Journal of NAMP 70, (2025) 155-166

The Nigerian Association of Mathematical Physics

Journal homepage: https://nampjournals.org.ng

AN AUTOMATED MACHINE LEARNING BASED ANALYSIS OF PROPAGATED RADIO SIGNAL PARAMETERS AND CONDITIONS IN OPERATIONAL BROADBAND CELLULAR NETWORK

[1]Emmanuel Nwelih and [2]Joseph Isabona

[1]*Department of Computer Science, University of Benin, Benin City*

[2]*Department of Physics, Federal University Lokoja, Lokoja, Kogi State, Nigeria*

ARTICLE INFO

Article history:
Received 11/6/2025
Revised 3/7/2025
Accepted 12/7/2025
Available online 17/7/2025

Keywords:
Network monitoring, coverage quality, RSRP, SNR, Machine learning, Fitrauto algorithm.

ABSTRACT

Radio signal coverage and quality shrinkage are two key factors that place critical limitations on good data transmission quality provisioning over mobile broadband networks channels. Owing to numerous multipath received signal fading conditions, eNodeBs transmitter deterioration and general frequent changes in radio propagation settings. Factors considered, include intracellular interference problems and stochastic background noise around the environment of the deployed operational networks. In contribution, practical monitoring and status service quality correlation analysis of deployed operational commercial LTE networks, considering signal coverage and quality indicators such as received signal power (RSRP), received signal strength indicator (RSSI), and, Signal-to-Noise ratio (SNR) is presented for a typical urban terrain. The aim realized by conducting a detailed field test measurement using TEMS investigation equipment. Post data analysis of collected LTE system network parameters provided, results and findings also could provide basis for effective design and performance optimisation of different mobile broadband networks.

1. INTRODUCTION

The few decades have seen a clear-cut and progressive phenomenal deployment and growth of a number of different wireless mobile broadband networks in the telecommunication industries globally. This in turn has revolutionized and reformed out rightly the way end-users subscribe, access information, and, relate with each other easily on the network. Particularly, in most African countries, operators and stakeholders in the industries are speedily introducing these broadband networks to support and boost their service delivery to the end users. In this situation, the importance of conducting a realistic analysis and routine proactive assessments of deployed networks has also been on the increased recently.

*Corresponding author: EMMANUEL NWELIH

E-mail address: emmanuel.nwelih@uniben.edu

https://doi.org/10.60787/jnamp.vol69no2.530

One main step to reliably access and evaluate the service quality status of deployed cellular broadband networks such as Long Term Evolution (LTE) is to conduct a real-time performance analysis of the networks while in operation. By network performance analysis, we mean "the review and examination of a set of network statistical parameters or indicators, to explain the service qualities obtainable by the network measured directly either from the service provider or from the end-user perspective.

There exists a range of indicators that can be explored to determine and assess the overall service quality of an operation LTE network. In this study, our scope is tied to signal coverage and quality indicators such as received signal power (RSRP), received signal strength indicator (RSSI), and, Signal-to-Noise ratio (SNR). All these peculiar indicators and their connections within the LTE network systems will be studied. Particularly, LTE is a complex networked system, therefore, it will be of utmost importance to relay the collected performance features of the systems networks' qualities during the analysis.

LITERATURE REVIEW

In literature, a number of statistical indicators have also been engaged by numerous researchers to conduct a realistic performance assessment of operational networks. In [1], two key performance parameters, namely GoS and QoS were engaged to examine mobile subscriber satisfaction in GMS and the authors found that there exists between the quality parameters and subscriber service satisfaction. Similar methods were also presented by the researchers in [2-4]. The authors in [2], also adopted similar approach for GMD network, but with emphasis on end points service availability at the cell-cluster level.

In [3], a measurement Survey method has been adopted to assess radio link quality in HSDPA broadband networks: A Holistic Technique for Efficient Networks Performance Monitoring in Wireless Communication Systems in Asaba Region, Nigeria, at the cell-Cluster level. The results displayed one-to-one correlations between the measured RSCP parameter and data throughput quality.

The influence of received signal parameters on service quality coverage via field measurement is shown in [4]. Based on the obtained field data and signal models developed, the rate of attenuation experience in the network as defined by the path loss exponent varies from one location to another. In [5]. The connection between link quality and signal coverage in HSPA is studied. The authors also observed a direct relationship between the two parameters.

A work that provides insight and in-depth interface analysis between transport later protocols and practical LTE network performance and similar networks is contained in [6-14].

Firstly,in this contribution, a practical monitoring and status service quality correlation analysis of deployed operational commercial LTE networks, considering signal coverage and quality indicators such as received signal power (RSRP), received signal strength indicator (RSSI), and, Signal-to-Noise ratio (SNR) is presented for a typical urban terrain.

Secondly, an automated machine learning based method termed Fitrauto regression optimisation algorithm (FROA) is proposed for provide an adept analysis of the acquired signal datasets. The algorithm that provide means to automatically select six data fitting regression models with tuned hyperparameters in Matlab computational environment.

RESEARCH METHODOLOGY

This research adopts a robust and streamlined Empirical based stepwise approach to actualise the research central aim, which is to reliably measurement and evaluate the service quality status of deployed LTE cellular broadband network. As displayed in figure 2, the first step is identifying the best drive test tools to carry-out the field drive test for the relevant signal data collection. This is followed planning and survey the drive test routes around the transmitting eNodeB station. The next phase is to configure the drive test tools to enable for automatic data collection. This is followed by relevant data extraction, machine learning based status analysis and documentation

Method of Data Collection

The data for this research is obtained at a single cell level, in particular, concentrating on the aforementioned radio link quality parameters such as RSRP and RSSI at different measurement distance. The field measurements were piloted by means of professional TEM Drive test tools. The combined tools such as a Global Positioning System, a mobile vehicle, compass, Inverter, Dongle, Data Card and TEMS pocket cell phones, all which can initiates and produce radio calls repeatedly and uniformly when lunched from a moving subscribers' location were engaged to obtained the relevant aforementioned cellular network data. A sample of the acquired sample signal RSRP and RSSSI data as function of different measurement distances are displayed in figure 1, figure 2 and table 1. RSSI, is a distinctive LTE indicator measured in dBm and it reveals the useful cell signal, the signal of adjacent eNodeB transmitters including the internal and external interference plus their respective noise power. The larger the RSSI value is, the stronger and better the signal is worth. Thus, the RSSI value is also used to provide a rough approximation of the LTE network system signal quality.

In LTE system, RSRP parameter is used to estimate the received power at the mobile antenna device in correspondence with the pilot signals that are being propagated from the eNodeB transmitter. Also, the larger the RSRP value is, the stronger and better the signal coverage is worth. So, the RSRP value is also used to provide a clear estimate of LTE network system signal coverage quality.

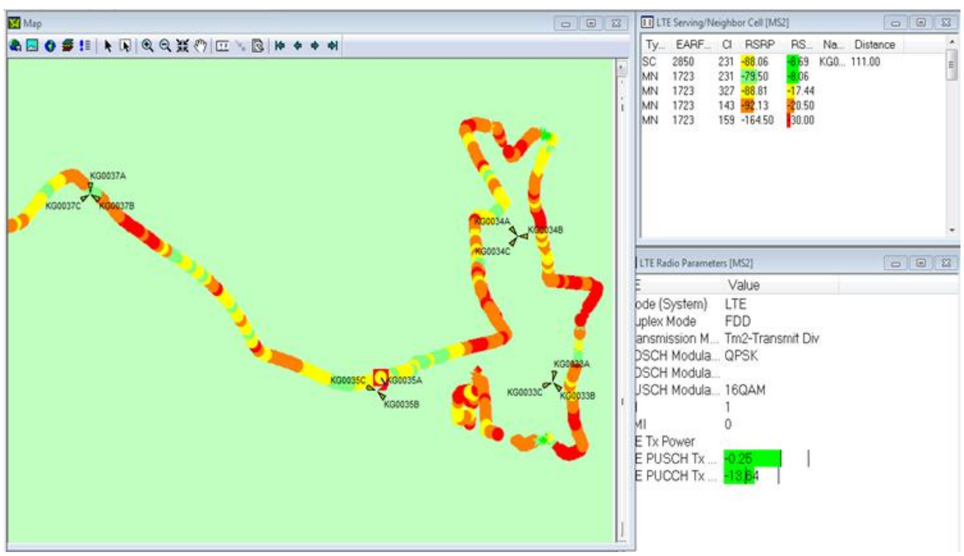


Figure 1: A Portrait of Field Drive Test Routes and Measured Signal Parameters

Table 1: A sample of the acquired sample signal RSRP and RSSSI data as function a of different measurement distances

BTS	DIST(m)	RSRP	RSRP LAT.	RSRP LONG.	RSSI (dBm)	ALT.(m)	
LAN0687	30	-69.38	6.2414	7.08810	-44.6088	124	
LAN0687	40	-82.56	6.2413	7.08798	-57.7888	126	
LAN0687	60	-85.75	6.2411	7.08784	-60.9788	129	

LAN0687	80	-83.25	6.2409	7.08775	-58.4788	131	
LAN0687	100	-80.19	6.2408	7.08761	-55.4188	132	
LAN0687	130	-76.81	6.2406	7.08748	-52.0388	134	
LAN0687	160	-71.81	6.2404	7.08737	-47.0388	135	
LAN0687	190	-75.38	6.2402	7.08727	-50.6088	136	
LAN0687	200	-77.88	6.2401	7.08717	-53.1088	136	
LAN0687	230	-73.63	6.2399	7.08708	-48.8588	138	
LAN0687	250	-70.81	6.2397	7.08696	-46.0388	139	
LAN0687	270	-77.00	6.2396	7.08685	-52.2288	140	

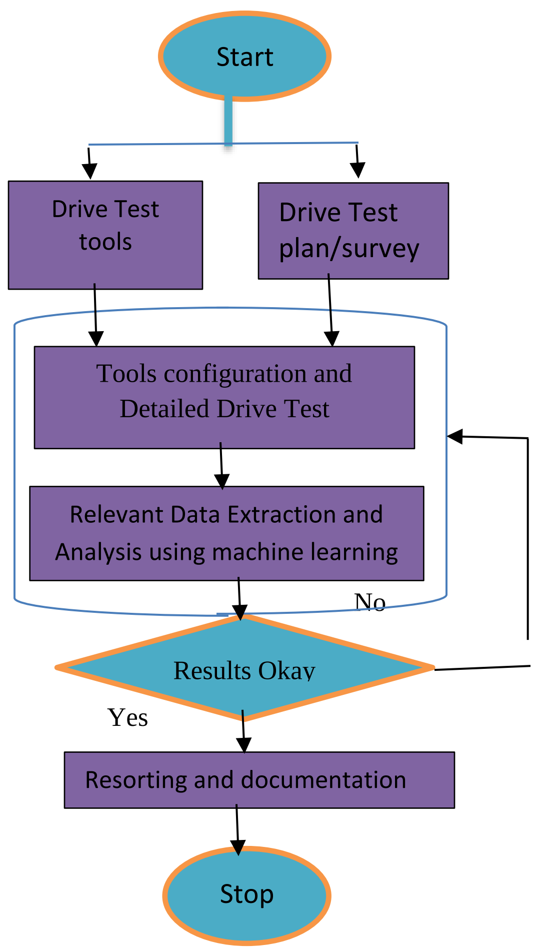


Figure 2: Drive Test Plan and Preprocessing Flowchart

Machine Learning based on Fitrauto Regression Optimisation Algorithm

In this paper, an automated machine learning analysis method termed Fitrauto regression optimisation algorithm (FROA) is proposed further provide an adept analysis the acquired signal datasets. The algorithm that provide means to automatically select six optimal data fitting regression models with tuned hyperparameters in Matlab computational environment.

Fitrauto Iterative regression optimisation algorithm (FROA):via the iteration optimisation process, the fitrauto algorithm iteratively runs through the acquired input data points indexed by $(x_i, y_i)^{i=1,2,3,\ldots,N}$, and then automatically select a sequence of six prognostic regression models using the fitrauto function with Bayesian optimisation (bayseopt) hyperparameters tuning method such that each selected model maintains a sequence of iteratation x(r). The number of iteration is indexed by T and a number of replications r. The six prognostic regression models includes the ensemble forest, Artificial neural network (ANN) support vector machine (SVM), Gaussian process regression (GPR), decision tree (DT), and the general additive model (GAM)

1. start
2. **Input:** $(x_i, y_i)^{i=1,2,3,\ldots,N}$, input function, f (x_i, y_i)
3. **Output:** $(xp_i, yp_i)^{i=1,2,3,\ldots,N}$, test error based on mean squared error (MSE) computation
   yp_i= f(xp_i) ; outpout solution
4. **run `fitrauto`:** Mdl = fitrauto("x,y");
5. for t=1, 2, …,T until convergence
   T = 100; iteration number
   options = statset('MaxIter',1000);
   Hyperparameter selection method:bayespot;Bayesian optimisation
6. Examine if iteration convergence criteria are met;
   observe yp_i= f(xp_i)
7. Compute the regression performance:objective function value and RegError=log(1+testMSE)
8. Repeat step 4 to 7 till stable iterative convergence is reached
9. end while
10. Return a solution

RESULTS AND ANALYSIS

This section is in two parts. The first part covers the correlation analysis of the various acquired LTE service quality parameters. The second part provide a detailed machine learning based analysis of the signal data using the proposed Fitrauto Regression Optimisation Algorithm (FROA)

(a) Correlation Analysis of service quality Indicators

As mentioned earlier, while the RSSI, is an LTE indicator that reveals the useful cell signal, the signal of adjacent eNodeB transmitters including the internal and external interference plus their respective noise power, RSRP is used to estimate the received power at the mobile antenna device in correspondence with the pilot signals that are being propagated from the eNodeB transmitter. Also, the larger the RSRP value is, the stronger and better the signal coverage is worth. So, the RSRP value is also used to provide a clear estimate of LTE network system signal coverage quality.

Another important LTE system indicator is the Signal to Noise (SNR).It expresses the power of the received signal power divided by background noise power plus the interference power. A higher SNR value *simply implies that the received signal power at the mobile station terminal is lower than the noise power*. The RSSI is linked with the SNR and the RSRP by:

$$\mathrm{SNR} = 30/\left(\left(\frac{1+5.2x10^{13}}{(102+RSSI)^{a}}\right)^{0.5}\right) \quad (1)$$

Where: $a = 9$.

$$RSSI = \mathrm{RSRP} + 10.\log 10(12\mathrm{xN}) \quad (2)$$

The SNR is one of the most preferred performance measures to assess the real operating conditions LTE networks, particularly at the end-user terminal. This is because, besides the signal strength, the SNR value integrates both the interference and noise states of the network. Fig. 4 displays the SNR values versus distances. The high fluctuating SNR values can be due owing to numerous multipath received signal fading conditions, eNodeBs transmitter deterioration and general frequent changes in radio propagation settings. Other vital critical limiting factors may include intracellular/ intercellular interference problems and stochastic background noise around the environment of the deployed operational networks. The same fluctuating pattern is also observed with RSSI and RSRP as a function of communication distances in figure 5 and 6.

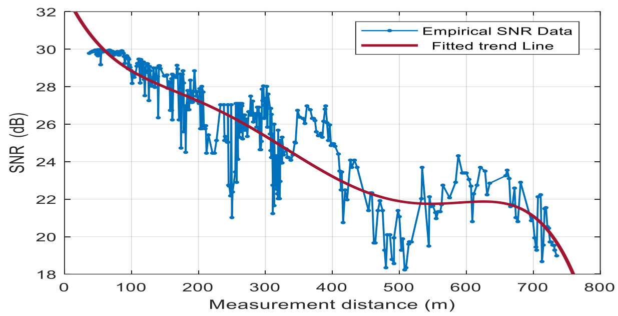


Figure 3: SNR as a function of Distance, X (m)

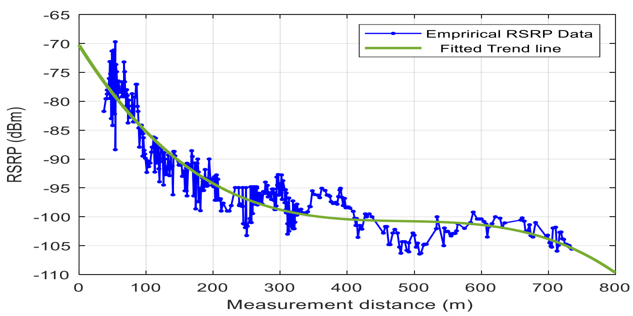


Figure 4: RSRP as a function of Distance, X (m)

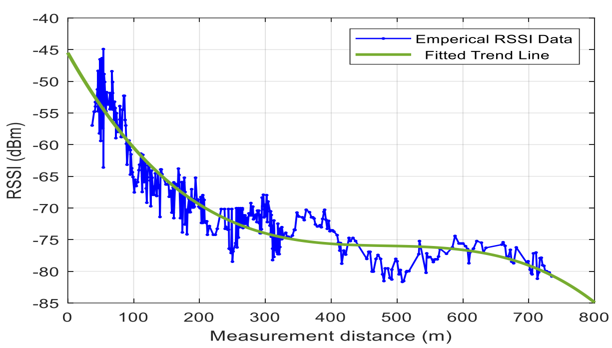


Figure 5: RSSI as a function of Distance, X (m)

Figures show the attained SNR values as a function of RSSI and RSRP data points around the eNodeB, using the expression in (1). We have fitted a polynomial regression contour to further examine the SNR values trend pattern are impacted by RSRP and RSSI variations. From the regression curve, we can see co-linear connections between SNR, RSRP and RSSI values as expected, where between 1-2dBm increase in RSRP and RSSI also lead to1-2dB increase in the obtained SNR values. Particularly, for larger RSSI and RSRP values, the SNR pattern trend to stability. This may be due to interference saturation effects at user equipment stations. In both figures, the SNR curve also flatten-off between 33and 33dBm RSSI values and between 33and 33dBmRSRP values, which point to intra-interference. This trend pattern may also suggests that an optimum performance can be attained if RSRP and RSSI values all above signal.

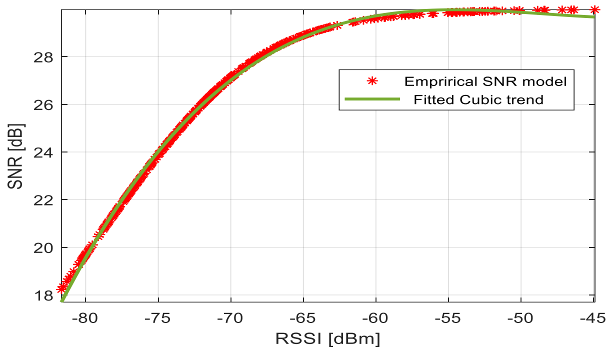


Figure 6: SNR as a function of RSSI

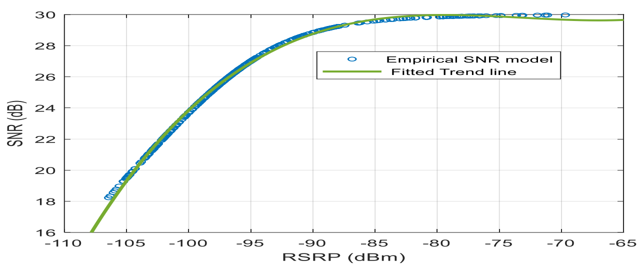


Figure 7: SNR as a function of RSRP

The respective impact RSRP, RSSI, and communication distance (X) are shown in figures 9-11. Particularly in Figure 9, increasing values of RSRP and RSSI indicators leads to direct enhancement of the SNR values. This simply implies that that improvement in both RSRP and RSSI values also improves on the SNR quality. The graphs of Figures 10 and 11 reveals the SNR values increment are more tilted towards the RSRP and RSSI values compared to the communication distance. This could simply imply that RSRP and RSSI qualities have more impact on the SNR quality compared to the communication distance.

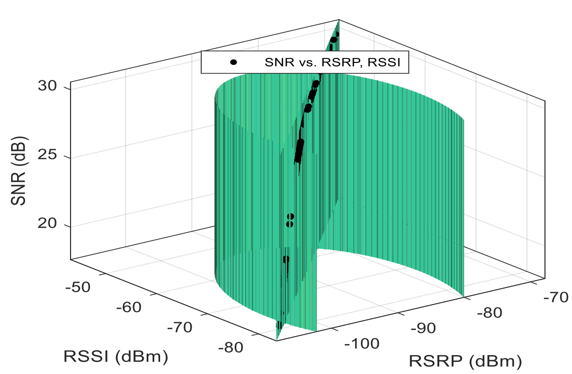


Figure 8: SNR as a function of RSRP and RSSI

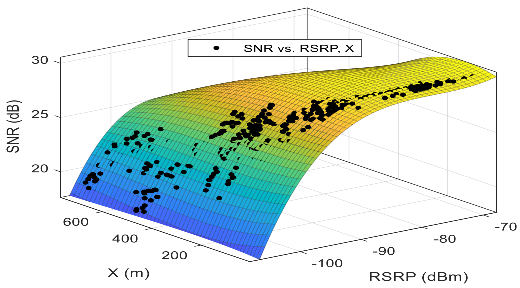
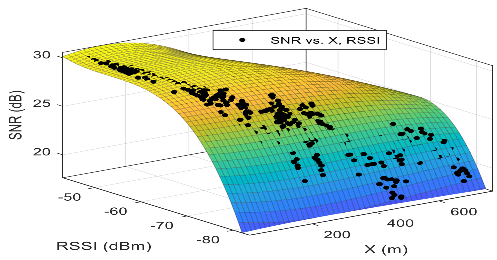


Figure 9: SNR as a function of RSRP and Distance (X)

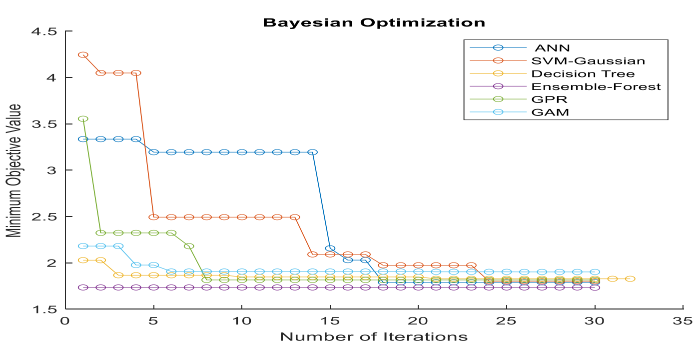


Figures 10: SNR as a function of RSRP and Distance (X)

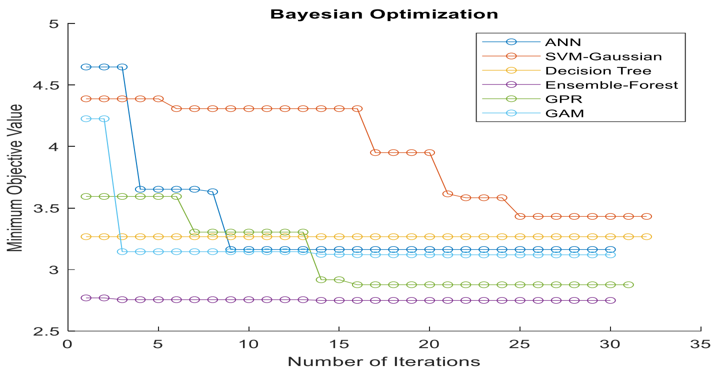
(b) Machine Learning Based Analysis of Signal Data using Fitrauto Regression Optimisation Algorithm

In any regression process, the target is to obtain the most favourable minimum objective function value, which is the lowest possible value that can achieve within a defined set of conditions or constraints when minimizing the error differences between the target data and final prediction output. Thus a lower and most stable objective function value is most preferable.

The graph in figures 11 and 12 depict the objective function values from the six regression models residing in applied the Fitrauto Regression Optimisation Algorithm, which operates iteratively by finding the decision hyperparameters and variables that yield the minimum objective function value. Two sets of RSRP data, namely data I and data II. While the first data was engaged to test the proposed regression algorithm, the second data, which was taken in a different environment was engaged to validate the initial tested results. The both graphs revealed that the ensemble forest method attained and maintained the lowest objective values of 2.8 and 1.75, respectively all through iterative regression process.



Figures 11: Fitrauto objective value-iteration performance with the six regression models on RSRP data I

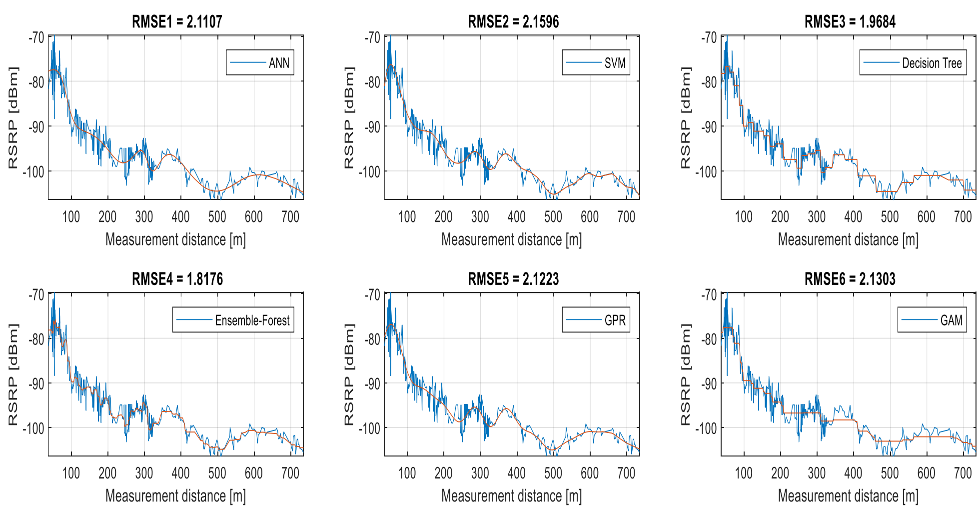


Figures 12: Fitrauto objective value-iteration performance with the six regression models on RSRP data II

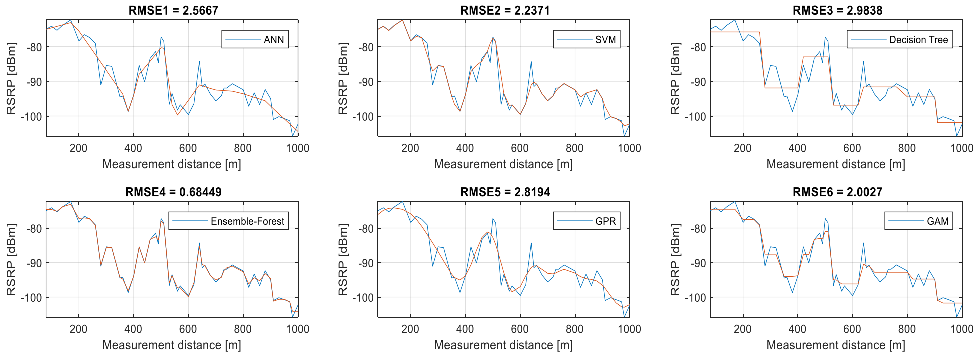
In addition to objective value-iteration performance, we also provide the root mean square error (RMSE) and correlation coefficient (R) analysis performance of the proposed algorithm to specifically reveal the data fitting capacity of the six regression models as shown in figures 13-16. The six regression models are are constituents of the Fitrauto function in the Matlab computational software. As shown on graphs, the ensemble forest attained best performance with smaller RMSE values of 1.81and 0.68 in figures 13 and 14, while ANN, SVM, Decision tree, GPR, an GAM attained 2.11, 2.15, 1.96, 2.12, 2.13 and 2.56, 2.23, 2.98, 2.81, 2.00, respectively.

Similarly, in figures 15 and 16, as shown on graphs, the ensemble forest attained best performance with better R values of 0.98 and 0.99, while ANN, SVM, Decision tree, GPR, an GAM attained R values 0.96, 0.96, 0.97, 0.96, 0.96 and 0.95, 0.96, 0.94, 0.94, 0.97, respectively.

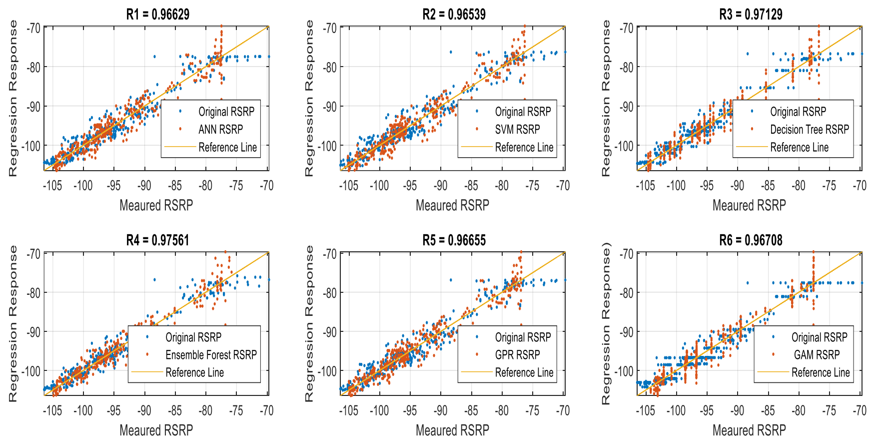
These lower RMSE values and higher R values attainment by the ensemble forest, in combination with its stable and lower objective values performance displayed in figures 13 and 14 clearly reveals that it possess the best regression fitting capacity on the acquired signal data in the study locations.



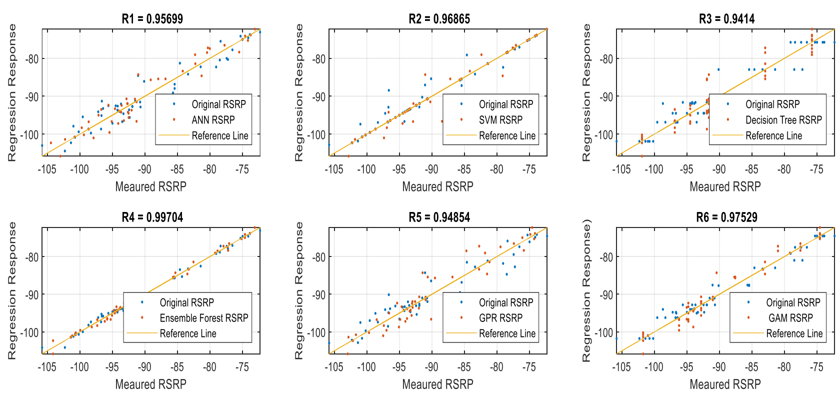
Figures 13: Fitrauto RMSE performance with the six regression models on RSRP data I performance with the six regression models on RSRP data 11



Figures 14: Fitrauto RMSE performance with the six regression models on RSRP data II



Figures 15: Fitrauto Rperformance with the six regression models on RSRP data I



Figures 16: Fitrauto RMSE performance with the six regression models on RSRP data II

CONCLUSION

The current evolution or deployment of new different mobile broadband communication systems worldwide is done to empower and support existing ones with robust multimedia packet data services such as web browsing, internet over internet protocols, online gaming, video calls, among other things. This scenario adds more complexity to the Radio Access Network formation while trying to maintain seamless communication and provide the desired service quality at different subscribers' locations with acceptable service agreement levels. In this contribution, practical monitoring and status service quality correlation analysis of deployed operational commercial LTE networks, considering signal coverage and quality indicators such as received signal power (RSRP), received signal strength indicator (RSSI), and, Signal-to-Noise ratio (SNR) is presented for a typical urban terrain. The sole aim has been realized by conducting detailed field test measurement campaign of the aforementioned key network parameters using professional TEMS investigation equipment. Furthermore, a detailed post data analysis of the collected LTE system network parameters has been provided to enable us reveal the true status service quality being providers to the end-user in the network.

More importantly, we also proposed and implemented an automated machine learning based analysis algorithm. The algorithm is termed Fitrauto regression optimisation algorithm (FROA). The six prognostic regression models include the ensemble forest, Artificial neural network (ANN) support vector machine (SVM), Gaussian process regression (GPR), decision tree (DT), and the general additive model (GAM). The algorithm that provide means to automatically select six optimal data fitting regression models with tuned hyperparameters to conduct adept analysis on the acquired signal datasets using Fitrauto function in Matlab computational environment. In terms of objective function, RMSE and R values, the results indicate that ensemble forest attained the best performance. The obtained results and findings could provide the basis for effective design and performance optimisation of different mobile broadband networks.

REFERENCES

[1]. Isabona J and Ekpenyong M. End-User Satisfaction Assessment Approach for efficient Networks Performance Monitoring in Wireless Communication Systems, African Journal of Computing & ICT, Vol 8. No. 1, pp.1-18, March, 2015.

[2]. Khatouni, A.S., et al. 2017. Speedtest-Like Measurements in 3G/4G Networks: The MONROE Experience. Proc. Int. Conf. on 29th International Teletraffic Congress (ITC 29). IEEE. pp. 169-177.

[3]. Iqbal M and Prasetyo D. 2019. Perbandingan Quality Of Service (Qos) Jaringan 4g Lte Beberapa Provider Menggunakan Sistem Operasi Linux Ubuntu Server 18.10. Jurnal Jaringan Sistem Informasi Robotik (JSR) 3(2) pp.239-249

[4]. Li, W., Wu, D., Chang, R. K. C. and Mok, R. K. P. 2018. Toward Accurate Network Delay Measurement on Android Phones. IEEE Transactions on Mobile Computing. 17(3) pp. 717 732

[5]. Joseph Isabona and Divine. O. Ojuh, Radio Link Quality Measurement Survey over HSDPA Radio Interface: A Holistic Technique for Efficient Networks Performance Monitoring in Wireless Communication Systems, Nigerian Journal of Physics Vol. 25(2), pp. 46-54, December 2014.

[6]. Joseph Isabona and Kingsley Obahiagbon, Practical optimization method to improve QoS and GoS-based key performance indicators in GSN network cell cluster environments, International Journal of Wireless & Mobile Networks (IJWMN) Vol. 6, No.5, pp.93-107, October 2014. DOI: 10.5121/ijwmn.2014.6508

[7]. Isabona. J .and Konyeha. C.C, Experimental Study of Umts Radio Signal Propagation Characteristics by Field Measurement, American Journal of Engineering Research (AJER) ,Vol. 02, Issue-07, pp-99-106.2013

[8]. Joseph Isabona and Viranjay M Srivastava, Coverage and link quality trends in suburban mobile broadband HSPA network environments, Wireless Personal Communications, Vol. pp.3955-3968.2017

[9]. N. Becker, A. Rizk and M. Fidler, "A measurement study on the application-level performance of LTE," *2014 IFIP Networking Conference*, Trondheim, Norway, 2014, pp. 1-9, doi: 10.1109/IFIPNetworking.2014.6857113.

[10]. E. Nwelih, J. Isabona, A.L. Imoize, "Optimization of Base Station Placement in 4G LTE Broadband Networks Using Adative Variable Length Genetic Algorithm." *SN COMPUT. SCI.* **4,** 121 (2023). https://doi.org/10.1007/s42979.022-01533-y

[11. Ayman A. El-Saleh, AbdulraqebAlhammadi, IbraheemShayea, Wan Haslina Hassan, Mohamed Shaik Honnurvali, Yousef Ibrahim Daradkeh, Measurement analysis and performance evaluation of mobile broadband cellular networks in a populated city, Alexandria Engineering Journal, Vol.66, pp. 927-946,2023. https://doi.org/10.1016/j.aej.2022.10.052.

[11] Baguena, Miguel et al. "Measurement-based modelling of LTE performance in Dublin city." *2016 IEEE 27th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)* (2015): 1-6.

[12] E. Nwelih (2022), "A Method for Real-time Adaptive Propagation Loss Modeling and Estimation Over LOS and NLOS Microcellular Radio Communication" *NIPES Journal of Science and Technology Research* 4(3): 133-140

[13]. V. M. Nguyen, C. S. Chen, and L. Thomas. A unified stochastic model of handover measurement in mobile networks. IEEE/ACM Trans. Netw., 22(5):1559–1576, October 2014.

[14] R. C. Park, H. Jung, K.-Y. Chung, and K. J. Kim. Performance analysis of lte downlink system using relay-based selective transmission. Personal Ubiquitous Comput. 18(3):543–551, March 2014.

[15] D. Baltrunas, A. Elmokashfi, and A. Kvalbein. Measuring the reliability of mobile broadband networks. In IMC '14, pages 45–58, New York, NY, USA, 2014. ACM.

[16] Y.-C. Chen, Y. Lim, R. J. Gibbens, E. M. Nahum, R. Khalili, and D. Towsley. A measurement-based study of multipath tcp performance over wireless networks. In IMC '13, pages 455–468, New York, NY, USA, 2013. ACM.