QoS Reliability in GPRS Systems

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Abstract

Wireless link quality is closely related to the received signal strength. Hence, transmit power control can be used to adjust the communication link quality to avoid asymmetric or weak links. This paper proposes a spatial radio resource model for quality of service (QoS) reliability in General Packet Radio Service (GPRS) networks. To model the propagation parameters, we adopt the empirical modeling approach by measuring signal outages at various base stations from a well established network, operating in Nigeria. We collect these data over a period of three months and apply the resultant data as parameters to the proposed model. We simulate the model under ideal conditions and evaluate the system's performance as well as the power control tradeoff. A qualitative analysis using processed GIS maps, calls for effective power control in the system. Simulation results indicate that the existing system still requires further improvements to enhance its QoS reliability.

Keywords: Quality of service, Signal outage, Power control, Radio resource management

1. Introduction

The sudden increase of mobile subscribers has posed great challenges on quality service delivery to the telecommunication industries. In Nigeria for instance, the poor quality of service (QoS), largely attributed to signal propagation defects has made some mobile users to subscribe to more than one network (service) provider in order to maintain seamless connectivity. QoS in cellular networks is defined as the capability of cellular service operators to provide satisfactory services such as voice quality, signal strength, low call blocking and dropping probabilities, high data rates for multimedia and data applications, etc. to customers. The satisfaction of users depends on propagation parameters such as call admission, connection quality and handover success. Though it is realistic to expect that at low loads, a network should satisfy all of its customers, there still remain some unsatisfied customers due to signal outage and high interference (Forkel, Schinnenburg and Wouters, 2003).

There has been lots of effort (in the telecommunication industries) at defining adequate and realistic end-to-end QoS indicators for cellular data services, which might be applicable for estimating the delivered QoS and for specifying the QoS control mechanisms for the underlying transport networks. Despite increased consideration for end-to-end performance required by user applications, the term QoS is usually not well defined or is loosely applied. QoS comes into focus when planning and deploying networks or when monitoring service quality. Aspects of networks and service provisioning are presented in Furuskar, Sara, Frank and Hakan (1999), but the standard is not application-oriented, and, in many areas, too vague for practical illustration. Nevertheless, Furuskar, Sara, Frank and Hakan (1999) set the QoS framework and the widely used definition as the collective effect of service performance which determines the degree of a user being served.

Service functions (such as service management, connection quality, billing, customer net/service management, etc.) and service quality criteria (such as speed, accuracy, availability, reliability, security, simplicity and flexibility) are considered for creating a QoS matric for each service. Considering the goals and achievements of both customer and provider involved in the service, one may devise four complementary viewpoints: customers' QoS requirements, perception and service provision, QoS offering and QoS achievement. Customers' requirements are important when creating a QoS test plan for estimating the QoS delivered by the service provider. The delivered QoS is expressed as values assigned to QoS indicators, which are used for tracking performance and directing optimization. These indicators contribute towards the overall performance of the service offered (Sedoyeka, Hunaity and Tairo, 2009).

Evaluating the QoS performance in a cellular environment is not a trivial task. One way of overcoming such a challenge is to organize individual services into four basic traffic classes (Hallman and Helmchen, 2001, Lee, 1998). For selected data services, acceptable performance boundaries for delay, delay variation and information loss are presented in Furuskar, Sara, Frank and Hakan (1999). Changes in the propagation environment and/or network traffic load will result in a major modification of the resources allocated to a user during a call or from call to call. The Gaussian distribution of performance measurements, inherent for non-variable radio environments and traffic load, creates room for highly skewed distributions (Cotanis, 2003). In the General Packet Radio Service (GPRS), resources are allocated based on radio channel condition, traffic load, requested QoS, etc. Thus, for the same network traffic load and service, the delivered QoS (e.g. throughput or session time) will depend on user-base transceiver station (BTS) distance. Users at close range may receive high data rate radio channels when compared with far-range users. Also, error control mechanisms, resource allocation and mobility management could further determine the delivered QoS.

This paper therefore proposes a spatial radio resource model for QoS reliability and presents a procedure for mapping the spatial data measurements of the key quality and performance indicators to a GIS system. In addition to proposing the resource model, the paper also serves as data source and knowledge base for further research in signal strength modeling. The research though limited to GPRS networks, is generic and can be adapted to third generation (3G) networks.

2. Statement of Problem

The performance of wireless systems is mostly affected by a number of propagation phenomena (Mehritra, 1994):

(i) path-loss variation with distance

(ii) random slow shadowing

(iii) random multipath fading

(iv) inter-symbol interference (ISI), co-channel interference as well as multiuser interference

(v) background noise

These phenomena greatly retard signal reception, leading to poor service quality. For network based services, QoS depends on the following factors (Jain, 2006):

(i) Throughput: the rate at which the packets go through the network. Maximum rate is always preferred.

(ii) Delay: the time at which a packet takes to travel from one end to the other. Minimum delay is always preferred.

(iii) Packet loss rate: the rate at which a packet is lost. This should be as minimum as possible.

(iv) Packet error rate: the errors which are present in a packet due to corrupted bits. This should be maintained at the bearest minimum.

(v) Reliability: the availability of a connection at both links (forward and reverse link)

These demands make QoS provisioning more challenging, even in recent times. Although there are cellular base station tower networks across many countries in the world, there are still many areas within these countries that do not possess good reception. Some rural areas are unlikely ever to be effectively covered, since the cost of erecting a cell tower is too high for only a few customers. Even in high reception areas, it is often found that basements and the interiors of large buildings have poor reception. Weak signal strength can also be caused by destructive interference of the signals from local towers in urban areas, or by the construction materials used in some buildings, causing rapid attenuation of signal strength. Large buildings such as warehouses, hospitals and factories, often have no usable signal further than a few metres from the outside walls. This is particularly true for networks operating at higher frequency, since these signals are attenuated more rapidly by intervening obstacles, although they are able to use reflection and diffraction to circumvent obstacles.

A cost effective approach to QoS provisioning using a power control model is therefore offered by this paper. This approach simulates a reliability model that improves the QoS of cellular networks.

3. Related Literature

Radio Resource Management (RRM) involves the various strategies and algorithms for controlling parameters like signal strength, transmit power, channel allocation, handover, etc. It is the system level control of co-channel interference and other radio transmission characteristics in wireless communication systems. Geographical Information System (GIS) has become an essential tool for easy analysis of large quantity of spatial information.

The application of GIS for GSM-related data handling, presupposes efficient spatial data storage and handling aimed at improving the effectiveness of managing radio resource parameters.

GPRS is designed for transmitting packet data. It takes its radio resource from a pool of unused channels of the GSM voice services. Obviously, the introduction of GPRS impacts on the voice services. However, the introduction of GPRS into GSM networks without allocating new spectrum will increase the interference probability of circuit switched services. In addition, the physical channel allocated to GPRS is shared by a few data users simultaneously. The co-channel interference to the voice users might vary rapidly and dramatically in the time interval from 20 ms to a few seconds depending on the transmitted packet data size (Ni, Liang and Haggman, 1999), because the locations of users using the data packets could be largely different. This effect could drive the system into an unpredictable and unstable state that could result in a degraded quality of voice services. Therefore, a preliminary resource planning for GPRS is necessary to guarantee quality of service for voice users.

Empirical measurements of wireless signal strength and its dependence on various factors have been carried out by cellular service providers and consulting companies. For instance, In Omnitele (http://www.omnitele.fi/), experiments have been conducted to measure call success rate, signal strength and throughput, along roads, train routes and in urban and rural areas. Their objective was to utilize the collected measurements to optimize operators' network performance for better customer service and hardware utilization. However, their data is not publicly available. Wagen (1991) conducts a series of experiments in small (62 x 65 meters) urban areas to measure signal loss in both line-of-sight and non-line-of-sight conditions. He developed an empirical model to characterize the relationship between signal strength and distance. Chen and Siew (2003) conduct indoor experiments to measure the performance of a wireless LAN. Their focus was to investigate how the packet and bit error level characteristics are affected by different environmental factors such as humidity, microwave interference, wall obstacle and distance. Wide-area measurements recording of GPRS signal strength at various locations and under a variety of conditions in Sydney, Australia, focusing particularly on several public transport routes have been conducted by Chan, Chung, Hassan, Lan and Libman (2005). Their analysis show that, among the factors studied, location is clearly the most dominant factor affecting signal quality, with the overall impact of all other factors being much less significant. Hence, even a simple outage prediction approach, taking into account only the location of the vehicle is most likely to cause a performance improvement in practice.

QoS should be evaluated for correctness. The expected QoS requirements may not be obtained at all times (calduwel, 2008). Sedoyeka, Hunaity and Tairo (2009) present the QoS required for developing countries using Tanzania as a case study. The authors discuss issues surrounding QoS requirements for the modern world and compare these requirements to that of developing countries. In Newton, Arockiam and Kim (2009), a QoS strategy to select an appropriate coding scheme that reduces data transfer complexities for applications based on the coding and data rate scheme characteristics in GPRS network is proposed. They also analyze coding schemes with various Internet applications and QoS parameters such as reliability, delay and bandwidth for mobile networks. Knowledge of the strengths and weaknesses of mobile systems provides a baseline for identifying ways of maximizing revenue and business potentials of such systems. QoS prediction techniques are necessary for the evaluation of the performance (with respect to reliability) of various applications and also to overcome QoS issues in GPRS networks (Calduwel and Arockiam, 2009).

4. Data Instrument and Field Survey Techniques

(i) Base Map and Survey of Mast Points using GPS

The base map of Akwa Ibom state is very essential in this research. The base map, showing local government areas, was obtained from the Akwa Ibom State Ministry of Lands and Environment's Geographic Department. The field techniques involve a survey of base stations (masts) location in Akwa Ibom State and taking the required measurements (longitude and latitude) using a GPS.

(ii) Map Processing

The raw map is processed in the following order: (i) scanning, (ii) geo-referencing and (iii) digitization. The Digital Elevation Model (DEM) of the study area is used to determine the slope pattern of Akwa Ibom State. This elevation model is useful for the appropriate identification of mast locations and slope pattern analysis. The slope pattern analysis will be done in future paper and shall not be discussed further.

(iv) Database and Simulation Programming

The collated empirical data (cell site locations and signal outage probabilities for each cell) are captured in the Microsoft Excel file format. To ease programming, we converted these data into an input (text data or comma separated value, .csv file) format. Then with the Visual Basic (VB) 6.0 programming language, a simulation program was written to implement the QoS reliability of the network using the system model. The result of the simulation were then written to an output (text) file, ported to Ms. Excel and finally represented in ArcGIS 9.1.

5. Empirical Signal Outage Data Analysis

Knowledge of observed data is required when carrying out a simulation study. The essence of this data is to enhance the accuracy of predictions. In this section, we analyze data measurements from Airtel Nigeria (formally Zain Communications Limited). We study the signal outage probability trend of the cellular system for Akwa Ibom State (east region of Nigeria). The resulting average outage probabilities are then used as simulation input to the derived model. During the data gathering stage, weekly signal outage durations were measured for a period of three months (September-November, 2009), at the various base station controllers (BSCs). Table 1 shows the average signal outage occurrences in minutes for the observed period at the different BSCs; each BSC covers a number of cells or base stations. From Table 1, we observe that signal outages occur in every 1.45 hours on the average. This reveals that Airtel Nigeria still requires the optimization of network parameters to avert further service degradation.

Presented in Appendix 1, is the signal outage rate (in percentage), obtained at the various base stations for the duration under study. Airtel has 148 base stations distributed across the entire state, with Uyo the state capital having the highest concentration of base stations. We observe from this data that on the average, there is a 0.01202 likelihood (i.e. 1.20%) of signal outages across the base stations.

Signal outage has been proved to have logarithmic characteristics (Kandukuri and Boyd, 2002). Hence, we fit a logarithmic predictive model (trend line equation) into a scatter plot in Figure 1, which relates the outage probability and number of base stations. The graph shows that on the average, signal outage slowly decreases as the number of base stations increase. We also discover that signal outages is not significantly influenced ny the number of base stations (i.e. R=0.06). Therefore Airtel should concentrate more on network optimization techniques such as efficient call admission and power control, proper bandwidth management and perfect channel allocation, rather than planting more base stations as witnessed in recent times.

We apply a 95% confidence interval (see Table 2) to predict new empirical results. This interval indicates that new observations are likely to fall within the specified limits.

6. The System Model

In the design of any radio system, a fundamental task is to predict the terrain coverage of the proposed system and determine whether the intended service objectives are met. Over the years, a wide variety of approaches have been developed to predict network coverage using propagation modeling. Propagation in this context refers to the transfer or transmission of signals from a transmitter to a receiver. Propagation modeling is therefore an attempt to predict what happens to signals en-route the transmitter to the receiver. The signal strength coverage largely depends on factors such as the users' capacity (i.e. the number of users the network supports), equipment quality and the frequency spectrum (bandwidth capacity).The most commonly used method for effective propagation modeling is the empirical or physical models.

Empirical models use measurement data to define the propagation behaviour. These measurements are called "predictors" or "specifiers" in generic statistical modeling theory. Predictors are parameters, which have been established through statistical analysis to have relationship (or correlate) with the quantity to be predicted. The accuracy of empirical models strongly depends on how universally applicable the environment is. A common problem is attempting to use empirical models in areas where the propagation environment widely deviate from the environment the data was gathered. With the recent advent of automated field strength measurement systems with GPS position logging, it now becomes relatively easy to acquire vast amount of measurements. This has led to the use of custom empirical propagation models, which equations are "tuned" for a given system or for a given transmitter or base station (cell) within the system.

Unlike empirical models, physical models do not use measurements for predictions but instead rely on physical laws governing the interaction of electromagnetic waves with the physical elements of the propagation environment. To be effective, physical models require detail description of elements of the propagation environment for their predictions. For this reason, their weakness is that they require extensive database information (terrain elevations, building wall locations, surface material characteristics, etc.) which in turn demand significant computer resources to accommodate the information necessary for the required computations.

To emulate and simulate realistic mobile radio networks, the propagation of electro-magnetic waves must be carefully modeled. An integral aspect of radio propagation besides path-loss and multi-path fading is loss due to shadow fading, also referred to as shadowing or long-term fading. This phenomenon is caused by the presence of obstacles lying in the propagation path of the radio waves (Walke, 2001, Lee, 1993). The electromagnetic waves thus exhibit significant variations largely due to the shadowing effects by obstacles. The resulting undulating signal is referred to as "shadowing signal". Hence, shadow fading represents signal fluctuations caused by obstructions (natural or artificial) around the average path-loss, in the way of propagating electromagnetic signals (waves). Here, signals are prevented from traveling along the shortest and direct path (usually also, the path that experiences the least attenuation) between a transmitter and a receiver. Having knowledge of shadowing signal will greatly enhance communication quality in all types of wireless networks and is used in the planning stages of second generation (2G) and third generation (3G) cellular networks (i.e. where best to locate the base stations). Three components of electromagnetic signal that could be used to perform predictions are path-loss, shadowing or large-scale fading signal and fast fading or small-scale fading signal.

Let the shadow fading value be ξ. This value is usually characterized by a Gaussian (normal) distribution in the logarithmic scale with zero mean and standard deviation in the magnitude of 8-10dB (Walke, 2001). The probability density function (PDF) is given by

$$p(\xi) = \frac{1}{\sigma_{\xi}\sqrt{2\pi}} e^{\frac{(\xi - \mu\xi)}{2\sigma_{\xi}^{2}}} \tag{1}$$

with mean, μ_{ξ} and standard deviation, σ_{ξ}. In the linear scale, shadow fading is log-normal and is referred to as log-normal fading. It is obvious that shadow fading values depend on the terrain and the surrounding property in the mobile's vicinity. These values must show a spatial correlation due to the structural stability of the terrain and ground morphology, which do not abruptly change. Moreover, another user may experience similar shadow fading effects when passing by same location and hence, the need for an accurate correlation model.

Now, let X_j be the number of ongoing data transmission of type j in some given sector, and $X = (X_1, X_2, ..., X_k)$. For cellular systems, in order to receive a signal, the ratio of its received power to the sum of the background noise and interference must exceed a given constant. Thus for some given X, this condition is represented as (Laiho and Wacker, 2001, Khumsi, Mori and Kobayashi, 2005):

$$\frac{P_j}{N + I_{own} + I_{other} - P_j} \cong \gamma_j \geq SIR_j; \quad j = 1,...k \tag{2}$$

where

$P_j = Pd^{\alpha}$ is the total received power of transmitted signal

N is the thermal or background noise

$I_{own} = (1+f)$ and $I_{other} = (n-1)$ are the total received power from mobiles within the considered sector, and within other sectors or cells respectively

γ_j is the ratio of the received power to total received interference and noise at the base station, *SINR*.

SIR_j is the required signal-to-interference ratio for each class of j.

Substituting P_j, I_{own} and I_{other} into equation (2), we arrive at

$$\gamma_j = \frac{Pd^{\alpha}}{N + (1+f)(n-1)Pd^{\alpha}} \tag{3}$$

where

P is the transmit power

d is the distance

n is the number of users

f is the reuse factor

α is the propagation exponent

The reliability model is then derived from the required Signal-to-Interference Ratio (SIR_j) given as (Kurniawan, 2003, Isabona and Ekpenyong, 2008):

$$SIR_j = \frac{\varepsilon_j}{N_0} R_j W \tag{4}$$

where

ε_j is the energy per transmitted bit of type j

N_0 is the thermal noise density

W is the modulation bandwidth

R_j is the call transmission rate of type j

In the above case, we assume perfect power control. Due to the inaccuracies of closed-loop fast power control mechanisms arising mostly from shadow fading of the radio signal, γ_j may not always equal SIR_j. To model these variations, we define SIR_j to be a random variable of the form, $\gamma_j = 10^{\frac{\xi_j}{10}}$ (Vertibi, Vertibi, Gilhousen and Zehavi, 1994, Wong, 1997), where $\xi_j \sim (\mu_\xi, \sigma_\xi)$ is normally distributed and includes the shadow fading and standard deviation components. The standard deviation of shadow fading has typical experimental values between 0.3 and 2dB (Koo, Ahn, Lee and Kim, 1999, Viterbi and Viterbi, 1993).

Signal quality is largely detected by the SINR, γ_j. On a large scale, both useful and interfering signals experience lognormal shadow fading (Gao, Xu and Ye, 2009). This implies that γ_j can be modeled by $(X_1 + ... + X_n)/(Y_1 + ... + Y_m)$, where all random variables $X_1,..., X_n, Y_1,..., Y_m$ are lognormally distributed. γ_j only characterizes the instantaneous quality and has a lognormal distribution (Anderson, 1988) given by

$$f_{\gamma_i}(x_j) = \frac{h}{x_j \sigma_\xi \sqrt{2\pi}} \exp\left(-\frac{(h \ln(x_j) - \mu_\xi)^2}{2\sigma_\xi^2}\right) \tag{5}$$

where $h = 10/\ln 10$.

Since γ_j is random and we desire the use of observed signal outage probabilities mean as predictor to the system's model, we rewrite equation (3) in terms of $\bar{\gamma}_j$, the average received SINR, and determine the required SIR, SIR_j, such that $\gamma_j = \overline{SIR_j}$, where $\overline{SIR}_j$ includes power control errors and replaces SIR_j. We then determine $\overline{SIR}_j$ for the outage condition: $\Pr[\gamma_j \geq SIR_j] = \beta$, where β is a reliability, usually set to 99% (Wu, Wu and Zhou, 1997).

Thus

$$\Pr[\gamma_j \geq SIR_j] = \beta = \int_{SIR}^{\infty} f_{\gamma_j}(x)dx = Q\left(\frac{h \ln SINR - \mu_\xi}{\sigma_\xi}\right) \tag{6}$$

where Q, herein defined as the outage probability function is given as (Ekpenyong, Umoren and Isabona, 2009):

$$Q(x) = \int_x^{\infty} \frac{1}{2\pi} e^{-\frac{t^2}{2}} dt \tag{7}$$

Substituting equation (3) into equation (6), we obtain

$$\beta = Q\left[\frac{h \ln\left(\frac{Pd^\alpha}{N + (1+f)(n-1)Pd^\alpha}\right) - \mu_\xi}{\sigma_\xi}\right] \tag{8}$$

Equation (8) is the QoS reliability model. The model is suitable for analysing the performance reliability in GPRS systems.

7. Model Simulation and Results Interpretation

Figures 2 and 3 show processed GIS maps for observed and simulated signal qualities, distributed across the various base stations, within the study area. The observed signal quality data (Table 2) were used as parameters in the SINR model (equation (3)). This equation, which represents a reliable measure of signal strength quality at the base stations, was then used to simulate the system and study the consequence of improved power control. The simulated result is summarized in Table 3. A qualitative view at Figures 2 and 3 reveal that Figure 3 shows a remarkable improvement in signal quality across the study area. We attribute this improvement to the effectiveness of the model at minimizing signal outages in the network, thus, illustrating the need for effective transmission power control in the network.

Comparing Tables 2 and 3, we observe that the simulation provides a 26% improvement on the present average signal quality (i.e. from 54.09% to 80.08%). This improvement is naturally achievable through the provision of good quality base station infrastructure with quality amplifiers and excellent power control mechanisms.

The performance of the system using the reliability model in equation (8) for urban and suburban environments was also simulated, using empirical parameters from the field (see Table 4). Figures 4 and 5 depict the sensitivity of outage probability on varied number of users. We observe from these figures that QoS degrades as the number of users' connection increases. This is due to mobile users' competition for available network resources, which calls for appropriate admission control to preserve ongoing user connections in the network. Outage performance as a function of users and their locations for urban and suburban environments are presented in Figures 6 and 7 respectively. An observation of these graphs show service stability in terms of QoS, making the network to be more reliable. In general, this performance proves that capacity and coverage are both provisional quantities and will be re-dominated by stability issues (more than the actual resource constraints) in urban and suburban areas.

8. Conclusion

The success of any wireless network depends on the signal strength. A strong signal is required for effective communication of all network devices or nodes. A weak signal causes low bandwidth, thus, preventing communication and causing network disruptions which occur as a result of inefficient power allocation. This paper has shown that power control is very critical in wireless networks to ensure longer battery life of mobile devices and for increased utilization of the limited wireless spectrum. We observed that the frequent rate of signal outages (i.e. outage probabilities) can be minimized by allocating power in a manner that each mobile has an extra signal to interference ratio (SIR), i.e., its SIR is somewhat above a minimum SIR^{th} value required for reception. Therefore, power control is very crucial when managing wireless communication systems.

We have also proposed a QoS reliability model for GPRS networks. This model was used to simulate a realistic network operating in Nigeria, which empirical data parameters served as predictors to the simulated system, for urban and suburban environments. We observed that QoS reliability is very essential in any communication system and wireless networks should be optimized for excellent reliability to ensure system stability.

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Table 1. Average outage duration data measured from the BSCs of Zain comm. Ltd.

BSC index	Number of BS	Sept	Oct	Nov	Average signal outage occurrence time (mins)
BSC 1	22	32.80	75.34921	82.97189	63.71
BSC 2	26	72.40	212.6984	124.5052	136.54
BSC 3	25	240.17	97.65633	108.68	148.84
BSC 4	27	117.83	136.7182	85.24272	113.26
BSC 5	24	24.50	91.72245	23.09744	46.44
BSC 6	24	168.26	94.95422	102.5988	121.94
Avg. time (mins)		109.33	118.18	87.85	105.12

Table 2. Average empirical signal strength data obtained from the BSCs of Zain comm. Ltd

BSC index	Number of base stations	Signal Strength (%)	95% Confidence interval (CI)
BSC 1	22	47.3031	47.3031 ± 14.7384
BSC 2	26	61.7261	61.7261 ± 11.0927
BSC 3	25	51.9846	51.9846 ± 14.2050
BSC 4	27	63.2647	63.2647 ± 11.8221
BSC 5	24	45.8737	45.8737 ± 15.0800
BSC 6	24	54.4019	54.4019 ± 13.1772
Average		54.0923	

Table 3. Simulated signal strength

BSC index	Number of base stations	Signal Strength (%)	Confidence interval (CI)
BSC 1	22	79.2419	79.2419 ± 7.1777
BSC 2	26	83.3915	83.3915 ± 3.7865
BSC 3	25	78.1179	78.1179 ± 8.3057
BSC 4	27	83.4506	83.4506 ± 3.9310
BSC 5	24	74.4031	74.4031 ± 9.0486
BSC 6	24	81.9124	81.9124 ± 4.3975
Average		80.0862	

Table 4. Simulation input parameters

Empirical parameter	Value
Outage probability function (Q(x))	0.01202
Transformation constant (h)	$10/\ln 10$
Transmit power (P)	43
Distance	1-5 Km
Thermal or background noise	-105
Number of users	20-100
Frequency reuse factor (f)	0.50
Propagation exponent (α)	3-urban, 3.5-suburban
Shadow fading (μ_{ξ})	6
Standard deviation of shadow fading (σ_{ξ})	0.8

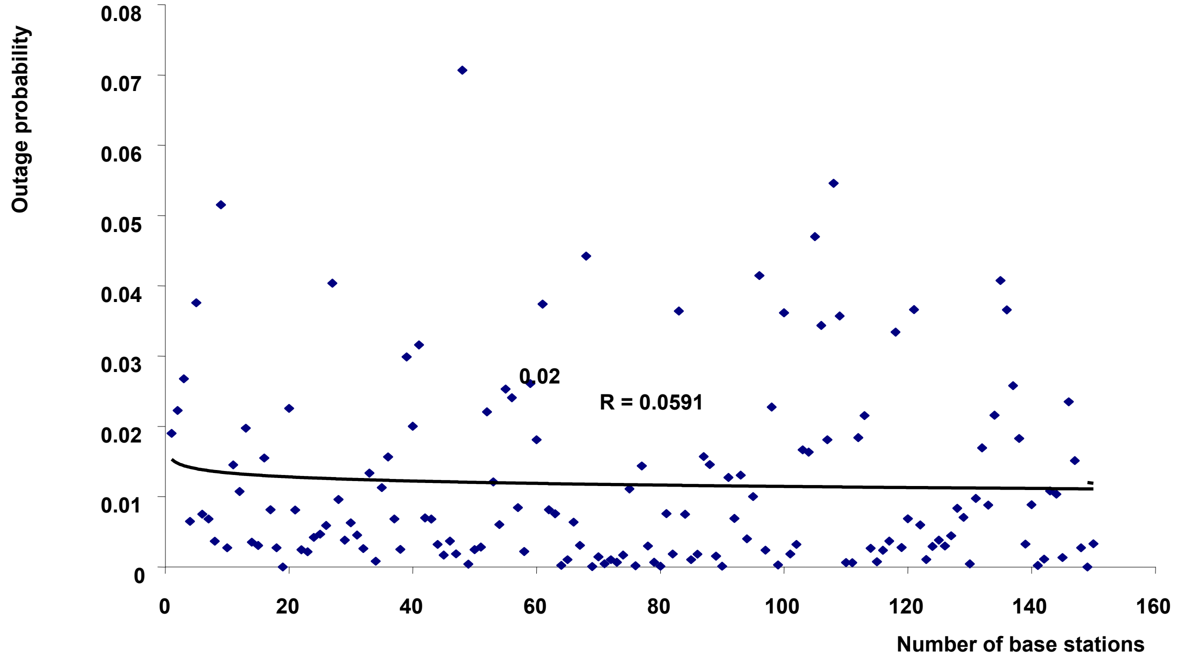

Figure 1. Distribution of signal outage data across the various base stations in Akwa Ibom State using a logarithmic predictive model

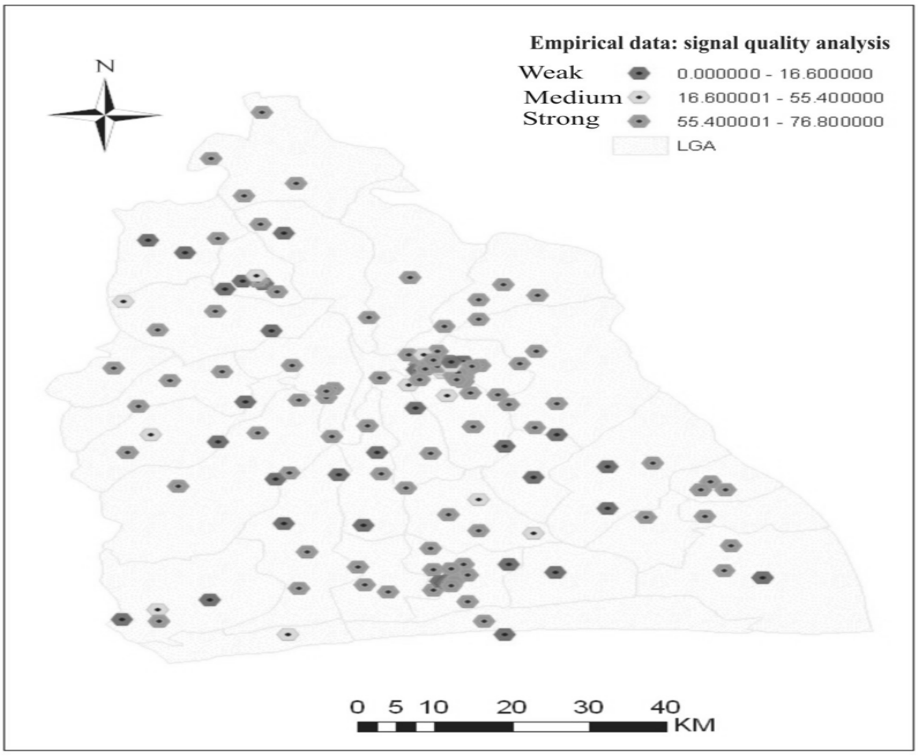

Figure 2. Processed GIS map showing the distribution of observed signal quality data over the study area

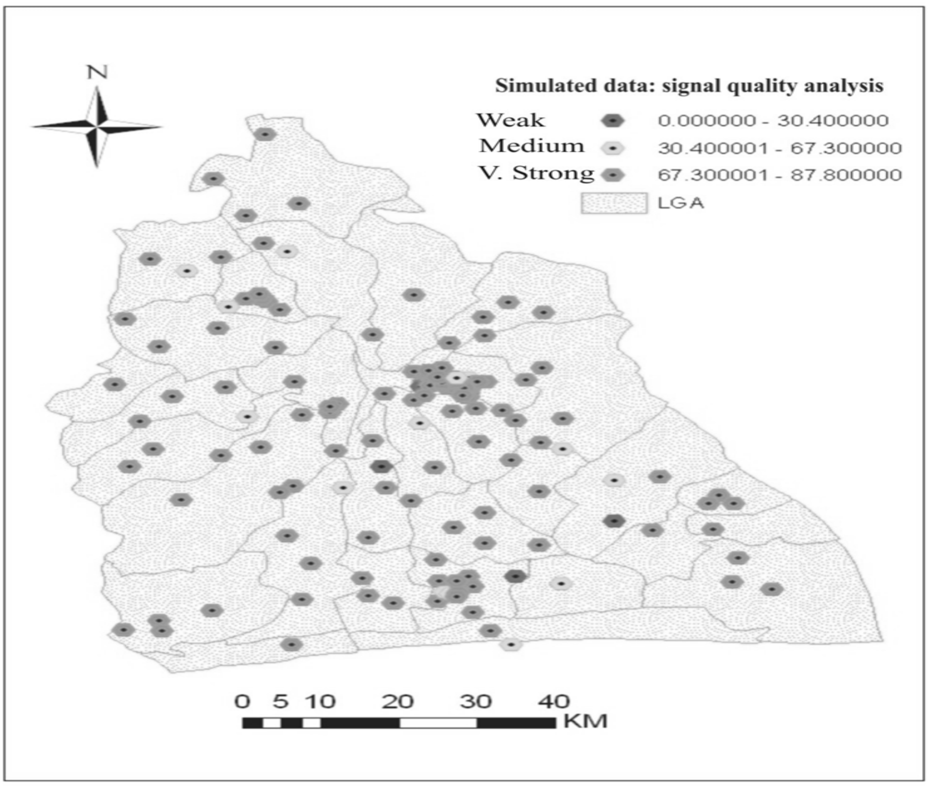

Figure 3. Processed GIS map showing simulated signal quality data over the study area

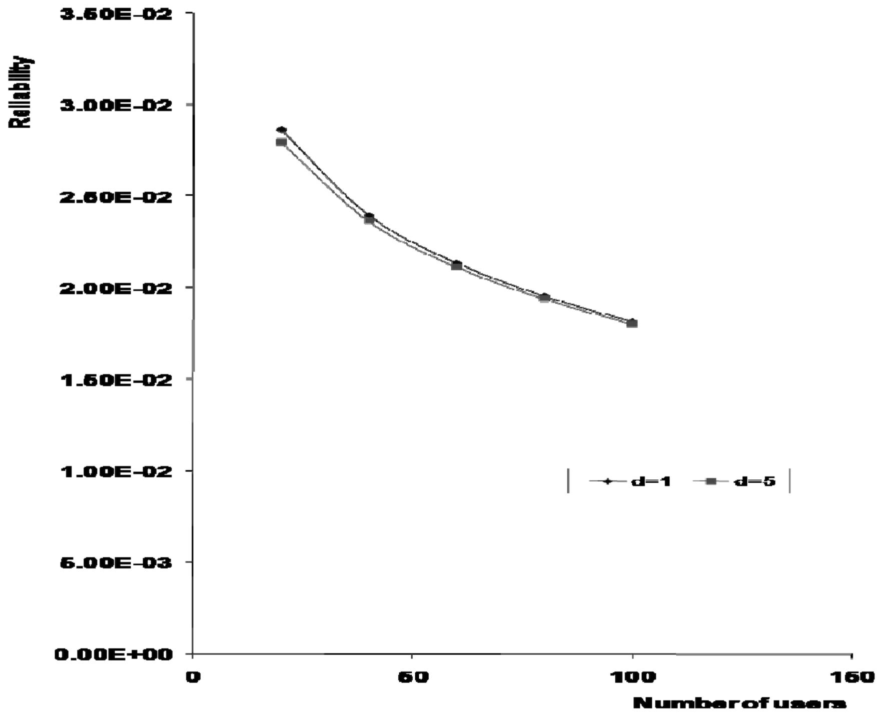

Figure 4. Graph of reliability vs. distance (for urban environments)

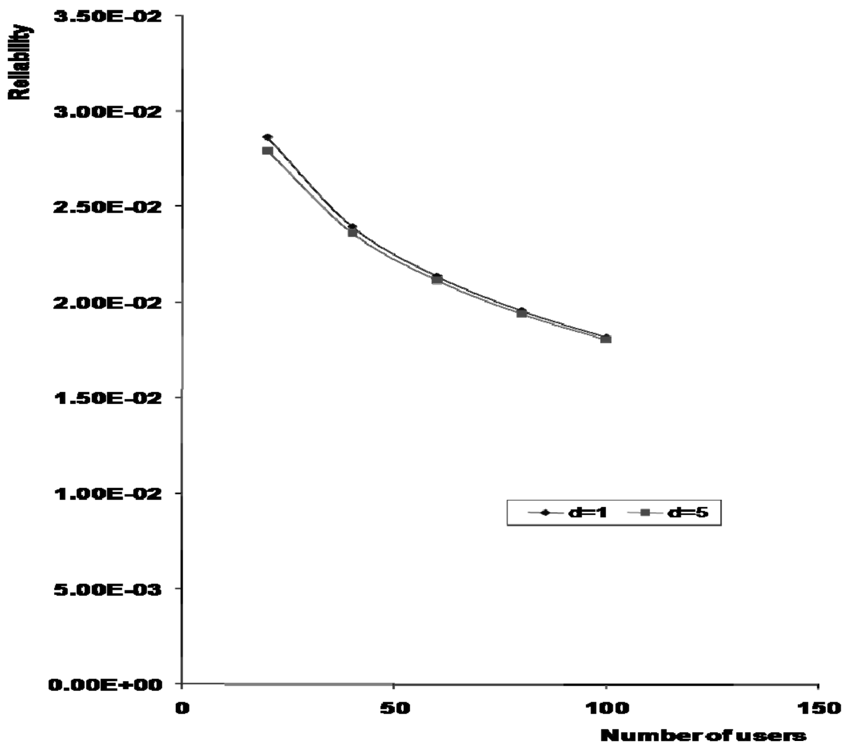

Figure 5. Graph of reliability vs. distance (for suburban environments)

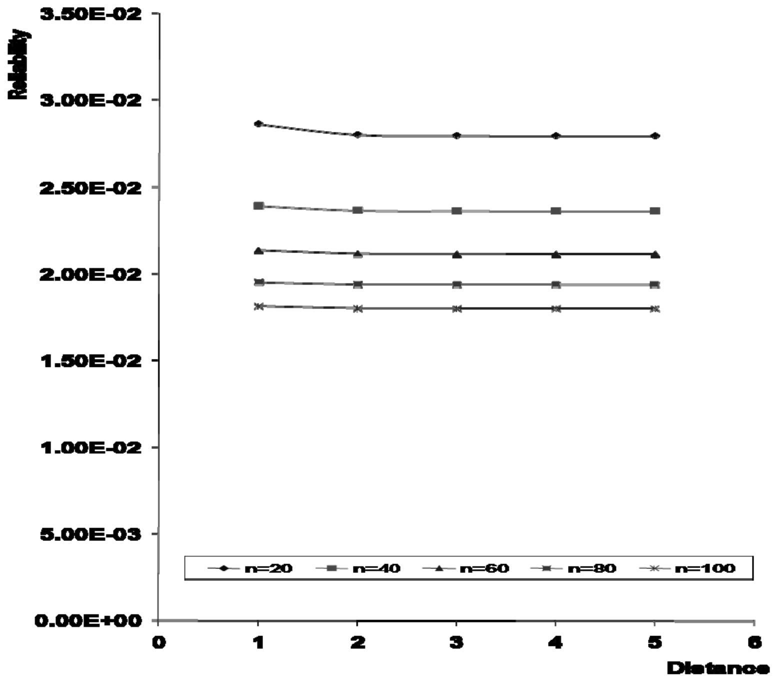

Figure 6. Graph of reliability vs. distance (for urban environments)

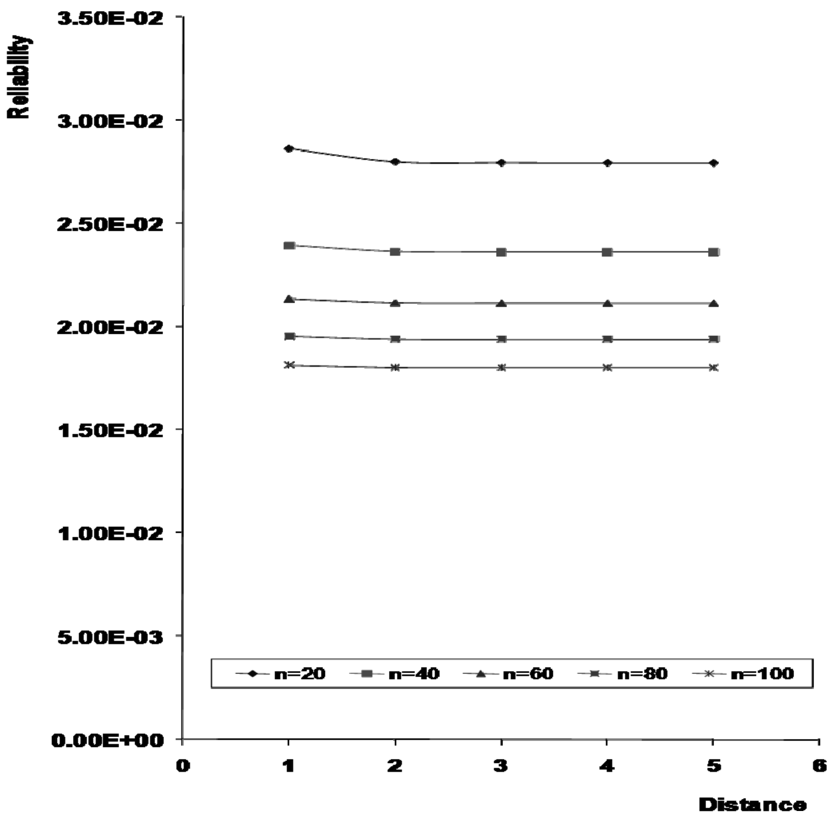

Figure 7. Graph of reliability vs. distance (for suburban environments)

APPENDIX 1: Percentage signal outage data recorded from the Zain communications Ltd.

Cell index	% Outage	Cell index	% Outage	Cell index	% Outage	Cell index	% Outage
Cell 0	1.900560	Cell 37	0.682263	Cell 74	0.169955	Cell 111	0.060257
Cell 1	2.225231	Cell 38	0.249375	Cell 75	1.108644	Cell 112	2.152410
Cell 2	2.678569	Cell 39	2.987739	Cell 76	0.018592	Cell 113	0.265182
Cell 3	0.647266	Cell 40	2.001488	Cell 77	1.436218	Cell 114	0.073982
Cell 4	3.759278	Cell 41	3.160384	Cell 78	0.297343	Cell 115	0.237083
Cell 5	0.752096	Cell 42	0.699443	Cell 79	0.064561	Cell 116	0.368860
Cell 6	0.682328	Cell 43	0.681711	Cell 80	0.009287	Cell 117	3.339874
Cell 7	0.365620	Cell 44	0.319251	Cell 81	0.759156	Cell 118	0.276557
Cell 8	5.154007	Cell 45	0.169159	Cell 82	0.184011	Cell 119	0.685075
Cell 9	0.273185	Cell 46	0.369225	Cell 83	3.641077	Cell 120	3.660492
Cell 10	1.839782	Cell 47	0.187309	Cell 84	0.749730	Cell 121	0.596638
Cell 11	1.453072	Cell 48	7.066487	Cell 85	0.102846	Cell 122	0.292760
Cell 12	1.073690	Cell 49	0.039532	Cell 86	0.181713	Cell 123	0.380567
Cell 13	1.974146	Cell 50	0.247301	Cell 87	1.569628	Cell 124	0.298694
Cell 14	0.352293	Cell 51	0.282981	Cell 88	1.458179	Cell 125	0.444400
Cell 15	0.303887	Cell 52	2.206515	Cell 89	0.153801	Cell 126	0.834968
Cell 16	1.549574	Cell 53	1.210779	Cell 90	0.010632	Cell 127	0.706207
Cell 17	0.815010	Cell 54	0.601800	Cell 91	1.272525	Cell 128	0.041909
Cell 18	0.272726	Cell 55	2.531127	Cell 92	0.690065	Cell 129	0.976166
Cell 19	0.000000	Cell 56	2.408651	Cell 93	1.306052	Cell 130	1.693507
Cell 20	2.255864	Cell 57	0.844827	Cell 94	0.399715	Cell 131	0.879778
Cell 21	0.809219	Cell 58	0.219527	Cell 95	0.999974	Cell 132	2.158879
Cell 22	0.244489	Cell 59	2.610258	Cell 96	4.145708	Cell 133	4.074515
Cell 23	0.215645	Cell 60	1.809252	Cell 97	0.238867	Cell 134	3.657940
Cell 24	0.419950	Cell 61	3.738092	Cell 98	2.274855	Cell 135	2.579154
Cell 25	0.467174	Cell 62	0.814857	Cell 99	0.028641	Cell 136	1.829099
Cell 26	0.589142	Cell 63	0.757454	Cell 100	3.616483	Cell 137	0.324157
Cell 27	4.035529	Cell 64	0.021668	Cell 101	0.184788	Cell 138	0.883919
Cell 28	0.961508	Cell 65	0.103086	Cell 102	0.321373	Cell 139	0.020069
Cell 29	0.379562	Cell 66	0.637107	Cell 103	1.667664	Cell 140	0.110643
Cell 30	0.627420	Cell 67	0.306750	Cell 104	1.632758	Cell 141	1.035283
Cell 31	0.454992	Cell 68	4.422125	Cell 105	4.700452	Cell 142	0.134190
Cell 32	0.261032	Cell 69	0.004034	Cell 106	3.435652	Cell 143	2.349385
Cell 33	1.336839	Cell 70	0.144336	Cell 107	1.809706	Cell 144	1.513420
Cell 34	0.081864	Cell 71	0.044674	Cell 108	5.458912	Cell 145	0.271109
Cell 35	1.128759	Cell 72	0.102713	Cell 109	3.570565	Cell 146	0.000000
Cell 36	1.565202	Cell 73	0.066474	Cell 110	0.063031	Cell 147	0.331064
						AVERAGE	**1.202214**