Base Station Availablity and Telecommunication Network Quality of Service – A Review

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***Abstract*—Network Quality of Service (QoS) is hinged on Base Transceiver Station (BTS) Availability. With the preparation of roll out of Next-generation 5G network, there is bound to be a massive influx of network infrastructure and higher demand for network availability. 5G intends to achieve all-time connectivity for diverse devices and this implies that the devices must remain connected not minding the state of the channel. This paper reviews the significance of a predictive tool for base station availability for Mobile Network Operators (MNO) for better service delivery. This forecast will enhance the smart planning of operations by Managed Service Providers (MSP) in a bid of improving Base Station availability by the reduction of the Mean Time to Repair (MTTR) as well as the increment of Mean Time Between Failure (MTBF) (MTBF can be improved by redundancy) to overcome envisaged network downtimes. It is a common practice for MNOs to engage the services of MSP as they have the capability of efficiently handling technical complexities more than the clients would (client here refers to the MNO). The MSP and the MNO enter into a contractual relationship and a service level agreement (SLA) is issued. This service level agreement is an important document in the contractual agreement binding the client (MNO) and the MS provider (MSP) and it defines the key performance indicators (KPI) that the MSP must meet up with. The parameters include a detailed description of required services, network restoration, network uptime, availability, systems repair, data transfer rate and expected performance measure.**

Keywords— Base Transceiver Station, Availability, Quality of Service, Mobile Network Operator, Managed Service Provider, Service Level Agreement.

I. INTRODUCTION

The massive influx of wireless mobile cellular technologies has made communication and other related applications more available than what it was in a few decades before now. With the emerging 5G, mobile applications will experience a tremendous surge, whereas, the bandwidth requirement of the cellular network becomes very high. To cater for such a great need in the cellular network infrastructure, several base stations have been designed, deployed to appropriate geographical locations to meet the expectations of the service coverage areas and improved quality of service [1], [2]. The base stations are then linked to the carrier network via the backhaul infrastructure using microwave links or fiber-optic lines. Though, this infers that the network service downtime will affect all the dependent base stations. It becomes very essential to consider the need to maintain an acceptable availability for both transmission route and base station so that service availability is sustained. A mobile cellular network is described as a communication infrastructure comprising network elements (NEs) that allow mobile stations or user equipment (UEs) access network services through radio channels [3]. Key performance indicators (KPI) for Quality of service (QoS) such as Call Setup Success Rate (CSSR), Drop Call Rate (DCR), Traffic Channel Congestion Rate (TCH-CR), Hand Over Success Rate(HOSR) are greatly enhanced with optimum base station availability [4]–[16]. In the remaining part of this paper, we will be looking at related work, basic concepts and terminology in the research domain, Managed Service (MS) and Service Level Agreement (SLA) effects on BTS Availability; models and network predictive tools presently in use, future direction and the conclusion.

II. RELATED WORK

Research work on base station availability have centered on optimal resources utilization; power-saving and improved radio network planning and maintenance. In [17], the availability of cloud Mobile Switching Server and Telecommunication Application Server were considered with the redundancy principle. Prior to the deployment of telecommunication networks on cloud, it is very important to have an idea on the level of network availability in comparison with that of the legacy equipment, hence the necessity of the availability prediction. This helps in proper planning of the project implementation and assurance of service quality. The simulated result indicated availability values equivalent to that of the legacy telecommunication equipment is achievable. However, the outcome of the simulation needs to be authenticated by the use of real field dataset. In [18], the paper discusses the evolution of Telecommunication Cloud, availability, basic dimensioning, design concepts and some challenges of practical implementation of the technology. [20] presented a

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framework for predictive model which used active and historical dataset as well as data from internet of things (IoT) devices and sensors. This work has the meritit of enabling the proactive planning for maintenance of the Radio Access Network (RAN) thereby increasing the telecommunication network availability and also reducing operational cost. Prediction of power supply failure was done by [21] by using a statistical analysis and the assessment of failure risk with the aid of fuzzy graphs and artificial intelligence. The work showed that future rectifier power failure can be avoided by predictive maintenance on the capacitors which can change in capacity as a result of ageing and electrical stress.

The papers [22], [23] both did a similar study on network availability. The authors in [22] considered that one of the main benefits of a network function virtualization (NFV) infrastructure is its high availability; the paper focuses on the analysis of the Virtualized Infrastructure Manager (VIM), a core element that is implemented through the OpenStack platform and is aimed at managing the whole NFV architecture. The system availability was evaluated by performing both a steady-state and transient analysis of Stochastic Reward Networks (SRNs) to obtain the best system configuration with the "five nines" (99.999%) availability requirement. Authors in [23] assessed how the distribution of the Software-Defined Networking (SDN) controllers contributes to the total availability of SDN. The quantity of homing and location of SDN controllers were altered. he results of the research showed how network operators can use the approach to determine the optimal cost implied by the connectivity of the SDN control platform by maintaining high values of availability. This approach may improve network flexibility and programmability, but it is likely going to introduce some challenges. In the work of [24], only a fraction of eNodeB site is powered by back up batteries during a temporary utility power cut off. The method used a modified sleep mode idea in cellular networks to control the working of the eNodeB sites in the case of electricity grid power outage. Simulations were carried out on the basis of network link with the use of radio network planning software known as ICS Designer. A significant availability was achieved during the backup period, but the research did not provide an algorithm in how to select the usable eNodeB sites. In the work of [1], a predictive model was formulated and they proposed an approach that boosts cellular network availability by event-driven base station battery profiling that identify and extract the features causing the degradation of back-up battery groups. The work indicated an 18.09% boost in the cellular network availability.

There is no doubt that base station availability is a critical factor in delivering quality services; a clear understanding of the requirement for availability and appropriate tools to achieve optimal service is thus paramount.

III. CONCEPTS AND TERMINOLOGY

Some common concepts and terminologies used in the reviewed papers are discussed here to be in the right frame to appreciate the subject matter of base station availability and telecommunication network QoS.

A. Definition of Availability

Availability has been defined by the International Telecommunication Union (ITU)) as the capability of a functional unit to be in a state to accomplish a vital purpose in a given circumstance at a given instant of time or over a given time interval, assuming that the required external resources if required are provided [25]. In short, availability is a fractional value of the amount of time the network is rendering services divided by the amount of time it is expected to deliver the services [26][11]. For a communication link like the synchronous digital hierarchy (SDH), availability as specified by ITU-T Standard G.826 is computed from the unavailable seconds (UAS). Refer to figure 1 below.

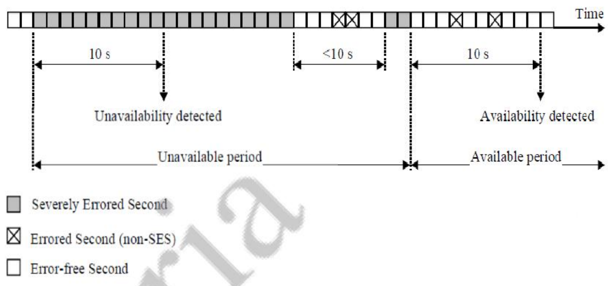

Fig. 1. Showing the Determination of UAS
Source: The ITU-T Standard G.826 Document.

- Availability, A:

$$A = \frac{(Measured\ Time - UAS) * 100}{Measured\ Time} \quad (1)$$

Analytically, A is defined in [11], [17], [24]–[29] as:

$$A = \frac{MTBF}{MTBF + MTTR} \quad (2)$$

Where the Mean Time Between Failure (MBTF) is a vendor warranty for the availability of the Telecommunication mobile network operator. It is the average time between two failures for repairable items.

Mean Time to Repair (MTTR) is the average period for repair and testing. This is the guarantee of the Managed Service Provider (MSP) for assurance of the availability of the telecommunication MNO. The major task of the MSP is to continually ensure that MTTR is kept at the barest minimum.

Un-availability (U)

$$U = 1 - A \quad (3)$$

Downtime for the period, T denoted as D_T is given by:

$$D_T = (1 - A) * T \quad (4)$$

B. Failure Rate, MTBF, MTTR,MTTF and FIT

Failure Rate (λ) of a unit (assembled from many components) is the number of failures that may occur during a given period. [17], [32]. It is constant over the life expectancy. The constant failure rate period falls between the initial 'infant mortality" and the final wear-out period as shown in figure 2 below.

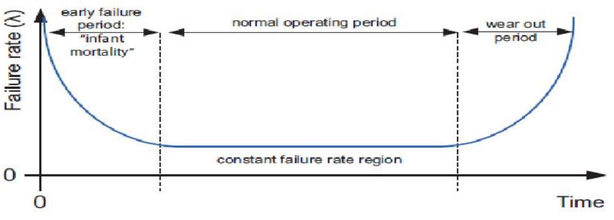

Fig. 2. Failure Rate Curve

Source: [17]

The Failures in Time (FIT) rate of a device is the ratio of the number of failures that can be expected, to a billion (10^9) device-hours of operation [17].

$$FIT = \frac{Number\ of\ failures}{10^9 hour} \qquad (5)$$

$$MTBF_{hour} = \frac{1}{\lambda} \qquad (6)$$

Mean-Time-To-Failure (MTTF) is the meantime expected until the first failure of a piece of equipment for a non-repairable item. MTTF is a statistical value and is meant to be the mean over a long period and a large number of units.

C. The BTS and the Mobile Cellular Network

The BTS processes speech encoding, multiplexing (TDMA), encryption, and modulation/demodulation of the radio signals. Its physical connection is achieved via the radio waves. A BTS is monitored by a base station controller (BSC) through the base station control function (BCF) [33]. A mobile cellular network is described as a communication infrastructure comprising network elements (NEs) that allow mobile stations or user equipment (UEs) access network services through radio channels [3]. Figure 3 below illustrates the mobile network and the BTS.

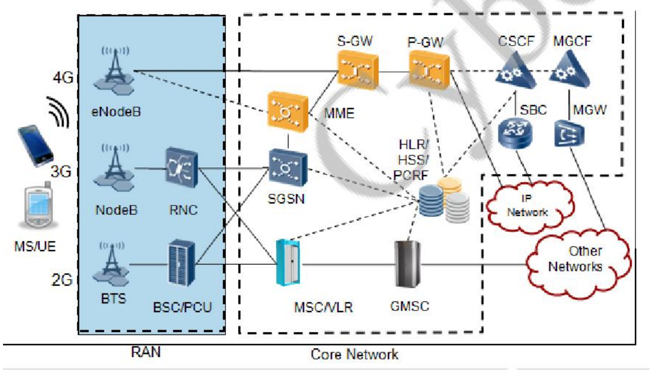

Fig. 3. Telecommunication Network
Source, [31]

D. Quality of Service (QoS)

The European Telecommunications Standards Institute (ETSI) defines QoS from the network perspective as *the capability to segment traffic or differentiate between traffic types for the network to handle certain traffic differently from others*", [23] and in the ISO definition, quality is defined as "*the totality of characteristics of a unit that bear on its ability to gratify stated and implied requirements* (ISO 8402*)*.

From reviewed papers, the most predominant Key Performance Indicators (KPIs) on which GSM are assessed for QoS are:

Call Setup Success Rate (CSSR). CSSR is the ratio of unblocked call attempts to the total number of call attempts.

$$CSSR = (1 - Blocking\ Probability) * 100\% \qquad (7)$$

Call Drop Rate (CDR). DCR is the ratio of dropped calls to the total number of call attempts.

$$DCR = (1 - Call\ Completion\ Rate) * 100\% \qquad (8)$$

Handover Success Rate (HOSR). HOSR is the ratio of the accomplished handovers to the total number of attempted handovers.

Traffic Channel Congestion Rate (TCHCR) ia s measure of how busy a cell is in setting up a call. The higher the TCHCR, the more difficult it is to access the channel.

Table 1 below shows the acceptable standard values of the KPIs according to the Nigerian Communication Commission.

TABLE I. KEY PERFORMANCE INDICATOR FOR QUALITY OF SERVICE

Parameter	Target Value
CSSR	≥98%
DCR	≤1%
SDCCH	≤0.2%
TCCH	≤2%

Source: The Nigerian Communication Commission (ncc.gov.ng)

E. Availability Requirement by ITU

Availability requirements are usually presented in terms of nines. For many telecommunications network equipment and BTS, there is a strict standard of five or six nines.

TABLE II. AVAILABILITY AND CORRESPONDING DOWNTIME

Availability (%)	Downtime Per Year
99.9999	32s
99.999	5min 15s
99.99	52min 36s
99.9	8h 46min
99	3 days 15h 40min

Source: Calculated Using Equation (4)

IV. MANAGED SERVICE AND SERVICE LEVEL AGREEMENT ON BTS AVAILABILITY

Managed Service renders services to MNO to improve BTS and other network availability [34]–[37]. The major task of MS is the reduction of MTTR term in equation 2. Reducing this value entails a lot of conscious effort to timely restore the network after outages and also the proactive planning of preventive maintenance (PM) work on network element (NE) [20]. SLA helps in controlling and enforcing compliance to contractual terms between the MNO and MSP to maintain a low MTTR which invariably improves availability as portrayed in [26], [30], [38], [39].

V. MODELS AND NETWORK PREDICTIVE TOOLS PRESENTLY IN USE

Predictive model uses data and statistics to predict or forecast future outcome based on learning from previous data. Some of the works used the artificial neural networks (ANN), the auto regressive integrated moving average

(ARIMA) and Bayesian Network (BN) model. BN exploits the capability to combine non-linear systems, their transparent probabilistic basis, and low computational cost as in the papers [29], [31], [37], [39]–[41]. Predictive BNs are generalizations of a system that have skill at forecasting outside of the training field. The predictive and descriptive expediency of a BN depends on its complexity and the amount of data available to train it, but there is often a trade-off; higher descriptive skill comes at the expense of condensed predictive skill.

A. *Artificial Neural Network*

Authors in [42]–[46] used ANN in their work. An artificial neural network is a computer simulation of a system that imitates the human brain. It contains several interconnected processing elements referred to as neurons that perform some mathematical operations. The weighted linkage of neurons is information stored in the neuron. According to [47], ANN has the advantage of a flexible non-linear capability. The model is adaptively designed based on the structures of a dataset, and there is no requirement to specify a specific method of a model. In scenarios where there is no theoretical guidance to suggest a suitable procedure that ANN would be a suitable model. A benefit of ANN over most other classes of the non-linear model is that ANNs are universally superb in giving approximations with a high level of accuracy [42], [43]. This is as a result of the parallel handing out of the information of the dataset.

ANNs have some components that are used in the process of building the model.

The Basic Components of ANNs are:

- Input.
- Interconnections or weights.
- Output.
- Neurons or nodes have internal state known as an activation signal. Neurons are connected to other neurons through interconnection link, this link is associated with a weight that has information about the input signal. The input signal combines with the activation signal of the neuron after obeying an activation rule to produce an output. Fig. 4 below is a general ANN model.

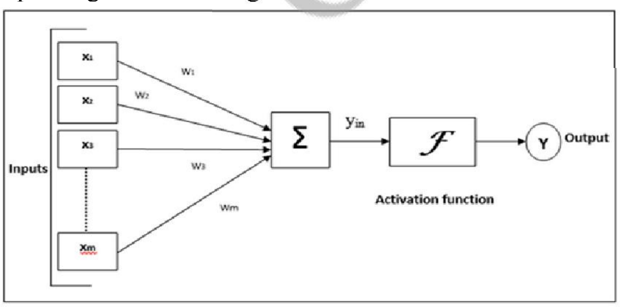

Fig. 4. General Model of Artificial Neural Network

Source:https://www.tutorialspoint.com/artificial_neural_network/artificial_neural_network_supervised_learning.htm

B. *Auto Regressive Integrated Moving Average*

The Auto Regressive Integrated Moving Average (ARIMA) written as Autoregressive (AR) (p) Integrated (I) (d) Moving Average (MA) (q) is a hybrid of models that exploits the functions of the Regressive, the differencing factor (Integrating) and the Moving Average in the models. The **p, d and q** are their respective orders. For the Autoregressive (AR) model, the output variable is linearly dependent on the previous values and a set of stochastic terms. The AR model having an order (p) is generally written as AR (p) and is mathematically defined as:

$$A_t = \sum_{i=1}^{P} \phi_i A_{t-i} + \mathcal{E}_t \tag{9}$$

Where $\phi_i,\ldots,\phi_p$ are the model's parameters and $\mathcal{E}_t$ is the random error. Similarly, the output variable (A_t) for the MA depends linearly on the present value and past values of stochastic terms.

For MA of order (q) written as MA(q), (A_t) is defined as:

$$A_t = \mu + \sum_{i=1}^{q} \theta_i \mathcal{E}_{t-i} + \mathcal{E}_t \tag{10}$$

Where μ is the mean of the series, $\theta_i,\ldots,\theta_q$ are the parameters for the MA model, $\mathcal{E}_t$ and $\mathcal{E}_{t-i}$ are the white noise errors.

The ARIMA (p, d, q) model where p, d and q are the respective orders for the AR, integrating (differencing) and the MA models which are the parameters to be determined and used for the model is indicated in equation (11) below.

$$\left(1 - \sum_{i=1}^{p} \phi_i L^i\right)(1-L)^d A_t = \left(1 + \sum_{i=1}^{q} \theta_i L^i\right)\mathcal{E}_t \tag{11}$$

According to [48], [49], L is a backshift or lag operator which operates on an element in a time series to give the previous element.

C. *Apache Hadoop*

Apache Hadoop is an open-source software platform used in [1], [20]. It is used for writing and running applications that require the processing of a huge amount of data for predictive analytics [50]. It has an efficient framework that utilizes a distributed parallel processing on heterogeneous data for forecasting. It can store and process very big dataset ranging in size from gigabytes to petabytes of data. Hadoop has some good features that have made it very useful in predictive analytics.

- Flexibility: It can store data easily even without prior processing, whether structured or un-structured such as audio, text or video. It is more flexible than SQL-based systems.
- Computational power: The distributed computing model enables the computation of enormous amount of data using many nodes. The more the number of nodes, the more the processing power.
- Scalability: The system can be increased by merely, connecting more nodes to the system.
- Tolerance to fault: Hadoop stores multiple copies of all data automatically and the failure in one of the nodes does not affect the data processing since the task is sent to other functioning nodes for processing.
- Low cost: It is an open-source framework.

D. Windchill

Windchill was used in [17]. It is a tool used for predicting reliability, availability and other reliability-related metrics [51]. It has the features that estimate MBTF, MTTR, failure rate and other user-defined metrics. Windchill is very instrumental in product life management. It provides a comprehensive easy-to-use tool for the estimation of system reliability and MTBF. It allows the early identification of the major contributors to system failure and measures environmental impact on the system.

E. Bayesian Network

Bayesian Networks (BN) are a category of Probabilistic Graphical Model that is used to design models from a dataset and/or several experts' opinion in the particular domain of the expert **[**37**]**, **[**39**]**, **[**40**]**. BNs can also find application in an extensive range of tasks with prediction, time series prediction, anomaly detection, diagnostics, automated insight, reasoning, and decision-making process.

BN has a direct acyclic graph (DAG) that represents the structure, as well as a set of conditional probability tables (CPT). The observed variables are the nodes in the structure, while the edges are called 'probabilistic independence'. The relationship between the variables in the graph is measured by the CPT. Bayes' theorem is used for computing the probability distribution for the nodes. For two events (X) and (Y), Bayes' theorem states that:

$$P(X|Y) = P(Y|X) * \frac{P(X)}{P(Y)} \tag{11}$$

VI. FUTURE CHALLENGES AND DIRECTION

Future work will entail the development of an intelligent real-time base station availability tool for efficient monitoring and service level delivery. A predictive Model for BTS Availability that will make use of artificial intelligence to adapt to technological advancement and risk mitigation for availability especially with the challenges that will accompany the next-generation technology, the fifth generation 5G.

VII. CONCLUSION

QoS has become very crucial in this era of stiff competition among the various MNOs. Subscribers of the mobile telecommunication network have become very aware of their right to get the best value from the MNOs. We cannot expect an improved QoS if the network availability of the access point – BTS is not guaranteed. Of what benefit will it be, if, after a well-prepared network, one cannot access it? In this paper, we looked at the need to predict the BTS Availability in a bid to proactively improve the BTS Availability and the QoS. To do this, the MSP is furnished with SLA to enforce adherence to the agreement on timely resolution of outages and this, in turn, brings about a reduction in MTTR and this consequently improves BTS Availability.

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