This article can be cited as M. E. Ekpenyong, U. G. Inyang, D. E. Asuquo, U. O. Ekong, P. U. Usip, U. A. Umoh, A. M. Jackson, J. Isobona and A. Tom, Intelligent Test Bed Tuning for Improved Wireless Local Area Network Service Quality in Academic Environments, International Journal of Artificial Intelligence, vol. 16, no. 1, pp. 60-87, 2018.


# Intelligent Test Bed Tuning for Improved Wireless Local Area Network Service Quality in Academic Environments

**Moses E. Ekpenyong[1], Udoinyang G. Inyang[1], Daniel E. Asuquo[1], Uyinomen O. Ekong[1], Patience U. Usip[1], Uduak A. Umoh[1], Aniekpeno M. Jackson[1], Joseph Isobona[2]** and **Akan Tom[3]**

[1]Department of Computer Science, University of Uyo, Nigeria,
E-mail: mosesekpenyong@{uniuyo.edu.ng, gmail.com}; udoinyanginyang@uniuyo.edu.ng; danielasuquo@uniuyo.edu.ng; uyinomenekong@uniuyo.edu.ng; patiencebassey@uniuyo.edu.ng; uduakumoh@uniuyo.edu.ng; aniekpenomfon@gmail.com

[2]Department of Electrical and Electronics Engineering, University of KwaZulu Natal, South Africa
E-mail: josabone@yahoo.com

[3]Department of Geography and Natural Resources Management, University of Uyo, Nigeria
E-mail: centom2012@gmail.com

**ABSTRACT**

*Developing real time wireless local area network (WLAN) solutions require in-depth understanding of the WLAN system, performance evaluation in realistic setting, and visualisation of the service quality (SQ) in a very efficient manner. This paper presents the design and construction of WLAN test bed infrastructure to support intelligent tuning and visualisation of the SQ. To achieve this, received signal strength indication (RSSI) information and SQ field trials were performed on an academic environment, and, the requirements as well as challenges for developing suitable test bed infrastructure, appraised. An intelligent system model was then developed using the Interval Type-2 Fuzzy Logic (IT2FL), to simulate the SQ using RSSI information captured across three major campuses of the study environment. The IT2FL enabled the efficient modelling of uncertainties inherent in the field data for accurate estimation of the SQ. The processed test bed infrastructure provided direct visualisation as an initial assessment, before deploying personnel for corrective measures. Such measures are indeed necessary to assist in solving the poor quality of experience in academic environments. To ensure intelligent test bed tuning for effective coverage optimisation of the study environments, a particle swarm optimisation (PSO)- and genetic algorithm (GA)- adaptive neuro-fuzzy inference system (ANFIS) (or evolutionary ANFIS: PSO-ANFIS and GA-ANFIS) were independently trained. Results obtained showed that both systems performed well – as their root mean square error (RMSE) and mean absolute error (MAE) for both test and train data were very close, but PSO-ANFIS yielded the lowest RMSE and MAE for test data – indicating a more quality and accurate algorithm.*

**Keywords:** Intelligent system; nature-inspired algorithm, quality of experience, service quality visualisation, test bed tuning; wireless LAN.

**Mathematics Subject Classification:** 62J12, 62G99

**Computing Classification System:** I.2; I.5.1.1; I.6.

## 1. INTRODUCTION

Wireless technology has increasingly enabled accurate remote localisation of users and objects within a predefined time frame. In academic environments, Wireless Local Area Networks (WLANs) add flexibility and independence irrespective of time and location; and can facilitate new approaches to teaching, research and community service. Advances in remote sensing, computing and networking have necessitated the quest for real time monitoring and deployment of ‘mission critical’ services and applications. These services and applications such as excellent data communication system are essential for robust communication and extended access to resources beyond borders. Hence, preventing service disruptions and poor quality of service are crucial to avert failure in academic and managerial operations. This paper carries out a detailed survey of a deployed WLAN with the goal of improving it through the use of efficient modelling procedures for uncertainties minimisation and service quality representation. An objective assessment of the service quality (SQ) including: design, infrastructure, communication, service characteristics and interference issues, were considered.

The novelty of this research is to cooperatively improve the accuracy of positioning through intelligent simulation of physical history of nodes position. Since location sensing technologies calibration is very expensive to deploy, a different approach is conceived in this paper to implement intelligent modelling and analysis techniques, with accurate representation and optimisation tools for self-configurable technologies that minimises unnecessary human intervention and calibration. A key obstacle to dwindling research progress in location aware computing is the lack of adequate large scale experimental infrastructure. The designed test bed infrastructure will therefore leverage physical infrastructure, and assist the creation and dissemination of benchmarks and testing methodologies for gradual evolution of an invaluable location aware system. The test beds may also serve as a standard for future large scale studies and speed up the commercialisation of our research results.

The academic institution under study is the University of Uyo – an academic environment located in the southeast coastal region of Nigeria, West Africa, where the terrain and topology structures, as well as and weather conditions are inconsistent and unpredictable. Figure 1 summarizes the major activities of this research, and will be accomplished in two phases.

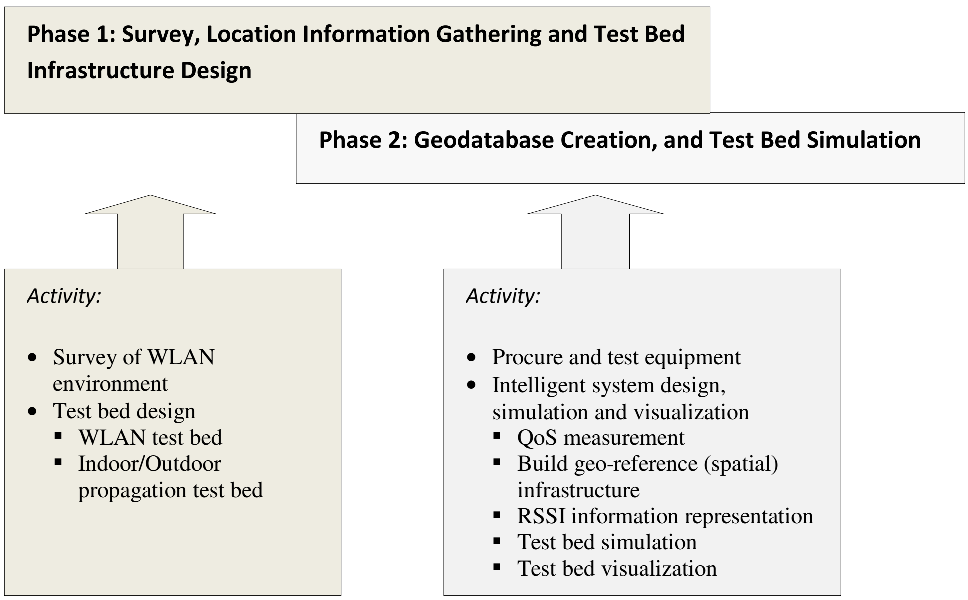



**Figure 1:** WLAN research workflow

The outcome of this research will impact the academic community, as well as bootstrap new services that will,

- motivate cooperative/interdisciplinary research with related disciplines such as Computer Science, Physics, Geology, Engineering, Geography and Natural Resources Management, etc;
- ensure shareability of knowledge and data resources across disciplines, and in real time;
- promote geo-processing and geodatabase access necessary for research and development purposes;
- support the publishing of geo-processing services and service compositions with semantic annotation and discovery;
- provide a persistent system that guarantees stable access to and maintenance of WLAN resources;
- allow iterative development for comparable (scientific) testing and resolution of network faults;
- enable seamless extensibility of wireless services.

The process of modifying an already deployed WLAN to support additional services (beyond a data-only deployment) is far from just adding additional access points (APs) or resources. It also requires additional site survey and possible relocation of existing APs. Kul, Ozyer and Tavli (2014) examined wireless localisation techniques for indoor positioning systems with explanation of the common approaches. They also offered useful performance metrics for such systems as well as experiments with real life data. Hence, considering the present demand for ubiquitous wireless coverage across academic environments and provision of indoor and outdoor coverage with expanded capacity, there is an urgent and unmet need to integrate suitable indoor and outdoor path loss models into test bed platforms.

## 1.1 The Propagation Environment

The University of Uyo has a total land mass of 1,535.055 hectares, and consists of five separate campuses namely, town campus, town campus annex, main campus, University of Uyo Teaching Hospital (UUTH), and Basic Studies Campus. The University deploys an inter-campus WLAN infrastructure that provides communication over a short geographical range using radio signals. The radio signals are propagated using network bridges – to create aggregate networks from either two or more communication networks and/or segments. The propagated signals are then regenerated along the next leg of the transmission medium to overcome the attenuation (loss of signal strength) caused by free-space electromagnetic-field divergence or cable loss, and to extend signals over a distance. The existing infrastructure consists of two layers: the Fibre Optic (FO) layer and the Wireless Network (WN) layer. The FO layer implements the Local Area Network (LAN) infrastructure and connects the various buildings, while the WN layer distributes signals to the buildings. Wireless Access Points (WAPs) are connected to the edge of the Fibres to enable clients/users communicate effectively with the Wireless Network Adapters (WNAs).

Currently, the three major campuses of the University under study (town campus: covering 56.956 hectares, town campus annex: covering 34.919 hectares, and main campus: covering 1,443.180 hectares) have been fully bridged in an intranet using the FO technology, and are considered in this paper. Figure 2 shows a schematic diagram of the inter-campus wireless network, while Figures 3, 4 and 5, show the network distribution in the three major campuses. In each figure, the network operating centre (NOC) is located at the centre while buildings are connected via fibre optic cables.

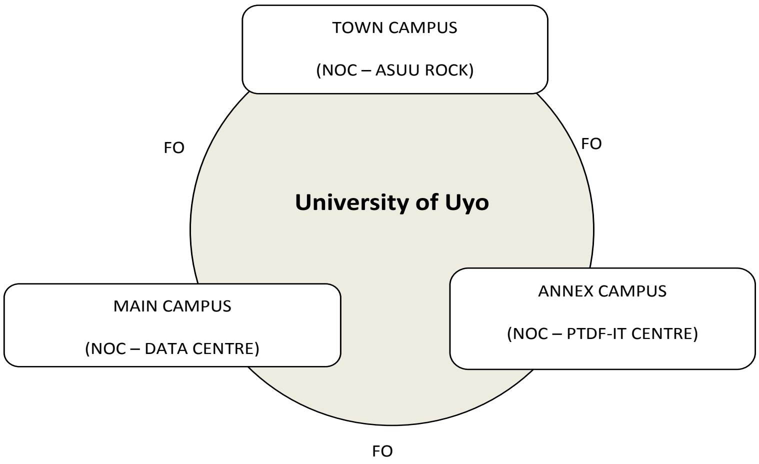



**Figure 2:** Structure of inter-campus WLAN network

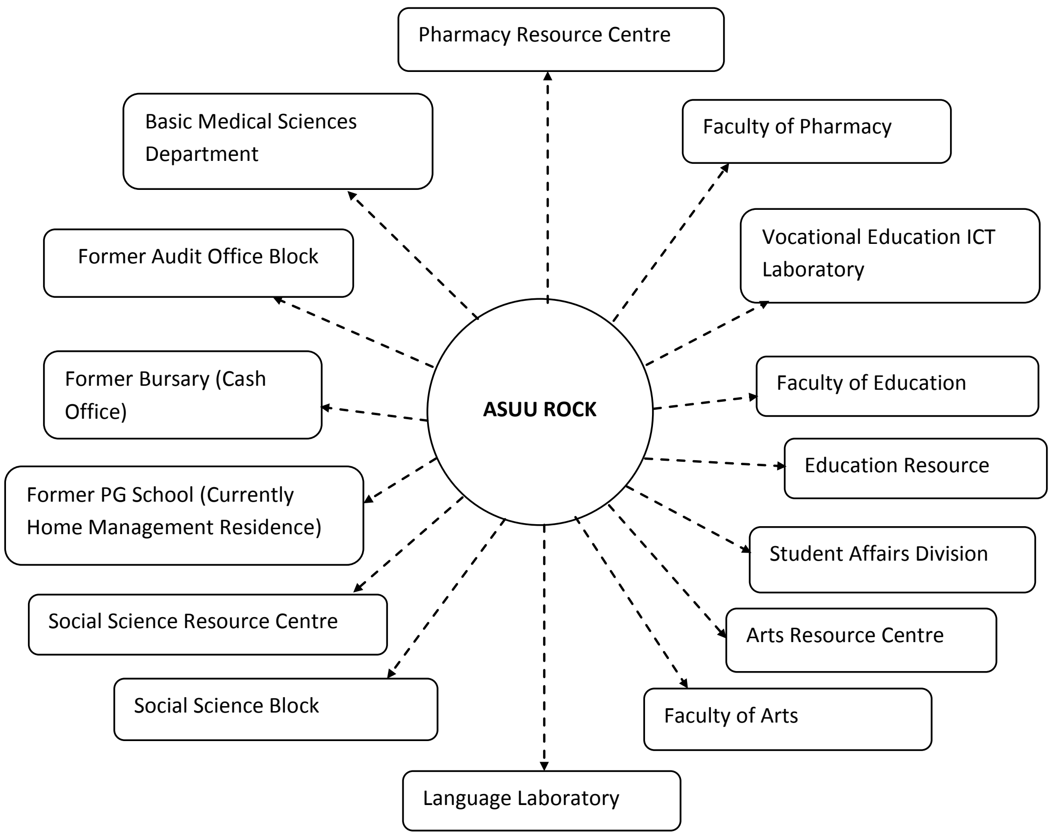



**Figure 3:** WLAN distribution (town campus)

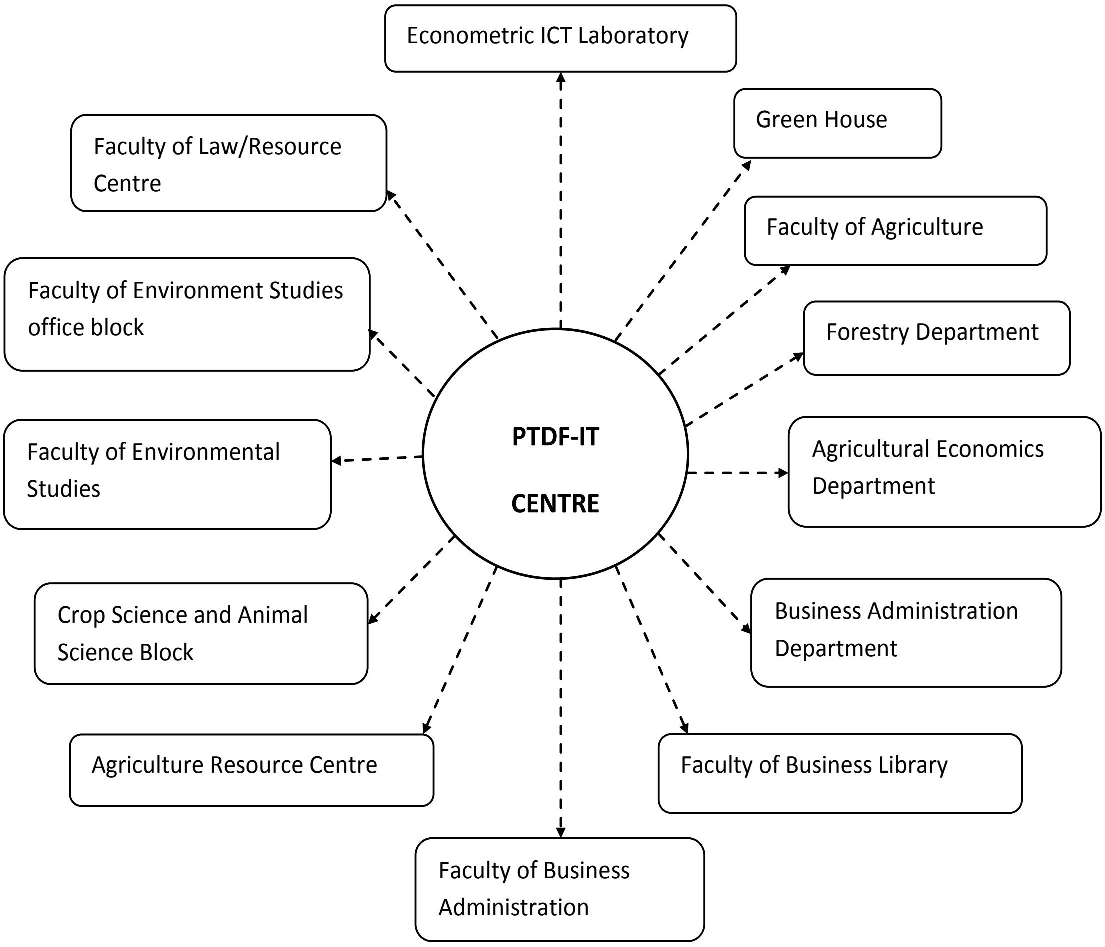



**Figure 4:** WLAN distribution (town annex campus)

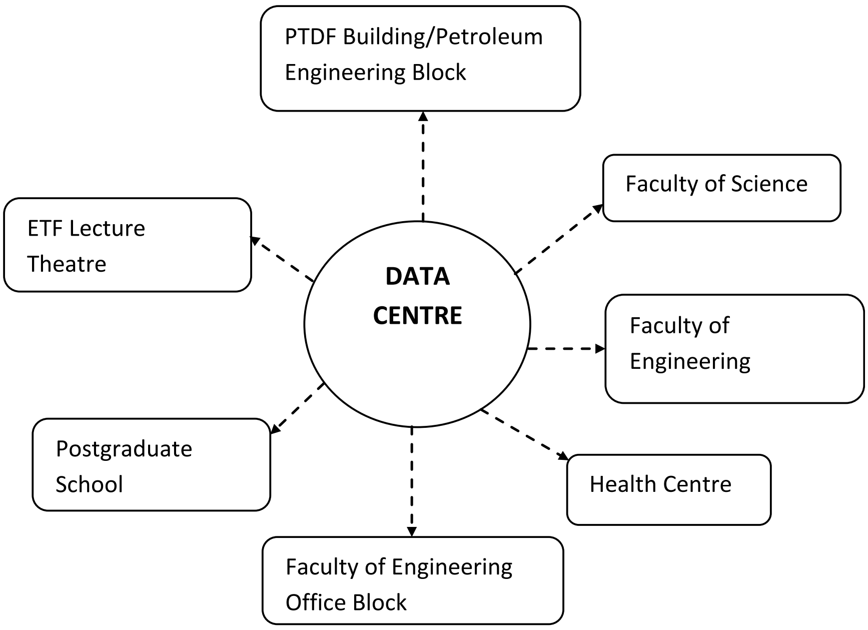



**Figure 5:** WLAN distribution (main campus)

## 2. RELATED WORKS

In Ozera, Inaba, Sakamoto and Barolli (2017), a triage test bed using Fuzzy-based Admission Control System (FACS) was implemented. Experimental results showed that the number of connected clients increased during the avoidance phase, but did not change during the monitoring phase. A comprehensive test bed implementing the fuzzy logic-based algorithm to guarantee seamless connection was simulated in Prithviraj, Krishnamoorthy and Vinothini (2016). Results obtained improved latency rate and packet loss over handoffs compared to existing approaches, which in turn improved the transmission quality. Abbas and Saade (2015) proposed a fuzzy logic-based approach for an automated network selection based on real-network implementations and measurements. Their network selection model was based on fuzzy inference rules considering features that affected the selection decision and were available on users' device. The model input features were linguistic variables representing the signal strength reflecting the channel quality of WiFi/3G links and network load. The performance of the proposed fuzzy logic approach for real-time network selection was evaluated and found to be superior to the separate use of WiFi and 3G links.

The type-2 fuzzy logic – an improvement on the traditional (type-1) fuzzy logic, has gained increasing popularity in a wide range of applications due to its capacity to handle high degrees of uncertainty (Melin and Castillo, 2013). Hence, it is now being used in the areas of classification, clustering and pattern recognition – to improve on the results of type-1 fuzzy logic. Another emerging dimension are neuro fuzzy systems (NFSs), which have found applications in various domains including the medical, science, social science, engineering, as well as the humanities. Kar, Dasb and Ghoshb (2014) surveyed the development of neuro fuzzy systems (NFSs) using classification and explored various NRS methodologies developed over the last five years. Their review indicated that (i) NFS methodologies are tending toward expertise orientation, (ii) various social science domains could be implemented using NRF methodologies, and, (iii) NFS methodologies are most likely to become the de factor methodologies given their adaptive and learning capabilities.

In the field of wireless communication, Cavdar (2016) proposed a particle swarm optimisation (PSO) tuned adaptive neuro fuzzy inference System (PSO-ANFIS) based channel equalizer, which is capable of identifying, estimating and equalizing wireless communication channels. The proposed equalizer used training data and fuzzyC-means (FCM) clustering to model a wireless communication channel unknown channel dynamics, and was simulated on a mobile communication model with inter-symbol interference (ISI), co-channel interference (CCI), and the additive white Gaussian noise (AWGN). The training method and FCM were found to provide best regression of system modelling that fit the wireless channel. The performance of the equalizer was then evaluated and compared to other nonlinear equalization techniques using the bit error rate and signal-to-noise ratio (BER–SNR) as performance metrics. Simulation results showed that the performance of the PSO-ANFIS equalizer with FCM clustering yielded the best performance.

Hybridised solutions (combining two or more algorithms) have also been found to improve the performance of applications and compensate for the weaknesses of non-robust algorithms. Kumar and Kumar (2017) for instance, proposed a hybrid algorithm combining artificial bee colony (ABC) and fuzzy c-means (FCM) algorithms to assist the FCM clustering escape from the local optima and provide better experimental results on well known data sets. Precup, Sabau and Petriu (2015) proposed a synergy of fuzzy logic and nature-inspired optimisation to optimally tune the input membership functions using Takagi-Sugeno-Kang (TSK) fuzzy models, for Anti-lock Braking Systems (ABSs). Two nature-inspired algorithms: Simulated Annealing (SA) and Particle Swarm Optimisation (PSO) were implemented to solve the optimisation problem and to obtain optimal TSK fuzzy models. Real-time experimental results showed that the optimised TSK fuzzy models were simple and consistent with both training data and validation data, and the optimised models outperformed the traditional TSK fuzzy models.

From the foregoing, recent research works have settled on hybridised solutions with the use of nature-inspired algorithms for solving optimisation problems. This paper therefore introduces intelligent test bed tuning using human cognitive approach and visualisation of real-life WLAN system for a dynamic domain-specific system – academic environments. The research represents a pioneering work in this direction – as no literature on the application of nature-inspired optimisation techniques to academic domain exists, to the best of our knowledge. We employ two independent nature-inspired algorithms: PSO and genetic algorithm (GA), to tune the adaptive neuro-fuzzy inference system (ANFIS) – for effective coverage monitoring of the study areas.

## 3. WLAN TEST BED DESIGN

Advances in data acquisition technologies and access are broadening the application of geospatial data and location-based services, which require global positioning system (GPS) localisation technologies, wireless communication, as well as mobile computing. First, we create a test bed (the WLAN setup environment required for experimenting and testing the validity of this research). The test bed supports the visualisation interface of the service quality, and the design methodology of the test bed is discussed in the following steps:

**Reconnaissance survey**

A reconnaissance survey of the three major campuses was carried out to examine the generic characteristics of the area and establish the start and end points of the WN and the FO installations. While reconnoitering on the ground, reference pegs were left to facilitate further survey operations. A catalogue of the physical network infrastructure was also developed to facilitate the design of the simulation *test bed*. The distance from the NOC to the various APs – for outdoor transmission, and distance from the APs to the buildings – for indoor transmission were also necessary to facilitate an investigation into the poor signal strength quality and wide *path loss* margins currently experienced in the existing system. The distance measurements were accomplished using ground reconnaissance survey – a general examination of the ground, by walking along the probable routes and collecting all available information necessary for evaluating same. The survey was carried out with the aid of field investigators including the ICT personnel of the University of Uyo.

**Database model**

The geodatabase of ArcGIS represents one of the most popular database models worldwide. It couples geometry with semantic attributes and is suitable for multiple resources management. In comparison with previous data models, the actual generation of geodatabase by ArcGIS proves more intelligent, as each element is no longer just a geometric field, but also a record of the object with attributes and behaviours. Hence, the geodatabase is essentially a relational database based on an object-oriented model (Wu, Xu, Wang and Xu, 2011). This paper integrates the geodatabase model to enable proper planning and management of the WLAN resources. The purpose of this integration is to bootstrap important management plans and provide solutions to users/clients in real time. The benefits envisaged include, but are not limited to,

- Risk management plan for identifying major risks, including constraints and assumptions, as well as planned response for each risk;
- Scheduled management plan using the developed WLAN test bed;
- Resource management plan through direct database visualisation;
- Cost management plan;
- Quality assurance/quality control plan;
- Communication plan using the developed indoor/outdoor path-loss/distance test bed.

**Location capture and feature extraction**

*Location capture using Global Positioning System (GPS):* GPS is obviously the most widely used (outdoor) location sensing technology. Capturing the various FO milestone and manhole locations was done using a GPS device. At every location, the GPS device was held over the FO milestones and manholes to obtain the exact coordinates. The *marked* button was then pressed and scrolled down to accuracy, allowing the accuracy to drop to the minimum. The coordinates were finally saved by pressing the *enter* button, and the resulting waypoint values were carefully copied for every manhole and milestone in each case.

*Feature Extraction:* Building and road layers within the three campuses were extracted from *satellite images or base maps* of the study area (see Figures 6 (a) and 6 (b)) through the process of digitisation using ArcGIS 10.3 software. The extracted features and the reconnaissance survey data allowed for the determination of any deviations required in the basic geometric standards to be adopted for the implementation of robust WLAN communication.

**Mapping of the extracted features**

Next, the GPS data (i.e., manhole and milestone data) were superimposed on the extracted surface after image digitisation to obtain a complete and accurate test bed for the three campuses (Figures 7 (a) and 7 (b)). The *Point feature* in ArcMap 10.3 was used to create shape-files for The Science

Technology and Education Post Basic: STEP-B/World Bank Project and Zinox and MTN Projects manholes and milestones, while the *Line feature* was used to create the FO line/path (route) for these Projects, and digitized accordingly to connect the manholes.

To design the distance test bed, related information about the buildings (type, size, purpose, and distance from building with installed WAPs to the NOC) were collected. The code guiding the description of the building type and purpose is presented in Table 1. The resultant test bed integrating the distance measurements for the town campus, town campus annex and main campus, are shown in Figs. 8 (a) and 8 (b), respectively. A total of sixty-eight (68) individual wireless network APs were installed in the three campuses and these APs were digitally mapped to their respective locations into a geodatabase. Materials used for constructing 95% of the buildings within the three major campuses are mostly concrete blocks with 5 inches thickness for bungalows, and 9 inches for storey, others use plywood-type materials. To achieve precise measurements, a physical visit to all APs was done and a GPS device used to determine the relative location of the AP antenna with respect to the elements of the buildings present on the test bed. Operation parameters of the environment under study are shown in Table 2.

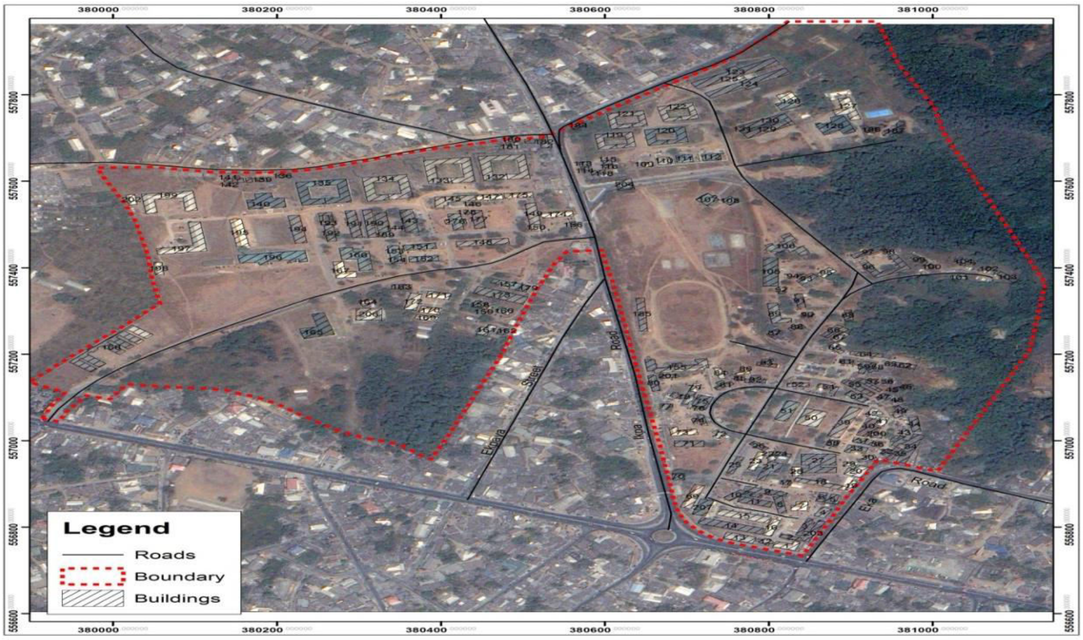



**Figure 6. (a):** Satellite image (base map) of the study area – town campus and town campus annex

**Figure 6. (b):** Satellite image (base map) of the study area – main campus

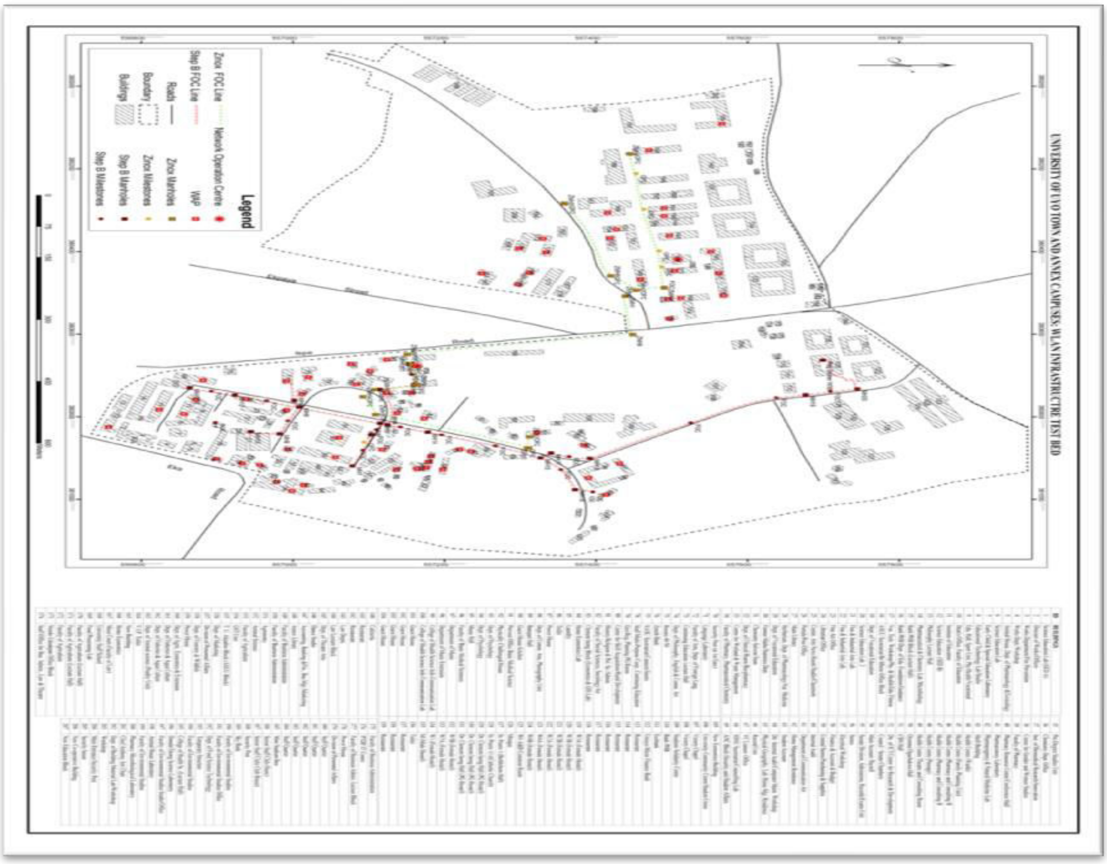


**Figure 7. (a):** Extracted test bed for the area under study – town campus and town campus annex

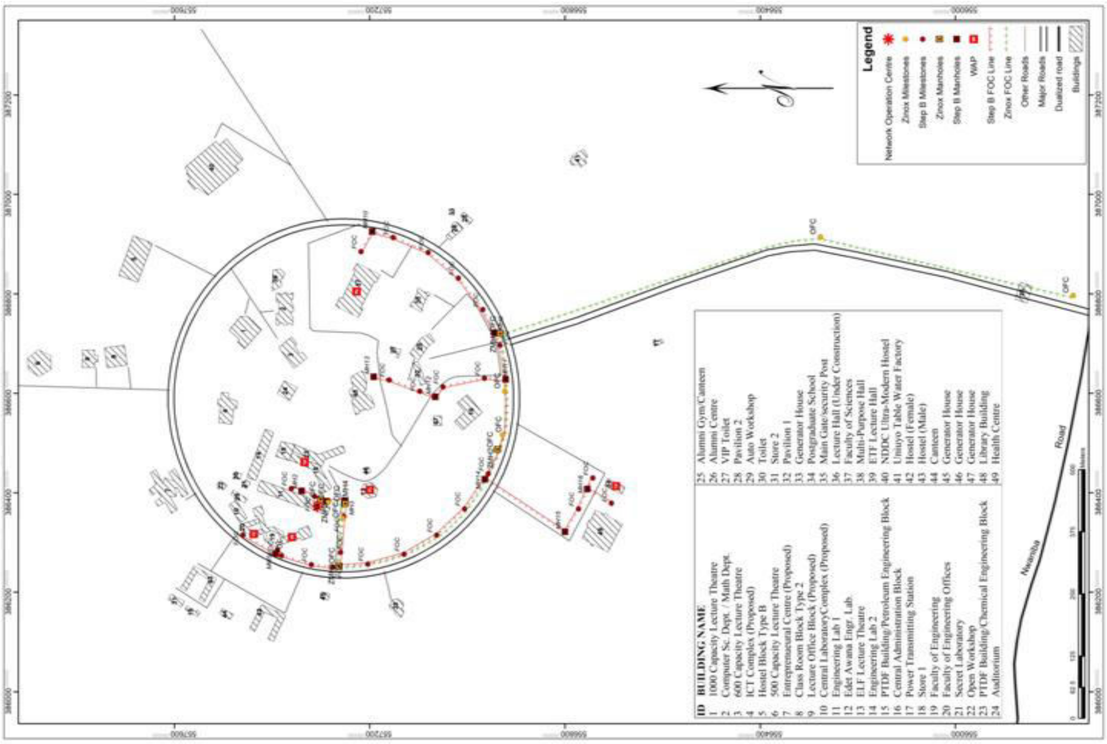



**Figure 7. (b):** Extracted test bed for the area under study – main campus

*Table 1:* Coding system for building type and purpose

| Type | Code | Purpose | Code |
|---|---|---|---|
| Bungalow | 1 | Teaching/lecture/examination | 1 |
| 1-storey | 2 | Study/reference | 2 |
| 2-Storey | 3 | Practical demonstration | 3 |
| 3-storey | 4 | Workshop/office | 4 |
| 4-storey | 5 | Social/recreation | 5 |
| 5-Storey | 6 | Commercial | 6 |
| 6-Storey | 7 | Store | 7 |
| | | Multipurpose | 8 |

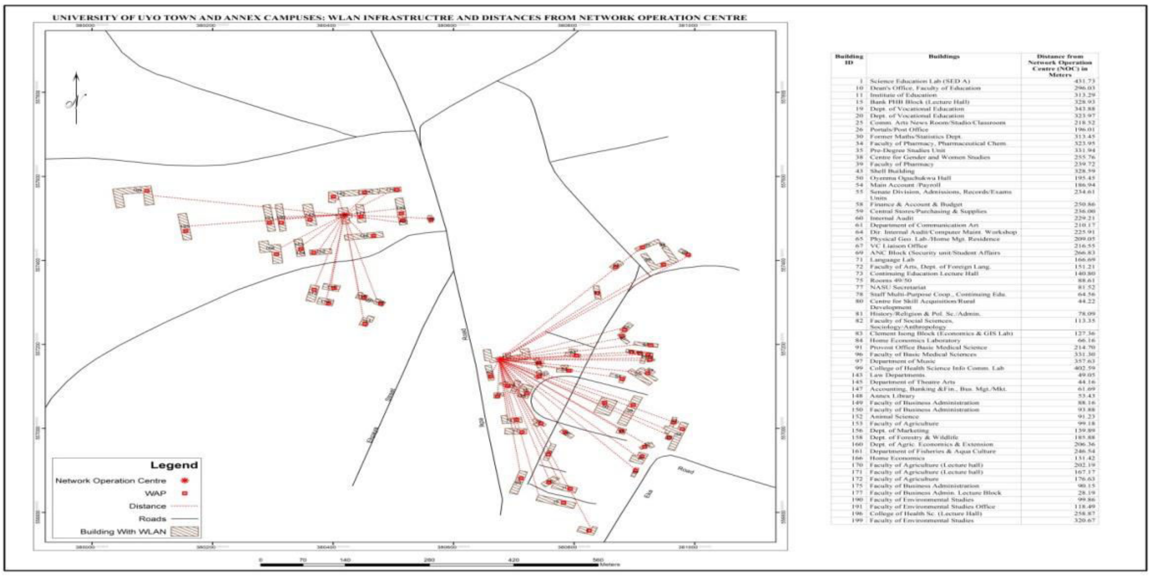



**Fig. 8 (a):** Extracted WLAN distance test bed for study area – town campus and town campus annex

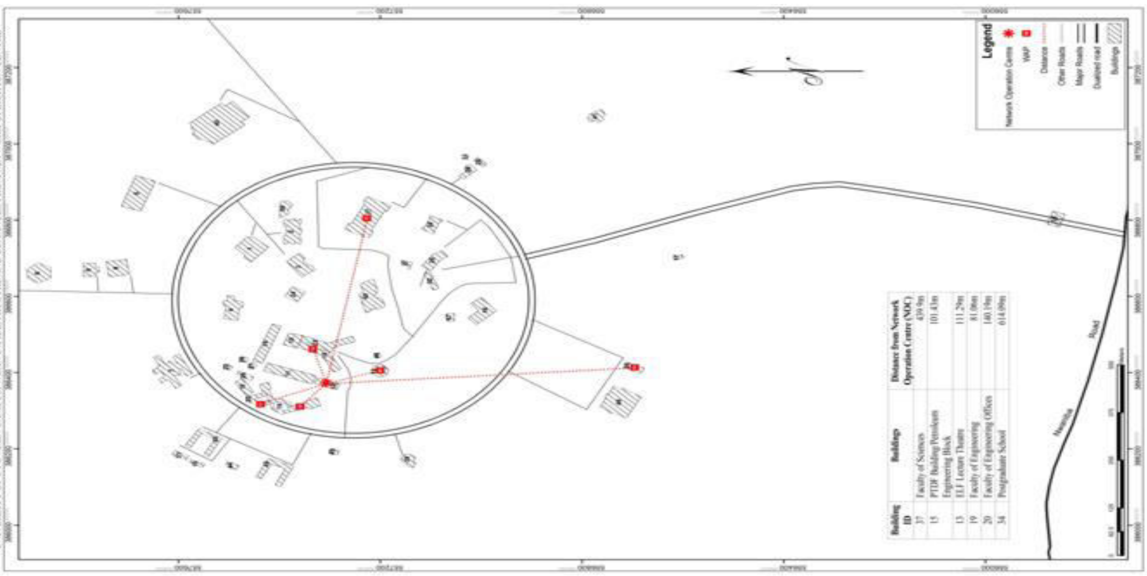


**Figure 8 (b):** Extracted WLAN distance test bed for study area – main campus

*Table 2:* Operation parameters obtained from the existing WLAN system

| Parameter | Value |
|---|---|
| Number of buildings/offices with WAPs | 68 |
| Number of base stations (BSs) | 3 |
| BS height | Town campus – 45.72 m, town campus annex – 36.58 m, main campus – 36.58 m |
| Distance between BS and building | See Table 1 |
| BS output power | 26 – 28 dBm |
| Bandwidth | 90 MHz |
| BS antenna | Isotropic (outdoor) |
| Carrier frequency | 5 GHz (scaled to 2.4 GHz on distribution) |
| Average packet size | 5 MB |

## 4. INTELLIGENT SYSTEM DESIGN

### 4.1. RSSI data capture

To capture the received signal strength indication (RSSI) information of the service area, a scan of the study environment (where APs are located) was performed using the Acrylic WiFi Professional – a WiFi analyser software that identifies access points and WiFi channels – and is useful for analysing and resolving incidences on 802.11a/b/g/n/ac wireless networks in real time. The functionalities of Acrylic include:

(i) efficient visualisation of wireless network performance and connected users;
(ii) access point data transmission speeds identification and channels optimisation;
(iii) access WiFi network detailed information collation and visualisation – including hidden wireless networks.

Scanning of the environment (at each access point) was delayed for about two to three minutes to allow for full device(s) detection. The detected infrastructure and measurements were finally exported to a comma separated value (CSV) file and compiled for the service areas under study. A list of the RSSI and site information is summarised in Table 3, while sample RSSI and site-specific measurements captured for the purpose of this study are presented in Appendix (A) and (B), respectively. In the next subsection, fuzzifiable RSSI features were identified and abstracted to serve as inputs to the signal-prints representation phase.

*Table 3:* RSSI and site information captured form the service area

| RSSI information – captured using Acrylic Professional software | | | |
|---|---|---|---|
| S/No. | RSSI parameter | Meaning | Data type |
| 1. | SSID | Service Set Identifier | String |
| 2. | MAC | Media Access Control address | String |
| 3. | RSSI | Received Signal Strength Indicator | Number |
| 4. | SNR | Signal to Noise Ratio | Number |
| 5. | NoChan | Signal communication channel | Number |
| 6. | ChanWidth | Channel bandwidth | Number |
| 7. | 802.11 | Infrastructure type | String |
| 8. | MBR | Maximum Baud Rate | Number |
| 9. | WEP | Wired Equivalent Privacy | String |
| 10. | Vendor | Infrastructure vendor | String |
| 11. | Mgt | Number of traffic managed | Number |
| 12. | VenType | Vendor type | String |
| 13. | Latitude | Geographic coordinate of study location (center of a building), north-south on the earth's surface | Number |
| 14. | Longitude | Angular distance of study location (center of a building), east-west of the equator | Number |
| 15. | Time | Time of capture | String |
| Site information – captured during site survey | | | |
| | Site parameter | Meaning | |
| 16. | BID | Building Identifier | String |
| 17. | BLoc | Building location indoor/outdoor? | String |
| 18. | BType | Building type | Number |
| 19. | BSize | Building size | Number |
| 20. | BPurp | Purpose for which building is used | Number |
| 21. | BHeight | Building height | Number |
| 22. | DFNOC | Distance of building from NOC | Number |
| 23. | Floor | Number of floors | Number |
| 24. | NOR | Number of Rooms | Number |
| 25. | Pathloss | Signal propagation pathloss | Number |

### 4.2. Signal-print representation and SQ Modelling using Interval Type-2 Fuzzy Logic

To eliminate the drawbacks of any individual variable, important parameters were abstracted and those with fuzzy membership function (FMF), characterized. The RSSI data formed our major parameters of interest, and were passed to the Fuzzy-type-2 Logic system (F2FLS) in order to provide precise representation of the SQ. An interval Type-2 fuzzy set (IT2FS), $\tilde{A}$ is characterized by a membership interval in the universe of discourse (UoD), $X$ , for continuous and discrete domains as (Mendel and Liu, 2007; Mendel and John, 2002):

$$\tilde{A} = \{ | (x,u), \mu_{\tilde{A}}(x,u) \,|\, \forall x \in X, \forall u \in J_x \subseteq [0,1] \} \text{ and } \tilde{A} = \Sigma_{i=1}^{p} \{ \Sigma_{u \in J_x} [1/u] \} / x_i \quad (1)$$

Where $x$ , is the *primary variable*, in the domain $X$ , and, $u \in U$ , is the *secondary variable*, and has domain $J_x \forall x \in X : 0 \le \mu_{\tilde{A}}(x,u) \le 1$ ; $J_x$ , is called the primary membership of $x$ ; and $\mu_{\tilde{A}}(x,u)$ , represents the secondary membership set (SMS). Description of a Type-2 membership grade, $\tilde{A}$, is a pair of the primary membership function (PMF) and SMS, which falls in the range [0,1]. The SMS gives the degree of membership of the PMS (Melin and Castillo, 2013). Uncertainty about $\tilde{A}$ is conveyed by the union of all the primary memberships, known as the *footprint of uncertainty* (FOU) of *A,* including all the embedded primary membership functions $J_x$ of $\tilde{A}$, and is given by,

$$U_{\tilde{A}}(x,u)=1, FOU(\tilde{A})=U_{\forall x\in X} J_x=\{(x,u): u\in J_x \subseteq [0,1]\} \quad (2)$$

where $FOU(\tilde{A})$, is bounded by *upper membership function* (UMF), $\bar{\mu}_{\tilde{A}}(x)$, and *lower membership function* (LMF), $\underline{\mu}_{\tilde{A}}(x), \forall x \in X$, respectively. thus,

$$\bar{\mu}_{\tilde{A}}(x) \equiv \overline{FOU(\tilde{A})}; \forall x \in X \quad (3)$$

$$\underline{\mu}_{\tilde{A}}(x) \equiv \underline{FOU(\tilde{A})}; \forall x \in X \quad (4)$$

$$J_x=\{(x,u): u\in[\underline{\mu}_{\tilde{A}}(x), \bar{\mu}_{\tilde{A}}(x)]\} \quad (5)$$

where $J_x$, represents an interval set. Equation (2) can now be expressed as,

$$FOU(\tilde{A})=U_{\forall x\in X}\{\underline{\mu}_{\tilde{A}}(x), \bar{\mu}_{\tilde{A}}(x)\} \quad (6)$$

The proposed IT2FL-WLAN-SQ framework is shown in Figure 9. The framework is composed of five major components namely, *fuzzifier*, *knowledge base*, *inference engine, type-reducer and defuzzifier*.

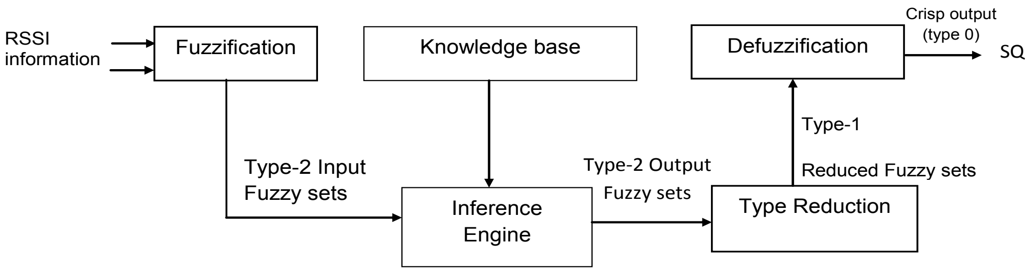



**Figure 9:** Structure of Interval type-2 fuzzy logic for WLAN service quality determination

An explanation of each of the components is discussed as follows:

The *Fuzzification* module maps the crisp input (RSSI information) to interval type-2 fuzzy sets (IT2FSs) using a defined triangular membership function (TMF) method. We considered the following RSSI parameters as inputs: RSSI, number of channels (NChannels), and Maximum Baud Rate (MBR), while, Service Quality (SQ) represents the output variable. The UoD for the input and output variables, and the domain intervals of the variables, as well as the range of each variable used to establish the fuzzy models are defined in Table 4.

*Table 4:* Domain Intervals of Input and Output Variables

| Variables | Lower Bound | Upper Bound | Unit |
|---|---|---|---|
| Input Variables | | | |
| RSSI | -100 | -5 | dBm |
| NChannels | 0 | 20 | - |
| MBR | 0 | 350 | ms |
| Output Variable | | | |
| SQ | 0 | 100 | % |

TMFs were adopted to evaluate each input and output MFs. Hence, the TMF (for a given input/output, $x$), $\mu(x)$, as shown in (7), and represented as a line or curve (see Fig. 10.), depends on three parameters $p_1$, $p$ and $p_2$. It indicates the mapping of each input (RSSI, NChannels and MBR) measurements, or output (SQ) parameters, required to obtain the membership values:

$$\mu(x)=\begin{cases}0; & if\ x<p_1\\ \dfrac{x-p_1}{p-p_1}; & if\ p_1\le x\le p\\ \dfrac{p_2-x}{p_2-p}; & if\ p\le x\le p_2\\ 0; & if\ x>p_2\end{cases} \tag{7}$$

where $p$, defines the triangular peak location, while $p_1$ and $p_2$, define the triangular end points.

Figure 10 shows the triangular shape IT2FS with its principal T1FS, bounded by an UMF and a LMF

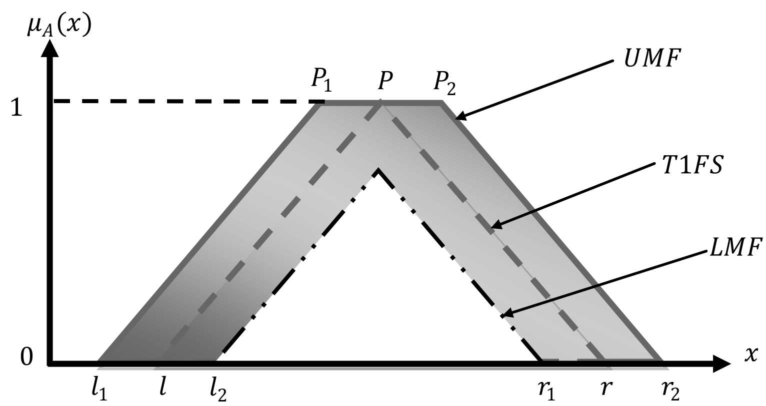



**Figure 10:** Triangular shape IT2FS

Now, applying the parameters in Figure 10 to (7), we derive (8) and (9) – the detailed computation formulae for the UMF ($\overline{\mu}(x)$) and LMF ($\underline{\mu}(x)$), respectively, given an input/output variable ($x$),

$$\bar{\mu}(x)=\begin{cases}0; & if\ \ x<l_1\\ \dfrac{x-l_1}{p_1-l_1}; & if\ l_1\le x<p_1\\ 1; & if\ \ p_1\le x\le p_2\\ \dfrac{r_2-x}{r_2-p_2}; & if\ \ p_2<x\le r_2\\ 0; & if\ \ x>r_2\end{cases} \tag{8}$$

$$\underline{\mu}(x)=\begin{cases}0; & if\ \ x<l_2\\ \dfrac{x-l_2}{p_2-l_2}; & if\ l_1\le x<p_1\\ \dfrac{r_2-x}{r_2-p_2}; & if\ \dfrac{r_1(p_2-l_2)+l_2(r_1-p_1)}{(p_2-l_2)+(r_1-p_1)}<x\le r_1\\ 0; & if\ \ x\ge r_2\end{cases} \tag{9}$$

where $l_1$ and $l_2$, represent the left end point of both UMF and LMF, respectively; and $r_1$ and $r_2$, represent the right end point of both LMF and UMF, respectively.

The domain intervals for the study were partitioned according to their lower and upper values, conditioned towards standard WLAN regulatory estimates (Mazar, 2016; Xue, Qiu, Hua and Yu, 2017), and used in controlling the models. The resulting fuzzy sets of the input and output variables, their associated values and labels are presented in Table 5.

*Table 5:* Input and Output Variables Fuzzy Sets

| Fuzzy linguistic label | TMF range (Lower) | | | TMF range (Upper) | | | Label |
|---|---|---|---|---|---|---|---|
| | $l_2$ | mean | $r_1$ | $l_1$ | mean | $r_2$ | |
| RSSI | | | | | | | |
| Low | -95 | -90 | -85 | -100 | -90 | -80 | LO |
| Medium | -88 | -78.5 | -70 | -90 | -78.5 | -65 | ME |
| High | -70 | -42.5 | -10 | -75 | -42.5 | -5 | HI |
| NCHANNELS | | | | | | | |
| Low | 1 | 2.5 | 4 | 0 | 2.5 | 5 | LO |
| Medium | 4 | 8 | 13 | 3 | 8 | 14 | ME |
| High | 12 | 15 | 19 | 11 | 15 | 20 | HI |
| MBR | | | | | | | |
| Low | 15 | 50 | 85 | 0 | 50 | 100 | LO |
| Moderate | 80 | 135 | 185 | 65 | 135 | 200 | MO |
| High | 150 | 230 | 335 | 135 | 230 | 350 | HI |
| SQ | | | | | | | |
| Very Poor | 5 | 20 | 35 | 0 | 20 | 40 | VP |
| Poor | 25 | 35 | 45 | 20 | 35 | 50 | PR |
| Good | 40 | 45 | 55 | 35 | 45 | 60 | GD |
| Very Good | 50 | 60 | 75 | 45 | 60 | 80 | VG |
| Excellent | 70 | 80 | 95 | 65 | 80 | 100 | EX |

An instance computation for the UMF of input variable, RSSI, with fuzzy term 'High' is given in (10),

$$\overline{\mu}_{High}(RSSI)=\begin{cases}0; & if\ RSSI<(-100)\\ \dfrac{RSSI-(-100)}{p_1-(-100)}; & if\ (-100)\le RSSI<p_1\\ 1; & if\ p_1\le RSSI\le p_2\\ \dfrac{(-80)-RSSI}{(-80)-p_2}; & if\ p_2<RSSI\le(-80)\\ 0; & if\ RSSI>(-80)\end{cases} \tag{10}$$

We employed the *Juzzyonline Fuzzy toolbox (http://juzzy.wagnerweb.net/)* – an open-source toolkit useful for the design, implementation, evaluation, and sharing of Type-1 and Type-2 fuzzy logic systems (Wagner, Pierfitt and McCulloch, 2014), to construct the input and output membership functions. The linguistic terms of the three input and output membership functions in Table 5 are described as follows:

RSSI:

[$\mu_{RSSIU}$LO],[$\mu_{RSSIL}$LO] – RSSI Upper and Lower membership function for Low

[$\mu_{RSSIU}$ME],[$\mu_{RSSIL}$ME] – RSSI Upper and Lower membership function for Medium

[$\mu_{RSSIU}$HI],[$\mu_{RSSIL}$HI] – RSSI Upper and Lower membership function for High

NCHANNELS:

[$\mu_{NCHANNELSU}$LO],[$\mu_{NCHANNELSL}$LO] – NCHANNELS Upper and Lower membership function for Low

[$\mu_{NCHANNELSU}$ME],[$\mu_{NCHANNELSL}$ME] – NCHANNELS Upper and Lower membership function for Medium

[$\mu_{NCHANNELSU}$HI],[$\mu_{NCHANNELSL}$HI] – NCHANNELS Upper and Lower membership function for High

MBR:

[$\mu_{MBRU}$LO],[$\mu_{MBRUL}$LO] – MBR Upper and Lower membership function for Low

[$\mu_{MBRU}$MO],[$\mu_{MBRUL}$MO] – MBR Upper and Lower membership function for Moderate

[$\mu_{MBRU}$HI],[$\mu_{MBRUL}$HI] – MBR Upper and Lower membership function for High

SQ:

[$\mu_{SQU}$VP],[$\mu_{SQL}$VP] – SQ Upper and Lower membership function for Very Poor

[$\mu_{SQU}$PO],[$\mu_{SQL}$PO] – SQ Upper and Lower membership function for Poor

[$\mu_{SQU}$GD],[$\mu_{SQL}$VG] – SQ Upper and Lower membership function for Good

[$\mu_{SQU}$GD],[$\mu_{SQL}$GD] – SQ Upper and Lower membership function for Good

[$\mu_{SQU}$EX],[$\mu_{SQL}$EX] – SQ Upper and Lower membership function for Excellent

The *IF-THEN rules* in IT2FLS are then specified in the form of *m* inputs and one output, $x_1 \in D_1, x_2 \in D_2, ..., x_m \in D_m$, and one output, $y \in E$, as;

$$IF\ x_i \in \tilde{D}_i^l\ AND,...,AND\ x_m\ is\ \tilde{D}_m^l\ THEN\ y\ is\ E^l \tag{11}$$

where $x_{i;i=1,...,m}$, are the antecedents, and $y$, is the consequent of the $jth$ rule, $l = 1,..., p$ of IT2FLS. The $\tilde{D}_i^l$'s are the MFs $\mu_{\tilde{D}_i^l}(x_i)$ of the antecedent part assigned to the $ith$ input $x_i$, The $E^l$'s are the MFs $\mu_{\tilde{E}_i^l}(x_i)$ of the consequent part assigned to the output $y$.

A total of 27 fuzzy rules were achieved from the MFs selected, and a snapshot of some of the rules necessary to drive the inference engine is shown in Figure 11,

**1.** If RSSI is Low and NO. of Channels is Less and MBR is Low **then** Service Quality is Very Poor

**2.** If RSSI is Low and NO. of Channels is Less and MBR is Moderate **then** Service Quality is Very Poor

**3.** If RSSI is Low and NO. of Channels is Less and MBR is High **then** Service Quality is Poor

**4.** If RSSI is Low and NO. of Channels is Medium and MBR is Low **then** Service Quality is Very Poor

**5.** If RSSI is Low and NO. of Channels is Medium and MBR is Moderate **then** Service Quality is Poor

**6.** If RSSI is Low and NO. of Channels is Medium and MBR is High **then** Service Quality is Very Good

**7.** If RSSI is Low and NO. of Channels is More and MBR is Low **then** Service Quality is Very Poor

**8.** If RSSI is Low and NO. of Channels is More and MBR is Moderate **then** Service Quality is Good

**9.** If RSSI is Low and NO. of Channels is More and MBR is High **then** Service Quality is Very Good

**10.** If RSSI is Medium and NO. of Channels is Less and MBR is Low **then** Service Quality is Very Poor

:: :: :: :: :: :: :: :: ::

**24.** If RSSI is High and NO. of Channels is Medium and MBR is High **then** Service Quality is Excellent

**25.** If RSSI is High and NO. of Channels is More and MBR is Low **then** Service Quality is Good

**26.** If RSSI is High and NO. of Channels is More and MBR is Moderate **then** Service Quality is Excellent

**27.** If RSSI is High and NO. of Channels is More and MBR is High **then** Service Quality is Excellent

**Figure 11:** Fuzzy rules for driving the inference engine

The firing set for the $ith$ rule is then computed as (Acampora, Alghazzawi, Hagras and Vitieli, 2016):

$$F^i(x') = [\underline{f}^i(x'), \overline{f}^i(x')] \equiv [\underline{f}^i, \overline{f}^i] \tag{12}$$

$$\underline{f}^i(x') = \underline{\mu}_{f_1^i}(x_1'),*...*\underline{\mu}_{f_m^i}(x_1') \tag{13}$$

$$\overline{f}^i(x') = \overline{\mu}_{f_1^i}(x_1')*...*\overline{\mu}_{f_1^i}(x_m') \tag{14}$$

where $F^i(x)$ is the antecedent of rule $i$, and $\mu_{f^i}(x)$, is the degree of membership of $x$ in $F$. $\bar{\mu}_{f^i}(x)$ and $\underline{\mu}_{f^i}(x)$ are upper and lower MFs of $\mu_{f^i}$.

The inference engine combines the fired rules and gives a mapping from input IT2FSs to output IT2FSs. The combined output fuzzy set, $\mu_{\tilde{E}_j^l(y_j)}$, is obtained by combining the fired output consequent sets, taking the union of the $ith$ *rule* fired as output consequent sets.

Type-reduction (TR) maps the type-reduced set into an interval of uncertainty for the output of an IT2FLS. The Karnik-Mendel algorithms were employed for computing the exact end-points, and are presented in (15) and (16), respectively (Mendel and Liu, 2007):

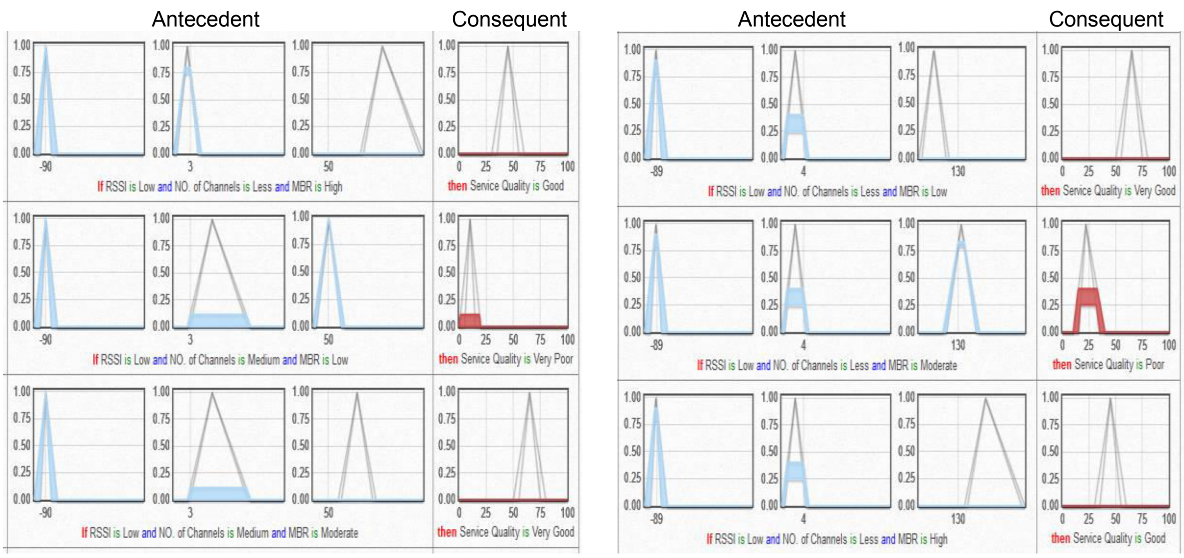
$$y_r = \frac{\Sigma_{i=1}^{N} f_r^l y_r^l}{\Sigma_{i=1}^{N} f_f^i} \tag{15}$$

$$y_l = \frac{\Sigma_{i=1}^{N} f_l^i y_l^i}{\Sigma_{i=1}^{N} f_f^i} \tag{16}$$

Defuzzification of the interval set was then performed using the average of $Y_{lk}$ and $Y_{rk}$, and the defuzzified crisp output for each output *k* was achieved by:

$$Y_K(X) = \frac{Y_{lk} + Y_{rk}}{2} \tag{17}$$

Snapshots showing the antecedent and consequent plots for different inputs, from the IT2FL system are presented in Figures 12 (a) and 12 (b).




(a) Plot of SQ for RSSI=-90, NChannels=3, and MBR=50

(b) Plot for SQ with RSSI=-89, NChannels=4, and MBR=130

**Figure 12:** Antecedent and consequent plots

## 5. RESULTS AND DISCUSSION

Many reported results have shown that IT2FLS handles uncertainties better than T1FLS (Castillo and Melin, 2008, 2013; Acampora, Alghazzawi, Hagras and Vitieli, 2016; Mendel, 2001; Wu and Tan, 2006). Using the abstracted RSSI datasets captured from the three major campuses, a simulation of the IT2FL system was performed, to generate the SQ (last column of Appendix (A)). Next, we separate the fixed and mobile infrastructure by extrapolating the spatial SSID data unto the designed test beds – for enhanced visualisation. Figures 13 (a) and 13 (b) show the WLAN SQ performance test beds for fixed and mobile infrastructure, respectively – at the town and town campus annex. To generate the desired contour lines on the test beds, a spatial interpolation (a prediction of cells value in a raster for the limited number of sample points, over the entire surface) was performed. This geo-processing activity assisted in the prediction of unknown SQ for inaccessible geographical points with severe elevation, noise levels, and terrains. The method was applied to conscript new data points within the range of a discrete set of known data points. The inverse distance weighting (IDW) – a local neighbourhood approach was adopted to perform the interpolation of the scattered data and smoothen the contour lines. IDW assumes that each point influences the resulting surface only up to a finite distance, and weights are inversely proportional to a power distance. Hence, at an un-sampled location *r*, the estimator is given as,

$$F(r) = \Sigma_{i=1}^{m} w_i z(r_i) = \frac{\Sigma_{i=1}^{m} z(r_i) / |r - r_i|^p}{\Sigma_{j=1}^{m} 1 / |r - r_i|^p} \qquad (15)$$

where $p$ , is a parameter, typically 2.

In Figure 13 (a), we observed that the service quality was generally good across the study area, with very few spots enjoying very good SQ. Areas with poor service quality were also identified, mostly close to the ravine areas. The resulting test bed reveals that mobile users received good SQ at the town campus, compared to the town campus annex which experienced very poor service quality. Further, patches of poor service quality were noticed at the ravine area, as well as the main gate (the transit area to the annex campus), and hostel areas of the university. The poor SQ is expected, as the signal coverage has not yet been replicated to these areas. More worrisome is the extreme poor service quality at the town campus annex – an area with a more stable terrain, compared to the town campus. A deeper research into this area is therefore expected to consider the type of infrastructure and site information as variables to a neural network that robustly models the interactions between variables, to reveal the specific contribution(s) of each variable to service quality. Indeed, poor service quality is not only associated with RSSI details, but also site information, infrastructure, topography, etc.

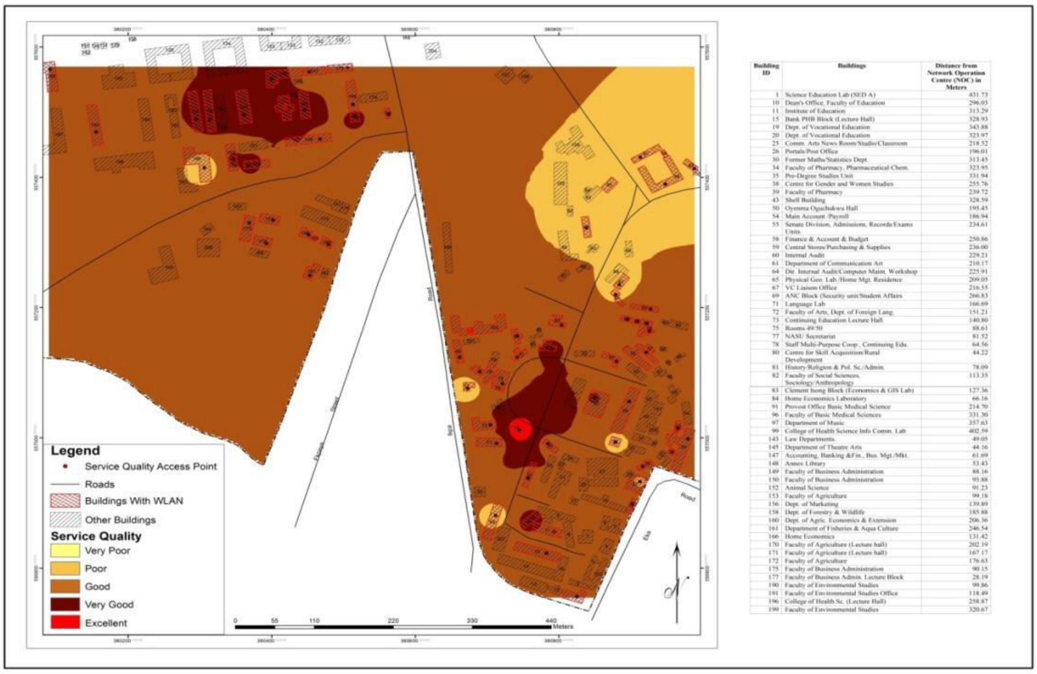



**Figure 13 (a):** WLAN SQ performance test bed for fixed infrastructure at town and town campus annex

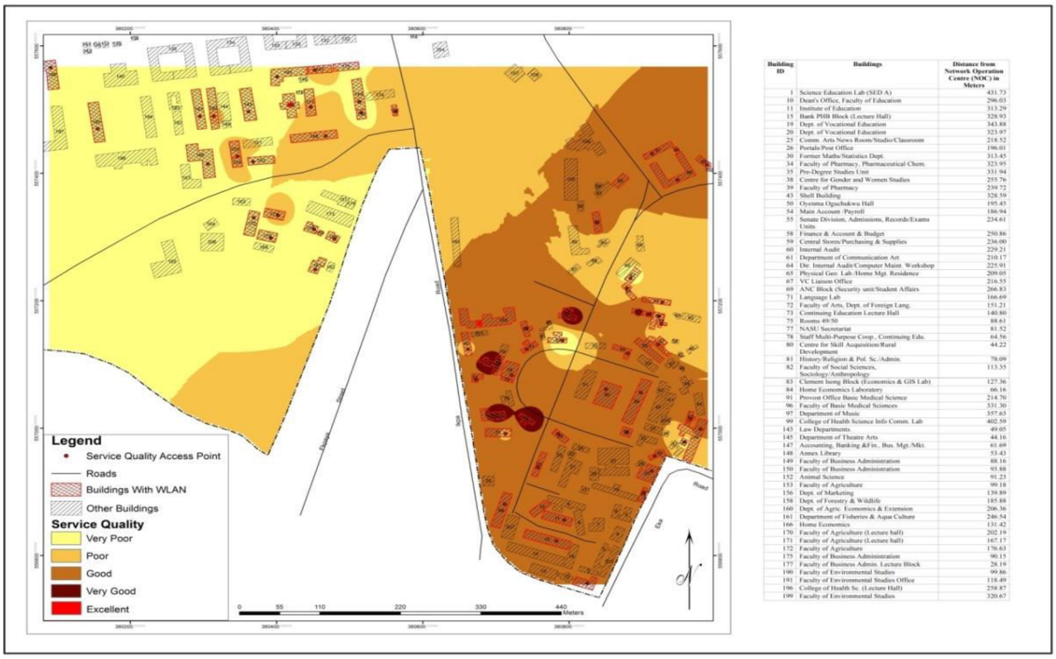
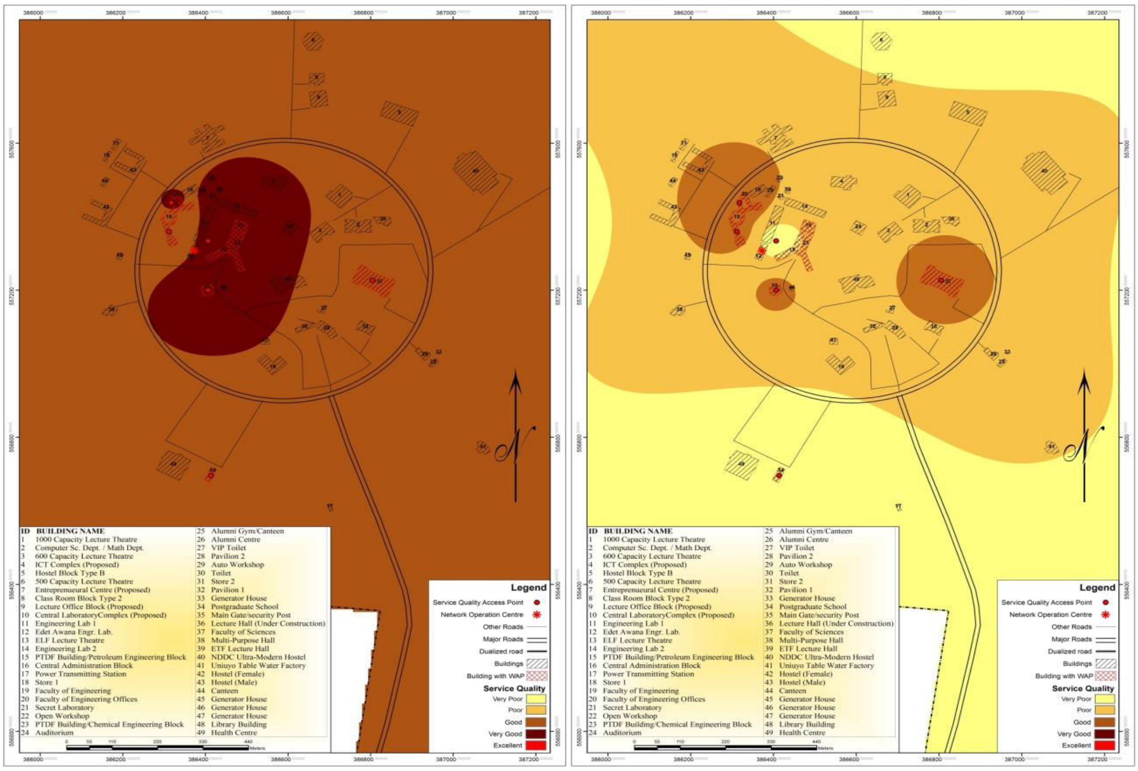



**Figure 13 (b):** WLAN SQ performance test bed for mobile infrastructure at town and town campus annex

The most likely cause of poor SQ may have been occasioned by the high mobile traffic usurping signals and causing unnecessary interference and severe service degradation, which greatly affected the town campus annex (see Figure 13 (b)).

Figures 14 (a) and 14 (b) show the service quality for fixed and mobile devices, respectively, at the main campus. Although only few APs have been installed at this campus, the entire coverage area under study seems to experience good SQ, with excellent SQ at the administrative area, postgraduate school, and engineering faculty. Mobile users generally experienced poor service quality (see Figure 14 (b)) – an indication that calls for a proper re-modelling of service infrastructure, and deeper studies to ensure an excellent service quality.




(a) fixed infrastructure (b) wireless infrastructure

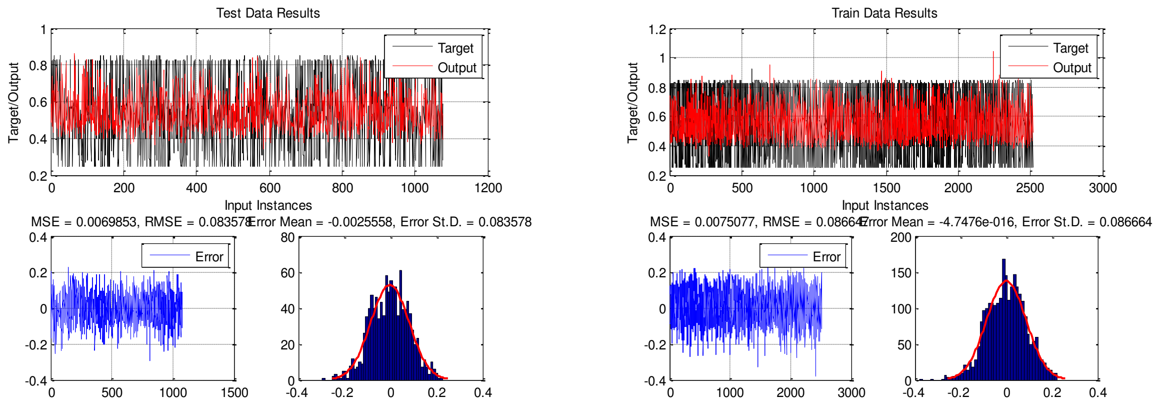
**Figure 14:** WLAN SQ performance test bed at main campus

To ensure intelligent test bed tuning for effective coverage optimisation, the adaptive neuro-fuzzy inference system (ANFIS) – a Sugeno-type fuzzy system endowed with neural learning and human cognitive capabilities was employed, and two evolutionary algorithms (PSO and GA), separately used to tune the NFS (Yarpiz, 2015). Swarm-based algorithms have emerged as a powerful family of optimisation techniques that applies the concept of social interaction to problem solving (Kennedy and Eberhart, 1995), and is a derivative-free global optimum solver. GAs are employed for solving both constrained and unconstrained optimisation problems that is based on natural selection – the process that drives biological evolution repeatedly and modifies a population of individual solutions (c.f. Mollaiy-Berneti, 2016). PSO and GA are demonstrated in this paper for the purpose of optimising the antecedent and consequent parameters of the ANFIS, which MFs are Gaussian (Talpur, Salleh and Hussain, 2017),

$$\mu_{A_i}(x) = \exp\left\{-\frac{1}{2}\left(\frac{x_i - c_i}{\sigma_i}\right)^2\right\} \tag{16}$$

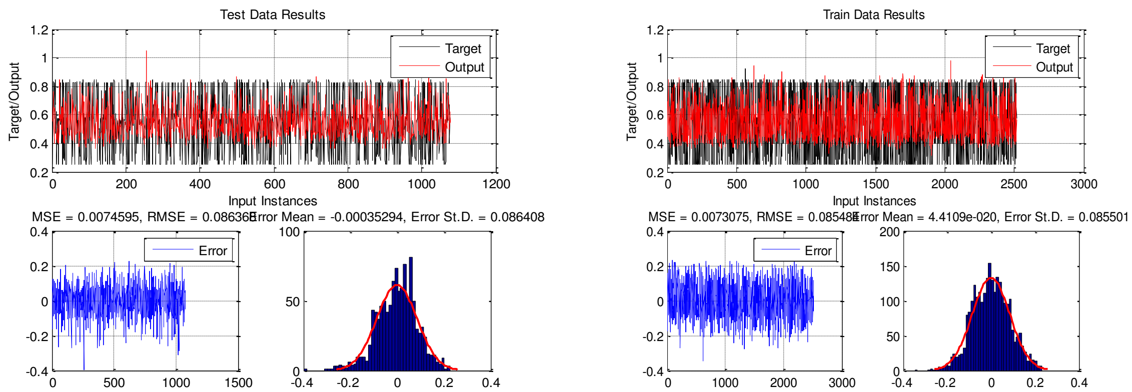
where, $\sigma_i$ and $c_i$, represent the width and center of the ith linguistic variable (or MFs). From the rules set in Figure 11, $x_i$ represents the input variables (RSSI, NChannels, MBR), and constitute the antecedent parameters, while $\{q_i, s_i, t_i, w_i\}$ are the consequent parameters; where, $q_i$, $s_i$ and $t_i$, are coefficients associated with the respective input variables; and, $w_i$, are constant parameters.

A MATLAB evolutionary ANFIS training source code for the implementation ANFIS tuning using GA and PSO (Yapiz, 2015: *http://www.yarpiz.com/319/ypfz104-evolutionary-anfis-training*) was adapted to suit our purpose, and used for training the datasets. Figures 15 and 16 show results of test and training data obtained from the ANFIS tuning, using PSO and GA, respectively. During the optimisation process, the field data for all campuses were merged, and the datasets distributed as follows: AllData: [3595x4 double], Inputs: [3x3595 double], Targets: [1x3595 double], TrainInputs: [2517x3 double], TrainTargets: [2517x1 double], TestInputs: [1078x3 double], TestTargets: [1078x1 double]. The root mean square error (RMSE) and mean absolute error (MAS) were used as performance metrics for measuring the quality and accuracy the two algorithms. We observed that the PSO tuning gave RMSEs of 0.0836 and 0.0867, for test and train data, respectively; while GA tuning gave RMSEs of 0.0864 and 0.0855, for test and train data, respectively. Although the results of both algorithms were close, the PSO algorithm was better, as its test data result was the least. Also, The mean absolute error




(a) Test data (b) Train data

**Figure 15:** Tuning ANFIS using PSO




(a) Test data (b) Train data

**Figure 16:** Tuning ANFIS using GA

## 6. CONCLUSION

In this paper, an intelligent system model was developed using the IT2FL to objectively assess infrastructure and site information of an academic environment. With this approach RSSI parameters (information) were dynamically optimised to minimise uncertainties, and maintain the required service quality. Simulation of the test bed infrastructure demonstrated the effectiveness of the approach for efficient modelling of uncertainties inherent in the existing system, and accurate estimation of the service quality. A visualisation of the simulated test bed indicated the need for intelligent coverage optimisation, and a NFS (ANFIS) was selected to achieve this. Rules for tuning the NFS were provided by the IT2FL rule base to drive the learning process and optimise the NFS. This tuning process – based on PSO algorithm and GA, was targeted at reshaping the membership functions by the modification and adjustment of the antecedent and consequent parameters of the fuzzy rules to enhance the system performance. In a future paper, an evaluation of interpolated areas not yet utilised by the university will be pursued. This initiative is very necessary as it will ensure excellent service quality, as well as precise infrastructural deployment to new areas, especially at mission critical areas in academic environments.

## ACKNOWLEDGEMENTS

This research is funded by The Tertiary Education Trust Fund (TETFund) National Research Fund (NRF) grant (Ref. No. TETFUND/NRF/UNI/UYO/STI/VOL.I/BE). We appreciate our Undergraduate and Postgraduate students, and the ICT personnel of the University of Uyo, for their involvement in the fieldwork phase of this project (test bed construction, field measurements, and deployment).

## REFERENCES

Abbas, N., Saade, J. J., 2015. A fuzzy logic based approach for network selection in WLAN/3G heterogeneous network. *Proceedings of 12th Annual IEEE Conference on Consumer Communications and Networking*: 631-636.

Acampora, G., Alghazzawi, D., Hagras, H. and Vitieli, A. (2016). An interval type-2 fuzzy logic based framework for reputation management in peer-to-peer e-commerce, *Information Sciences*, **333**: 88-107.

Castillo, O., Melin, P. 2008. Type-2 fuzzy logic *theory and applications*. Berlin: Springer-Verlag.

Cavdar, T. (2016). PSO tuned ANFIS equalizer based on fuzzy c-means clustering algorithm. *International Journal of Electronics and Communications (AEÜ),* **70(2016)**: 799–807.

Kar, S., Das, S., Ghosh, P. K., 2014. Applications of neuro fuzzy systems: A brief review and future outline. *Applied Soft Computing*, **15**: 243-259.

Kennedy, J. and Eberhart, R., 1995. Particle swarm optimization. *Proceedings of 1995 IEEE International Conference on Neural Networks*, 4: 1942-1948.

Kul, G., Ozyer, T. and Tavil, B., 2014. IEEE 802.11 WLAN based real time indoor positioning: literature survey and experimental investigations. *Pocedia Computer Science*, **34(2014)**, 157-164.

Kumar, A. and Kumar, D., 2017. A hybrid clustering method based on improved artificial bee colony and fuzzy C-means algorithm. *International Journal of Artificial Intelligence,* **15(2)**: 40-60.

Mazar, H., 2016. *Radio spectrum management: policies, regulations and techniques*. John Wiley and Sons.

Melin, P., Castillo, O., 2013. A review on the applications of type-2 fuzzy logic in classification and pattern recognition. *Expert Systems with Applications*, **40(13)**: 5413-5423.

Mendel, J. M., 2001. *Uncertain rule-based fuzzy logic systems: introduction and new directions*. Upper Saddle River, NJ: Prentice-Hall.

Mendel, J. M., Liu, F. 2007. Super-exponential convergence of the karnik-mendel algorithms for computing the centroid of an interval type-2 fuzzy set. *IEEE Trans on Fuzzy Systems*, **51(2)**: 309-320.

Mendel, J., John, R. 2002. Type-2 fuzzy sets made simple, *IEEE Transactions on Fuzzy Systems*, **10(2)**: 117–127.

Mollaiy-Berneti, S. (2016). Optimal design of adaptive neuro-fuzzy inference system using genetic algorithm for electricity demand forecasting in Iranian industry. *Soft Computing*, **20(12)**, 4897-4906.

Ozera, K., Inaba, T., Sakamoto, S., Barolli, L., 2017. Implementation of a WLAN triage testbed using fuzzy logic: evaluation for different number of clients. *Proceedings of International Conference on Innovative Mobile and Internet Services in Ubiquitous Computing*: 73-86. Springer, Cham.

Precup, R. E., Sabau, M. C., Petriu, E. M., 2015. Nature-inspired optimal tuning of input membership functions of Takagi-Sugeno-Kang fuzzy models for anti-lock braking systems. *Applied Soft Computing*, **27***:* 575-589.

Prithviraj, A., Krishnamoorthy, K., Vinothini, B., 2016. Fuzzy logic-based decision-making algorithm to optimize the handover performance in HetNets. *Circuits and Systems*, **7(11)**: 3756-3777.

Talpur, N., Salleh, M. N. M. and Hussain, K., 2017. An investigation of membership functions on performance of ANFIS for solving classification problems. *IOP Conference Series: Materials Science and Engineering*, **226(2017)**: 1-7.

Wagner, C., Pierfitt, M., McCulloch, J. (2014). Juzzy Online: An online toolkit for the design, implementation, execution and sharing of Type-1 and type-2 fuzzy logic systems. *Proceedings of 2014 IEEE International Conference on Fuzzy Systems*, Beijing, China: 1-6.

Wu, D. and Tan, W. W. (2006). Genetic learning and performance evaluation of fuzzy type-2 logic controllers. *Engineering Applications and Artificial Intelligence*, **19(8)**: 829-841.

Wu, K., Xu, X., Wang, X., Xu, Y., 2011, A method for modeling power spatial data based on object-relational model. *In Proceedings of International Conference on Computer Science and Information Technology*, IPCSIT, **51**, IACSIT Press, Singapore.

Xue, W., Qiu, W., Hua, X., Yu, K., 2017. Improved Wi-Fi RSSI measurement for indoor localization. *IEEE Sensors Journal*, **17(7)**: 2224-2230.

Yarpiz (2015). Evolutionary ANFIS training MATLAB source code: implementation of training ANFIS using GA and PSO. *www*.http://yarpiz.com/319/ypfz104-evolutionary-anfis-training. Accessed on 19th June, 2017.

## APPENDIX

### (A) SAMPLE RSSI DATASET CAPTURED FROM THE TOWN CAMPUS DURING FIELD WORK

| S/N | SSID | MAC | RSSI | SNR | NChan | CWidth | 802.11 | MBR | WEP | Vendor | Mgt | VenType | Location | Time | SQ (%) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | RAPIDA WIRELESS | 24:A4:3C:FE:04:FE | -56 | 17.230769 | 8 | 20 | b, g, n | 130 | Open | Ubiquiti Networks | 93 | Infrastructure | outdoor | afternoon | 82.7375438 |
| 2 | UniUyo Hotspot | 24:A4:3C:7A:2D:AB | -71 | 21.846154 | 12 | 40 | b, g, n | 300 | Open | Ubiquiti Networks | 82 | Infrastructure | outdoor | afternoon | 82.61703644 |
| 3 | UniUyo Hotspot | 24:A4:3C:A6:BD:17 | -79 | 24.307692 | 18 | 40 | b, g, n | 300 | Open | Ubiquiti Networks | 39 | Infrastructure | outdoor | afternoon | 82.6524189 |
| 4 | UniUyo Hotspot | DC:9F:DB:34:55:0E | -86 | 26.461538 | 4 | 20 | b, g, n | 130 | Open | Ubiquiti Networks | 3 | Infrastructure | outdoor | afternoon | 50 |
| 5 | RAPIDA WIRELESS-2 | 68:72:51:0A:77:91 | -72 | 22.153846 | 18 | 40 | b, g, n | 300 | Open | Ubiquiti Networks | 76 | Infrastructure | outdoor | afternoon | 82.64937146 |
| 6 | UniUyo Hotspot | 48:F8:B3:53:A8:92 | -64 | 19.692308 | 1 | 20 | b, g, n | 144 | Open | Cisco-Linksys. LLC | 91 | Infrastructure | outdoor | afternoon | 57.5 |
| 7 | UniUyo Hotspot | 24:A4:3C:A6:88:76 | -86 | 26.461538 | 14 | 40 | b, g, n | 300 | Open | Ubiquiti Networks | 20 | Infrastructure | outdoor | afternoon | 82.5 |
| 8 | GiONEE M5 | 96:92:BC:E4:2C:1D | -83 | 25.538462 | 3 | 20 | b, g, n | 72.2 | SharedKey | Unknown | 3 | Infrastructure | outdoor | afternoon | 28.26822741 |
| 9 | UniUyo Hotspot | 24:A4:3C:7A:2D:AB | -95 | 29.230769 | 12 | 40 | b, g, n | 300 | Open | Ubiquiti Networks | 36 | Infrastructure | indoor | afternoon | 27.10181639 |
| 10 | RAPIDA WIRELESS-2 | 68:72:51:0A:77:91 | -80 | 24.615385 | 18 | 40 | b, g, n | 300 | Open | Ubiquiti Networks | 21 | Infrastructure | indoor | afternoon | 76.78020632 |
| 11 | UniUyo Hotspot | 0A:18:D6:25:5A:F0 | -81 | 24.923077 | 6 | 40 | b, g, n | 300 | Open | Unknown | 19 | Infrastructure | indoor | afternoon | 82.6600474 |
| 12 | UniUyo Hotspot | 48:F8:B3:53:A8:92 | -95 | 29.230769 | 1 | 20 | b, g, n | 144 | Open | Cisco-Linksys. LLC | 40 | Infrastructure | indoor | afternoon | 57.27272727 |
| 13 | UniUyo Hotspot | 24:A4:3C:A6:BD:17 | -82 | 25.230769 | 18 | 40 | b, g, n | 300 | Open | Ubiquiti Networks | 26 | Infrastructure | indoor | afternoon | 82.6524189 |
| 14 | UniUyo Hotspot | DC:9F:DB:34:55:0E | -84 | 25.846154 | 4 | 20 | b, g, n | 130 | Open | Ubiquiti Networks | 9 | Infrastructure | indoor | afternoon | 78.92858127 |
| 15 | UniUyo Hotspot | DC:9F:DB:34:5A:34 | -82 | 25.230769 | 3 | 20 | b, g, n | 130 | Open | Ubiquiti Networks | 13 | Infrastructure | indoor | afternoon | 25 |
| 16 | UniUyo Hotspot | 24:A4:3C:A6:88:76 | -89 | 27.384615 | 14 | 40 | b, g, n | 300 | Open | Ubiquiti Networks | 2 | Infrastructure | indoor | afternoon | 82.6524189 |
| 17 | ADYYZXllcmVrdXRh | 7A:7D:48:3E:FA:B0 | -91 | 28 | 4 | 20 | b, g, n | 72.2 | Open | Unknown | 2 | Infrastructure | indoor | afternoon | 50 |
| 18 | UniUyo Hotspot | DC:9F:DB:34:55:0E | -95 | 29.230769 | 4 | 20 | b, g, n | 130 | Open | Ubiquiti Networks | 3 | Infrastructure | outdoor | morning | 48.24421723 |
| 19 | UniUyo Hotspot | DC:9F:DB:34:5A:34 | -95 | 29.230769 | 3 | 20 | b, g, n | 130 | Open | Ubiquiti Networks | 15 | Infrastructure | outdoor | morning | 82.5 |
| 20 | ADYYZXNzZWhzYW11ZWw1 | A6:44:D1:83:E5:DC | -85 | 26.153846 | 11 | 20 | b, g, n | 72.2 | Open | Unknown | 13 | Infrastructure | outdoor | morning | 40 |
| 21 | UniUyo Hotspot | 24:A4:3C:A6:88:76 | -94 | 28.923077 | 16 | 40 | b, g, n | 300 | Open | Ubiquiti Networks | 13 | Infrastructure | outdoor | morning | 82.67274183 |
| 22 | ADYYSW5maW5peEhPVDQ | 7A:FF:CA:8B:67:D8 | -85 | 26.153846 | 6 | 20 | b, g, n | 72.2 | Open | Unknown | 16 | Infrastructure | outdoor | morning | 40 |
| 23 | UniUyo Hotspot | 24:A4:3C:A6:BD:17 | -95 | 29.230769 | 18 | 40 | b, g, n | 300 | Open | Ubiquiti Networks | 17 | Infrastructure | outdoor | morning | 25 |
| 24 | pman | 52:9F:27:BA:7F:05 | -10 | 3.0769231 | 1 | 20 | b, g, n | 72.2 | SharedKey | Unknown | 18 | Infrastructure | outdoor | morning | 82.7375438 |
| 25 | Comternet3_07089483474 | 14:1F:BA:70:5F:A0 | -92 | 28.307692 | 1 | 20 | b, g, n | 300 | Open | IEEE Registration Authority | 3 | Infrastructure | outdoor | morning | 82.61703644 |

### (B) SAMPLE SITE SPECIFIC DATASET CAPTURED FROM THE TOWN CAMPUS DURING FIELD WORK

| BID | Description | Btype | BSize ($m^3$) | BPurp | BHeight (m) | DFNOC | Floor | NOR | Lattitude | Longitude | Pathloss |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Science Education Lab (SED A) | 1 | 682.67 | 3 | 4 | 431.731 | 1 | 4 | 5.0361298 | 7.9249439 | 146.5564 |
| 10 | Dean's Office, Faculty of Education | 1 | 1076.54 | 4 | 4 | 296.032 | 1 | 22 | 5.0371722 | 7.92434079 | 141.6402 |
| 11 | Institute of Education | 1 | 1947.86 | 4 | 4 | 313.298 | 1 | 5 | 5.0371722 | 7.92434079 | 142.3787 |
| 15 | Bank PHB Block (Lecture Halls) | 1 | 3494.72 | 1 | 4 | 328.93 | 1 | 4 | 5.0370291 | 7.92465605 | 143.0131 |
| 19 | Dept. of Vocational Education I | 1 | 491.04 | 4 | 4 | 343.878 | 1 | 6 | 5.0374232 | 7.92563863 | 143.5921 |
| 20 | Dept. of Vocational Education II | 1 | 1027.26 | 4 | 4 | 323.967 | 1 | 4 | 5.0377297 | 7.92573359 | 142.815 |
| 25 | Comm. Arts News Room/Studio/Classroom | 1 | 2528.30 | 3 | 4 | 218.518 | 1 | 6 | 5.0377753 | 7.92433026 | 137.6846 |
| 26 | UNIUYO Portal/Post Office | 1 | 697.28 | 4 | 4 | 196.014 | 1 | 6 | 5.0382543 | 7.92457766 | 136.2686 |
| 30 | Former Maths/Statistics Dept. | 1 | 944.28 | 4 | 4 | 313.45 | 1 | 6 | 5.0379404 | 7.92577143 | 142.385 |
| 34 | Dept. of Pharmaceutical Chemistry | 1 | 2942.92 | 3 | 4 | 323.953 | 1 | 5 | 5.0383242 | 7.92633401 | 142.8145 |

| BID | Description | Btype | BSize ($m^3$) | BPurp | BHeight (m) | DFNOC | Floor | NOR | Lattitude | Longitude | Pathloss |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 35 | Former Pre-Degree Studies Unit | 1 | 254.80 | 1 | 4 | 331.939 | 1 | 1 | 5.0381396 | 7.92614101 | 143.1317 |
| 38 | Centre for Gender Studies | 1 | 776.89 | 4 | 4 | 255.761 | 1 | 6 | 5.0382749 | 7.92542722 | 139.735 |
| 39 | Faculty of Pharmacy | 3 | 11333.23 | 8 | 12 | 239.716 | 3 | 22 | 5.0388399 | 7.92559812 | 138.8909 |
| 43 | Shell Building | 1 | 254.80 | 4 | 4 | 328.599 | 1 | 3 | 5.0384652 | 7.92620968 | 143 |
| 50 | Oyenma Oguchukwu Hall | 2 | 7410.96 | 8 | 8 | 195.447 | 1 | 4 | 5.0388871 | 7.92517086 | 136.2309 |
| 54 | Main Account /Payroll Unit | 1 | 1743.48 | 4 | 4 | 186.943 | 1 | 8 | 5.0393987 | 7.92543492 | 135.6513 |
| 58 | Final Account & Budget | 1 | 1115.34 | 4 | 4 | 250.861 | 1 | 12 | 5.0398158 | 7.92584949 | 139.483 |
| 59 | Central Stores/Purchasing and Supplies | 1 | 1496.68 | 7 | 4 | 236.002 | 1 | 8 | 5.0399235 | 7.92582067 | 138.6875 |
| 60 | Internal Audit | 1 | 232.99 | 4 | 4 | 229.205 | 1 | 6 | 5.039952 | 7.92569891 | 138.3067 |
| 61 | Dept. of Communication Arts | 2 | 1197.00 | 4 | 8 | 210.165 | 1 | 6 | 5.0399805 | 7.92557716 | 137.1768 |
| 64 | Directorate of Internal Audit/ Computer Maintenance Workshop | 1 | 866.59 | 4 | 4 | 225.905 | 1 | 2 | 5.0401245 | 7.9258633 | 138.1178 |
| 65 | Physical Geo. Lab./Home Management Residence | 1 | 1677.96 | 8 | 4 | 209.047 | 1 | 7 | 5.0403234 | 7.92542624 | 137.1073 |
| 69 | ANC Block (Security unit/Student Affairs) | 1 | 2573.83 | 4 | 4 | 266.825 | 1 | 8 | 5.0372567 | 7.92392063 | 140.2868 |
| 71 | Language Lab | 1 | 1934.87 | 3 | 4 | 166.696 | 1 | 4 | 5.0382547 | 7.92393331 | 134.1578 |
| 72 | Faculty of Arts, Dept. of Foreign Lang. | 2 | 969.31 | 4 | 8 | 151.207 | 1 | 12 | 5.0384418 | 7.92421938 | 132.8872 |
| 73 | Continuing Education Lecture Hall | 1 | 2342.83 | 1 | 4 | 140.804 | 1 | 4 | 5.038513 | 7.92385413 | 131.9584 |
| 75 | Rooms 49, 50 | 1 | 2385.24 | 1 | 4 | 88.61 | 1 | 2 | 5.0390876 | 7.92400354 | 125.9245 |

Key or code identifying the type and purpose of buildings

| Type | Code | Purpose | Code |
|---|---|---|---|
| Bungalow | 1 | Teaching/lecture/examination | 1 |
| 1-storey | 2 | Study/reference | 2 |
| 2-Storey | 3 | Practical demonstration | 3 |
| 3-storey | 4 | Workshop/office | 4 |
| 4-storey | 5 | Social/recreation | 5 |
| 5-Storey | 6 | Commercial | 6 |
| 6-Storey | 7 | Store | 7 |
| | | Multipurpose | 8 |