the training data, a process known as bootstrap aggregation or bagging [41]. Second, at each split in a tree, the algorithm considers only a random subset of the available features, preventing any single feature from dominating the entire forest [42-45]. This random subspace method helps to reduce the correlation between the trees. To make a final prediction, a new data point is passed through every tree in the forest. Each tree outputs a numerical value, and the random forest's final prediction is the average of all these individual predictions. This averaging process is highly effective at reducing the model's variance and protecting against overfitting, a common issue with individual decision trees [46].

Random Forest Regressors are highly versatile and are used in a variety of fields to predict continuous outcomes. They are effective at handling noisy or incomplete data and can work with both numerical and categorical features without extensive preprocessing. Common applications include estimating house prices, forecasting stock trends, and predicting weather conditions.

1.2. Extreme Gradient Boosting

Extreme Gradient Boosting (XGBoost) is an advanced implementation of gradient boosting that is highly efficient and scalable, making it one of the most popular algorithms for machine learning tasks. Developed by Chen and Guestrin [47], it represents an optimization of the original gradient boosting framework proposed by Friedman [48].

XGBoost's superior performance can be attributed to several important features. One of its key strengths is the inclusion of regularization terms in the objective function, which helps to prevent overfitting and produce more generalized models [47]. Another important aspect is its ability to perform parallel processing. Although decision trees are built sequentially, the algorithm parallelizes the process of finding the best split, thereby reducing training time considerably on large datasets [47]. XGBoost is also capable of handling missing values automatically, as it learns the best direction for missing data at each node during training. In addition, it is designed to be sparsity-aware, which makes it particularly effective for working with sparse datasets that frequently occur in real-world applications such as text analysis [47].

The algorithm operates by constructing a series of decision trees in sequence, where each new tree is trained to correct the errors of the previous ones. The overall prediction is obtained by summing the outputs of all the trees. To ensure both accuracy and generalization, the model minimizes an objective function that combines a loss function, which measures the error between predicted and actual values, with a regularization term that penalizes complexity. This balance between accuracy and simplicity prevents overfitting while maintaining strong predictive performance.

2. Methodology

The study applied machine learning techniques to forecast SDCCH congestion. Monthly congestion data for MTN, Airtel, Globacom, and 9mobile were obtained from the NCC, covering the period from January 2015 to December 2024. These figures were compiled from specialised counters at the NOCs of each MNO, with each value representing the proportion of signaling requests that could not be processed due to insufficient channel capacity.

For the predictive component, two machine learning regression algorithms, the Random Forest Regressor (RFR) and the Extreme Gradient Boosting (XGBoost) were employed to generate forecasts for the period January to December 2024, using historical data spanning from January 2015 to December 2023. The methodological framework comprised four main stages: data preparation, model training, recursive multi-step forecasting, and performance evaluation.

For **RFR**, the monthly SDCCH time series was reformatted into a supervised learning structure. Twelve lag variables representing values from the preceding twelve months were generated to capture temporal dependencies, while twelve month-of-year dummy variables were added to model seasonal effects. For example, forecasting January 2024 involved using lagged values from January to December 2023 and a January dummy indicator. The training dataset covered January 2016 to December 2023 (the first twelve months reserved for lag computation). During training, multiple decision trees were constructed on bootstrap samples of the data, with each split considering a random subset of features to reduce correlation among trees. Final predictions were obtained by averaging across trees, a process that improves generalisation and mitigates overfitting. Forecasts for 2024 were produced recursively: the model first predicted January 2024, then appended this value to the historical dataset to serve as a lag for forecasting February 2024, and repeated the process until December 2024. While effective for multi-step forecasting, this approach also introduced cumulative error propagation.

For **XGBoost**, the same supervised structure was applied, with twelve lag features and twelve seasonal dummy variables. Training data spanned January 2016 to December 2023. Unlike RFR, XGBoost constructs trees sequentially, with each new tree correcting the residuals of prior predictions. Its regularised objective function (combining training error with penalties for complexity) reduces overfitting and enhances generalisation. Key hyperparameters, including learning rate, maximum depth, number of estimators, and subsampling ratios, were tuned to optimise performance. Forecasting for 2024 also followed a recursive strategy: the model predicted January 2024 using lags from January to December 2023, appended the output to the dataset, and iteratively generated forecasts up to December 2024. Although recursive prediction enabled long-horizon forecasts, it also amplified error accumulation over time.

The accuracy of each model was assessed using three error metrics: Mean Absolute Error (MAE), which measures the average magnitude of prediction errors; Root Mean Squared Error (RMSE), which penalises larger deviations more heavily; and Mean Absolute Percentage Error (MAPE), which expresses prediction errors as a percentage for easier interpretation. The model that produced the lowest errors for each network was considered the most accurate.

All computations and visualisations were carried out in Python, with Pandas used for data management, NumPy for numerical processing, Matplotlib and Seaborn for data visualisation, Scikit-learn for implementing the machine learning models, and SciPy for statistical computation and optimisation. The results of the forecasts and performance comparisons are presented in the next section through figures and tables, along with detailed discussions.

3. Results and Discussion

Forecasts of SDCCH congestion for MTN, Airtel, Globacom, and 9mobile were successfully generated for the period January–December 2024 using the RFR and XGBoost models. The outcomes are presented in tables and graphical plots, enabling both quantitative and visual comparison between predicted and observed values. For all four networks, the models were able to capture month-to-month variations in SDCCH congestion.

3.1. Forecast and Performance Evaluation for Airtel Network

Figure 1 illustrates the actual and forecasted SDCCH congestion for the Airtel network. In the plot, the actual values are represented by a red line, while the Random Forest forecasts are depicted in black and the XGBoost forecasts in violet, enabling a clear visual comparison of model performance against observed values. The actual SDCCH congestion values ranged widely between 0.02 and 0.11, but both the Random Forest (0.0281–0.0284) and XGBoost (0.0280–0.0282) models produced nearly constant predictions around 0.028, closely matching low congestion months (0.02–0.03) but severely underestimating higher values (0.08–0.11), indicating that both models flattened variability and leaned toward the mean, with XGBoost giving slightly lower estimates than RF.

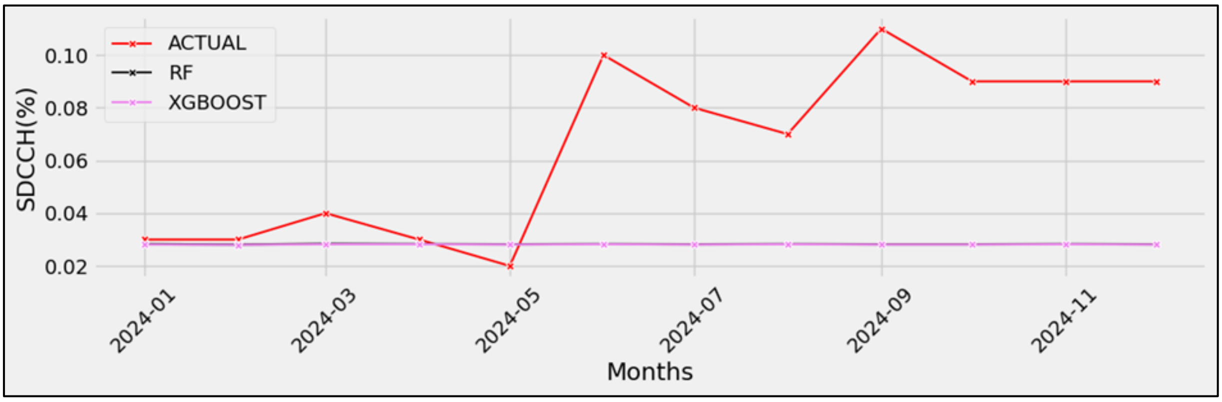

Figure 1 Actual and Forecast SDCCH Plot for Airtel Network

Table 1 Performance Evaluation Metrics for Airtel Network

Model	MAE	RMSE	MAPE (%)
XGBoost	0.0321	0.0341	13.25
Random Forest	0.0320	0.0340	13.19

In terms of performance, as presented in Table 1, both models performed very similarly, but the Random Forest showed a slight advantage with marginally lower error values. This indicated that, for the SDCCH data, Random Forest was slightly better at capturing variations than XGBoost, although the difference was almost negligible.

3.2. Forecast and Performance Evaluation for 9mobile Network

Figure 2 shows the actual and predicted SDCCH congestion for the Airtel network. In the graph, the actual values are plotted in blue, the Random Forest forecasts are shown in black, and the XGBoost forecasts are represented in violet, providing a clear visual comparison of the models' performance relative to the observed data. From the graph, actual SDCCH congestion values ranged from 0.75 to 2.18, showing wide fluctuations across the months, whereas the Random Forest forecasts (0.2561–0.3415) and XGBoost forecasts (0.2519–0.4006) remained within a narrow band, consistently underestimating the true values; although XGBoost occasionally produced slightly higher estimates than Random Forest, both models flattened variability and leaned toward mid-range predictions, indicating a systematic bias and poor representation of peak congestion levels

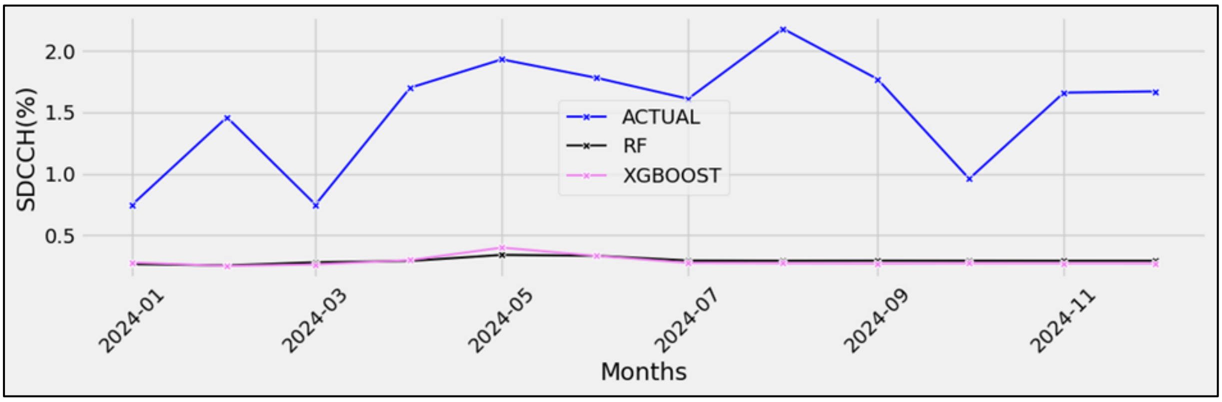

Figure 2 Actual and Forecast SDCCH Plot for 9mobile Network

Table 2 Performance Evaluation Metrics for 9mobile Network

Model	MAE	RMSE	MAPE (%)
XGBoost	1.3100	0.03741	148.38
Random Forest	1.3100	0.03726	148.26

As shown in Table 2, both RF and XGBoost yielded almost identical error metrics, indicating similar performance. However, the extremely high MAPE reveals that neither model provided reliable predictions for this dataset. This shortcoming is likely a result of sharp fluctuations and nonlinear spikes in the actual values, which the models were unable to capture effectively. Consequently, additional preprocessing, enhanced feature engineering, or further model optimisation would be required before the forecasts could be applied for mobile network decision-making.

3.3. Forecast and Performance Evaluation for Glo Network

Figure 3 presents the actual and forecasted SDCCH congestion for the Airtel network. In the plot, the actual values are shown in blue, the Random Forest predictions in black, and the XGBoost predictions in violet. The actual congestion values ranged from 0.09 to 0.15, indicating moderate variation across the months. By comparison, the Random Forest forecasts fell within 0.1286–0.1613, while the XGBoost forecasts ranged from 0.1272–0.1582. Both models tended to overestimate lower actual values and slightly overpredicted or closely matched higher actual values. In all, the two models produced nearly identical results, with differences generally less than 0.01, but both consistently showed a bias toward overprediction, particularly at the lower end of the congestion range.

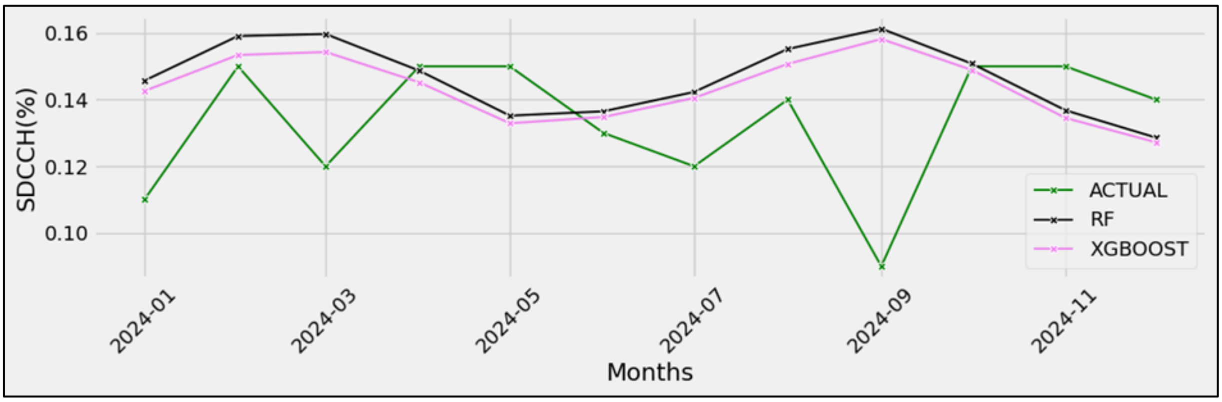

Figure 3 Actual and Forecast SDCCH Plot for Glo Network

Table 3 Performance Evaluation Metrics for 9mobile Network

Model	MAE	RMSE	MAPE (%)
XGBoost	0.0385	0.0445	32.05
Random Forest	0.0396	0.0461	32.75

The results in Table 3 indicate that XGBoost performed marginally better than Random Forest across all evaluation metrics, producing forecasts that were closer to the actual values. Nonetheless, both models exhibited relatively high percentage errors, which can be attributed to the significant month-to-month variability in actual SDCCH congestion. From a mobile network perspective, this suggests that XGBoost may offer a more dependable option for short-term forecasting of SDCCH congestion in GLO. However, the accuracy of both models could likely be improved by incorporating additional historical lag features or external factors such as traffic load and time-of-day effects.

3.4. Forecast and Performance Evaluation for MTN Network

Figure 4 presents a comparison of the actual SDCCH congestion with forecasts from the Random Forest (RF) and XGBoost models for the Airtel network, while Table 4 summarises the performance evaluation of the two machine learning models. In the plot, the actual values are shown in yellow, the RF forecasts in black, and the XGBoost forecasts in violet.

As shown in the graph, the actual congestion values ranged from 0.08 to 0.21, reflecting noticeable fluctuations across the months. By contrast, RF predictions fell within 0.0729 to 0.1418, while XGBoost forecasts were more tightly clustered within 0.1291 to 0.1361. Overall, the RF model tended to underestimate higher congestion values and occasionally overestimate lower ones. XGBoost, on the other hand, produced stable predictions consistently centred around 0.13, with very little variation across months. This made XGBoost appear closer to the actual values when congestion was low, but it still significantly underestimated the higher values. Thus, while RF showed greater variability in its forecasts, it was more prone to underpredicting high congestion levels, whereas XGBoost provided smoother but flattened outputs that did not fully reflect the observed fluctuations.

The performance evaluation in Table 4 further confirms these observations. XGBoost consistently outperformed RF across all evaluation metrics, although both models displayed relatively weak predictive ability due to the limited dataset. RF performed particularly poorly, with high MAE and very large MAPE values, indicating that it failed to capture the underlying trend and would be unsuitable for reliable decision making. XGBoost achieved comparatively better accuracy, with lower MAE and RMSE and a reduced but still high MAPE, suggesting better alignment with the actual data but still insufficient for deployment in live network optimisation.

In summary, XGBoost demonstrated greater reliability than RF for forecasting SDCCH congestion, but both models require further refinement, such as access to larger datasets, improved feature engineering, or enhanced modelling approaches, before they can be considered suitable for operational telecom network forecasting.

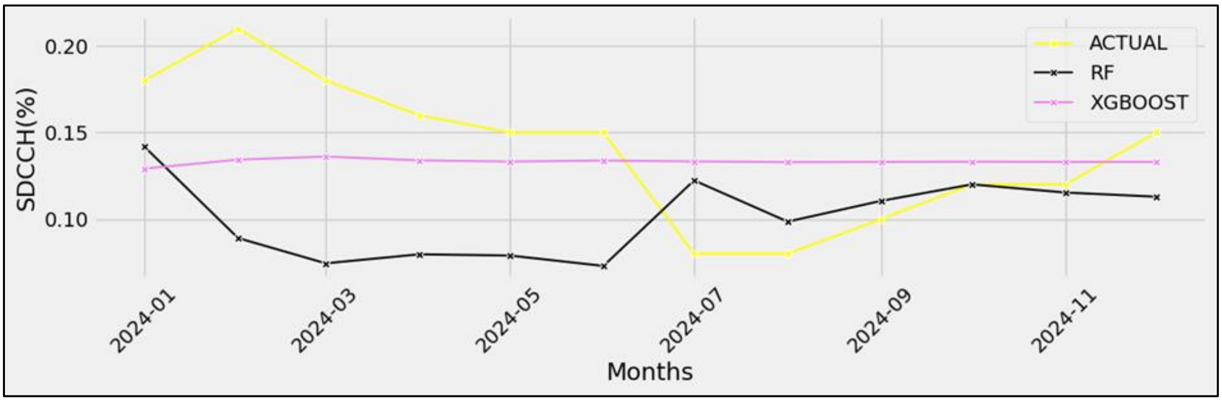

Figure 4 Actual and Forecast SDCCH Plot for MTN Network

Table 4 Performance Evaluation Metrics for MTN Network

Model	MAE	RMSE	MAPE (%)
Random Forest	0.0505	0.0635	33.48
XGBoost	0.0343	0.0396	27.16

4. Conclusion

This study applied Random Forest and XGBoost regression models to forecast SDCCH congestion across four major mobile networks in Nigeria using long-term operational data. The results revealed that while both models were able to provide short-term forecasts, their overall performance varied across the networks. Random Forest produced slightly better results for Airtel, whereas XGBoost showed marginal improvements for Glo, 9mobile, and MTN. In general, however, both models exhibited limitations, including high percentage errors and a tendency to either flatten variability or underestimate peak congestion levels.

The findings highlight the potential of machine learning techniques for proactive network performance management but also underscore the need for refinement. Improvements such as incorporating larger datasets, additional lag variables, and exogenous features like traffic load, time-of-day effects, and seasonal demand could enhance predictive accuracy. Hybrid approaches that combine multiple algorithms may also mitigate error accumulation in recursive forecasts.

In all, XGBoost demonstrated greater reliability than Random Forest overall, but both models require further optimisation before they can be confidently deployed for operational decision-making in Nigerian mobile networks. Future research should therefore focus on more advanced modelling techniques and richer feature sets to support more accurate and actionable forecasts that can guide capacity planning and ensure regulatory compliance.

Compliance with ethical standards

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Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] 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.

[2] 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.

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

[4] 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.

[5] 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.

[6] Ozovehe A, Okereke OU, Anene E, Usman AU. Traffic congestion analysis in mobile macrocells. In Proceedings 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).

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

[8] 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

[9] 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

[10] 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.

[11] 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.

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

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

[14] 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

[15] 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.

[16] 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.

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

[18] 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.

[19] 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.

[20] 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.

[21] 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.

[22] 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.

[23] 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.

[24] 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)

[25] 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.

[26] 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.

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

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

[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] 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.

[31] 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.

[32] 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.

[33] 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.

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

[35] 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.

[36] 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.

[37] 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 & Engineering Research. 2015;6(10):1484-97.

[38] 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.

[39] 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.

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

[41] Breiman L. Bagging Predictors. Machine Learning. 1996;24(2):123-140.

[42] Liaw A, Wiener M. Classification and Regression by randomForest. R News. 2002;2(3):18-22.

[43] Prasad AM, Iverson AL, Liaw A. Classification and regression by random forest. A practical guide to implementing the random forest algorithm. 2006.

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

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

[46] Geman S, Bienenstock E, Doursat R. Neural Networks and the Bias/Variance Dilemma. Neural Computation. 1992;4(1):1-58.

[47] Chen T, Guestrin C. XGBoost: A Scalable Tree Boosting System. In: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining; 2016 Aug 13–17; San Francisco, CA. New York, NY: Association for Computing Machinery; 2016. p. 785–794.

[48] Friedman JH. Greedy function approximation: a gradient boosting machine. Annals of Statistics. 2001;29(5):1189–1232.