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A Fuzzy Knowledge-Based System for Modeling Handoff Prediction in Mobile Communication Networks

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Key words: Adaptive Intelligence Multi-Factored Algorithm (AIMFA), fuzzy knowledge-based system and multiple criteria VHD algorithms

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Abstract: Modeling wireless communication networks is essential for sound decision making regarding network planning, network optimization, resource allocation and scheduling. In mobile networks, most commonly used indicators to measuring handoff performance include Received Signal Strength (RSS), signal strength from the target base station, Handoff Latency (HL) and congestion control of the Target base Station. Handoff plays a critical role in wireless communication. It is a process by which Mobile Network (MN) moves from one point of network attachment to another. As wireless communications technologies evolve dramatically, the recent focus has shifted to the development of 4th-Generation (4G) mobile systems and even 5G networks. Instead of developing a new uniform standard for all wireless communications systems, 4G communication networks strive to seamlessly integrate various existing wireless communication technologies. However, the major challenges in this migration is to realize seamless handoffs among various communications systems with minor handoff latency. Indeed, maintaining seamless connectivity along with minimizing poor Quality of Service (QoS) is one of the major challenges in mobile networks. Nevertheless, handoff prediction can overcome these challenges. It is accountable for, given that seamless communication among Base Stations (BSs) when user moves from one cell to another. In this study, a computational intelligence framework based on fuzzy knowledge-based system and multiple criteria VHD algorithms is considered. The work proposed an Adaptive Intelligence Multi-Factored Algorithm (AIMFA) and Multi Criteria Algorithm to predict and optimize handoff decision. Consequently, the simulation results show that the proposed algorithm seems to reduce the probability of call-drops as well as unnecessary handoffs in heterogeneous network environments. The evaluation also shows that with Gaussian Membership Function (GMF), the Optimized Handoff Decision (OHD) initiates handoff efficiently for Quality of Service (QoS) provisioning in Mobile networks.

INTRODUCTION

Over the past decades, mobile wireless communication systems have encountered a remarkable change. The mobile wireless Generation (G) for the most part alludes to an adjustment in the idea of the framework, speed, technology, frequency, data capacity, latency, etc. Each generation has some standards, different capacities, new techniques and new features which separate it from the previous generations. The First Generation (1G) mobile wireless communication network was analog utilized for voice calls only. The Second Generation (2G) is a digital technology and support text messaging. The Third-Generation (3G) mobile technology provided higher data transmission rate, increased capacity and gave interactive media bolster. The Fourth Generation (4G) incorporates 3G with fixed internet to help wireless mobile internet which is advancement to mobile technology and it beat the limitations of 3G. As mobile wireless networks increase in popularity and pervasiveness, we are faced with the challenge of combining a diverse number of wireless networks. The Fourth Generation (4G) of wireless communications is expected to integrate a potentially large number of heterogeneous wireless technologies in what could be considered a huge step toward universal seamless access. One of the main challenges for seamless mobility is the availability of reliable horizontal (intra-system) and vertical (inter-system) handoff schemes. Mobile communication is the process of performing computations on a portable device and transmission of data to single or many more devices. However, there exist a lot of challenges in design and implementation of 4G systems that will support all the expected features based on current communication systems and standards. Hence, providing high quality of service and great flexibility to network providers and the method for predicting handoffs in 4G communication has been in progress for decades. Basically, handoff prediction to be precise, the identification of the boundaries and the significance of the user locations is required. The importance of wireless communication is increasing day by day throughout the world due to cellular and broadband technologies. Everyone around the world would like to be connected seamlessly anytime, anywhere through the best network. The 4G wireless system must have the capability to provide high data transfer rates, quality of services and seamless mobility. In 4G, there are a large variety of heterogeneous networks. The users for variety of applications would like to utilize heterogeneous networks on the basis of their preferences such as real time, high availability and high bandwidth. When connections have to switch between heterogeneous networks for performance and high availability reasons, seamless vertical handoff is necessary. Over the year's different handoff schemes and conventional algorithm have been developed to perform handoffs. This conventional scheme compares the Received Signal Strength (RSS) from saving base station with that from one of the target base station, using a constant handoff threshold or margin. This conventional RSS handoff method selects base station with stronger signal at all times. This conventional method observed many unnecessary handoffs even when the signal is still at acceptable rate or level which will in turn degrade quality of service (QoS). Using some computing approaches like Genetic Algorithm (GA), artificial neural network, fuzzy logic, etc. The performance of these systems can be further enhanced by considering some factors like handoff latency, velocity of the mobile terminal which may constitute the cause of unnecessary additional handoffs. Predicting the location of a user or a user's mobile device is an inherently interesting problem and one that presents many open research challenges. Providing complete seamless service along with minimizing the poor Quality of Service (QoS) is one of the highest challenges in mobile wireless networks. Hence, handoffs prediction is considered to overcome these challenges. Thus, this research aim at predicting handoff in 4G mobile communication by using fuzzy-knowledge based approach to improve on the Quality of Service in mobile communication networks.

Literature review: The main network primitive that enables continuous connectivity in cellular networks is handoff, or the transfer of a device's connection from one cell sector to another. Although, handoffs are necessary for mobile devices to maintain connectivity, a recent study[1] showed that handoffs generally cause short-term disruptions in application performance. Similarly, simulation studies[2] have shown that handoffs could degrade performance of real-time applications such as VoIP. Many works are done deploying the artificial intelligence techniques for smooth handoff in mobile communication. Some of the works are discussed accordingly.

Nkansah-Gyeky[3] proposed an intelligent vertical handoff decision algorithm in next generation wireless networks, the objective of their proposed system was to design vertical handoff decision algorithms in order for mobile field workers and other mobile users equipped with contemporary multimode mobile devices to communicate seamlessly. The proposed system uses fuzzy logic and fuzzy inference systems to design a suitable handoff initiation algorithm that can handle imprecision and uncertainties in data and process multiple vertical handoff initiation parameters (criteria); used the fuzzy multiple attributes decision making method and context awareness to design a suitable access network selection function that can handle a tradeoff among many handoff metrics including quality of service requirements (such as network conditions and system performance), mobile terminal conditions, power requirements, application types, user preferences and a price model; used genetic algorithms and simulated annealing to optimize the access network selection function in order to dynamically select the optimal available access network for handoff. Traditional type-1 fuzzy sets (T1 FSs) and type-1 fuzzy inference systems (T1 FISs) was used in their proposed system. Although, T1 FSs have been successfully used in many applications, however such FSs have limited capabilities to directly handle lots of data uncertainties which can be handled by type-2 fuzzy sets (T2 FSs).

Javed *et al*.[4] study predictability of handoffs in 3G network based on the data from a major US cellular provider's radio network. He started by showing that, attributes that reflect recent mobility history, connected cell density and signal strength variation are correlated with future handoff rates. Then, develop a two-phase machine learning framework that uses a combination of these attributes to predict the occurrence and the frequency of handoffs in the near future while Signal-to-Noise Ratio (SNR) from a Radio Network Controller (RNC). Their evaluation on a large number of real handoff traces shows promising results. Using information available at either the handset or the network infrastructure were able to achieve 80% accuracy in predicting the occurrence of a handoff in the near future much better than the 53% accuracy achieved by a simple, naive predictor. Overall, their analysis provides a promising start towards a practical framework that handsets could use to accurately predict handoffs and better tolerate the performance disruptions that can accompany them.

Sati[5] study application of soft computing techniques for handoff management in wireless cellular networks highlighted some soft computing techniques for handoff prediction such as genetic algorithms, artificial neural networks, fuzzy logic and then proposed a fuzzy logic based soft computing technique to find out the handoff decision of the mobile terminals in wireless cellular networks using three inputs which were signal strength of the current base station, signal strength of the neighbor base station and the velocity of the mobile terminal. It results shows that the handoff decisions are taken in appropriate positions so that the load at base stations and Mobile Switching Center (MSC) is reduced. Since fuzzy type 1 system was used here, it has limited capabilities to directly handle lots of data.

Shen *et al*.[6] proposed wireless vertical handoff decision algorithm with parameter prediction. He then uses an adaptive network parameter prediction algorithm which establishes the prediction function for each network parameter and computes the network's QoS. Then the handoff process based on network parameter prediction is present to guide the handoff execution. Their result shows that the proposed algorithm can keep handoff stability. The handoff decisions based on real value and prediction value are compared in the WLAN inter-network environment. Their results show that the proposed prediction model can eliminate the unnecessary handoffs which caused by the performance shake of the access network.

Jhamta[2] uses grey prediction algorithm for 4G user acceptance technology with the objective of predicting 4G user acceptance in India. The grey prediction algorithm is the very powerful algorithm that will give better result for short term prediction. The presented method establishes the suitable model according to the characteristics of data and also improves the prediction accuracy of small data sets. He uses the 3G predictive based to improve accuracy of mobile user acceptance. For 4G user acceptance prediction the proposed grey prediction approach utilizes the grey system to predict reliability.

Miyim *et al*.[7] proposed a handover technique based on movement prediction in wireless mobile (WiMAX and LTE-Advanced) environment. The technique enables the system to predict signal quality between the mobile User Equipment (UE) and eNodeB stations/Access Points (APs) in two different networks. This prediction was achieved using Dynamic Regressive Integrated Moving Average (DRIMA) model by keeping track of the signal strength of mobile users. With the help of the prediction, layer-3 handover activities were able to occur prior to layer-2 handover and therefore, total handover latency can be reduced. This demonstrates that the method predicts the future signal level accurately and reduces the total handover latency. The handover scheme takes into cognizance velocity, current RSS and predicted RSS of candidate networks as the network parameters. The algorithm adopts predictive RSS, capable of triggering a handover in advance. For the network to accurately trigger handover and filter out the unnecessary data, a pre-decision process is applied before the handover decision module. The novel algorithm can save time and identify the best candidate network among them, the results shows that the new technique provides good ground to minimize ping-pong in heterogeneous network which can be executed intelligently to decide the dynamism of the network conditions.

Umoren and Owolabi[8] proposed a handover manageability and performance model for mobile communication networks then formulated a model for soft handoff in CDMA networks by initiating an overlap region between adjacent cells which facilitating the derivation of handoff manageability performance model. The study employed an empirical modeling approach to support their analytical findings, measure and investigated the performance characteristics of a typical communication network over a specific period in an established cellular communication network operator. The analysis has shown theoretically and mathematically that capacity depends on the size of the overlapping area between adjacent cells, the numbers of channels per cells and distribution of traffic. The higher the overlapping area, the higher the trucking efficiency gain(s). The attractive features is that the research has helped establish a practical solution using handover manageability models to improve the performance of soft handoffs in CDMA networks without increase in the system complexity.

Mendel[9] proposed a vertical handoff decision algorithm to reduce unnecessary handoff for heterogeneous wireless networks, the algorithm is based on fuzzy logic which considers many parameters like RSS, monetary cost, bandwidth, time delay and BER, meanwhile a Sole fuzzy logic based handoff algorithm was compared with Proposed algorithm and the simulation results shows that the proposed algorithm's performance is enhanced by reducing unnecessary handoffs because the proposed algorithm considers many different parameters and adds the pre-handoff decision method which filters the candidate network set.

Madaan and Kashyap[10] proposed a vertical handoff decision algorithm to choose the optimum target network based on user preference, power consumption, cost, network performance, network condition and available bandwidth. The proposed algorithm selects the target network depending upon the bandwidth, power consumption, cost and type of application to achieve the desired quality of service requested by the user. This algorithm used predicted received signal strength of service network and neighbor network to initiate the handoff at appropriate time. The inclusion of Hysteresis margin and dwell timer reduces the effect of fluctuating RSS and thus, reduces the number of unnecessary handoffs. Also, the pre-calculation of candidate network list further reduces the processing delay. This algorithm selects the optimum target network and considerably reduces the number of vertical handoff and increases the utilization of WLAN network.

Vallati *et al*.[11] proposed a handoff procedure based on a forecasting model of the link quality for mobile routers operating in vehicle-roadside wireless local area network-based networks. First, a preliminary set of experiments was performed in a realistic environment to study the behavior of the wireless channel when mobility in urban environment is considered. Then, considering the hands-on experience gained from the initial set of experiments, a novel handoff procedure was designed which exploits a forecasting technique to predict link channel quality. The proposed procedure is then exploited in a cross-layer manner to proactively reduce the number of transmitted layers during handoff in the case of real-time video traffic based on H.264/SVC encoding. The proposal is assessed by means of simulation and compared with existing solutions. Results demonstrate that their proposal guarantees performance comparable with other algorithms. Tso *et al*.[1] proposed a vehicular handover approach based On LTE in urban road scenario for the efficient data transmission that takes place high mobility of vehicles and continuous topology change. In this work, a framework for data aggregation using VANET with LTE is proposed. The proposed framework used cluster-based data aggregation and also provides handovers scheme for efficient data dissemination. The proposed model considered eNB's as central data control authority for providing information about signal strength to vehicles. The obtained simulations results show that the proposed scheme is efficient to aggregate information and provide a centralized control for check requirement of handover based on signal strength as the key parameter. In future the results can be evaluated for large amount of traffic and complex networks.

The studies made by Qiao *et al*.[12] emphasis the significance of the traffic in mobile internet to predict the user behavior. Here, the traffic in 2G/3G/4G networks are analyzed to predict the user behavior. This scheme has a number of advantages: more data to learn, high cost efficiency, low energy consumption, etc. The analysis of so collected data is done through Mobility analytical framework which uses cloud to handle the data. The construction of user trajectories is done through rules. Noise reduction and identification of hotspots is also a part of the work.

Sasikala *et al*.[13] proposed a handoff prediction based on user behavior using artificial neural network and association rule mining to determine the necessity of handoff. These method uses normalized min-max algorithm to scale the network parameter values. It deploys Apriori algorithm to confirm the decision made my ANNs to determine the necessity of handoff. Comparison was done between Neural Network and SVM (Support Vector Machine), for a dataset of size 100, ANNs predicts the handoff necessity better than SVM. At 1000 size dataset the accuracy of neural network was 89% whereas the accuracy the of SVM was 84%. Which infer that the SVM performs better for small size data but as the size of data increases, artificial neural network offers better results. Nevertheless, this research work adopts fuzzy based approach in order to improve upon the existing system, to predict handoffs in 4G mobile communication. This Approach is intended to provide efficiency in prediction of handoff. New parameter is introduced into the prediction system such as handoff latency and type-2 fuzzy sets which was recommended by Nkansah-Gyekye[3] is considered for the implementation to provide basis for handoff prediction.

MATERIALS AND METHODS

Existing system architecture: Existing architecture shows in Fig. 1 indicated fuzzy logic-based handoff controller, the three-input parameters for consideration are:

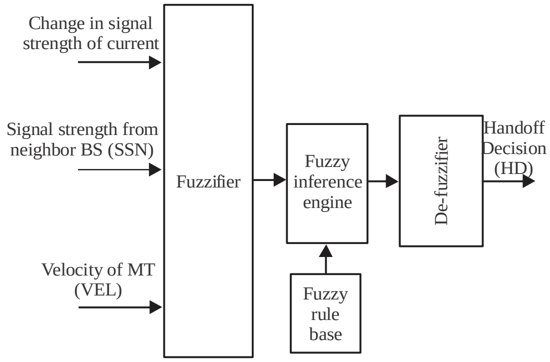

Fig. 1: Architecture of existing system; Sati[5]

- Change of the signal strength of present base station (CSSP)
- Signal Strength from Neighbor base station (SSN)
- Velocity of mobile station (VEL) while the output linguistic parameter taken is "Handoff Decision" (HD)

The term sets of CSSP, SSN, VEL and HD are defined as:

- T(CSSP) = [Small Change, No Change, Big Change] = [SC, NC, BG]
- T(SSNs) = [Weak, Normal, Strong] = [WK, NOR, STRG]
- T(VEL) = [Low, Medium, High] = [LO, MD, HG]
- T(HD) = [No Handoff, Wait, Handoff] = [NH, WT, HO]

Change of the signal strength of present based station (CSSP): The channel associated with the current connection (Base Station) while a call is in progress, is changed. The existing call may then change to a new Base Station (BS). Either crossing a cell boundary of current BS by the mobile caller also called Mobile Station (MS) or deterioration in quality of the signal in the current channel is primarily responsible for initiating this new connection.

Signal Strength from Neighbor base station (SSN): As a particular mobile device moves from one location to another, it may close down contact with one sector and initiate contact with another sector in such a way that the communications to and from the device are not disturbed. These sectors may or may not reside on a single base station. A neighbor list is a table that associates each sector with its neighbor sectors. Neighbor sectors often include adjacent sectors but may also include sectors that are not physically adjacent to one another. If a new sector is not listed in the neighbor list of a particular sector, a handoff from that particular sector to the new sector is difficult or impossible in most cases, resulting in a dropped call or other communication disruption.

Velocity of mobile station (VEL): Mobility is the most important service offered by next generation wireless cellular communication networks and has been a consistent part of wireless hierarchy and design. With the evolution of cellular communication systems and saturation of usable frequency spectrum, service providers are switching to higher frequencies and consequently, a smaller cell size. Quality of Service (QoS) in IEEE 802.11 networks demands that a mobile terminal should be connected to its Host Base Station (HBS) at all times[14]. As Mobile Terminals (MTs) crossover cell boundaries frequently during the course of an active call, wireless resources must be provided for them to continue; otherwise active calls would be forced to terminate and overall efficiency of the system would depreciate. This process of wireless resource reservation and transfer of a mobile user to the next visited cell is called Hand Off (HO). However, HO can also be initiated by the network to reallocate its wireless resources and to improve network efficiency.

Conceptual architecture: Architecture is the essential organization of a system personified in its components, their relationship to each other and the environment and the principles governing its design and development (Fig. 2).

Description of key components: The key components of this system are presented below; The following components constitute the fuzzy logic model used in this work.

Fuzzifier segment: This segment takes care of the associated measurement uncertainty for each input variable by mapping the crisp inputs to a more realistic fuzzy sets using a gaussian membership functions.

Rule base: This is a database that comprises of rules, this rules from proficient knowledge to be used for inference system.

Inference engine: This segment helps to determines the degree of match between fuzzy input and the rules. Based on the percentage of match, it determines which rules need implement according to the given input field. After this, the applied rules are combined to develop another fuzzy set.

Type reducer: Type-reduction methods are extended versions of type-1 defuzzi cation methods. Type reduction captures more information about rule uncertainties than the defuzzi ed value (a crisp number), however, it is computationally intensive.

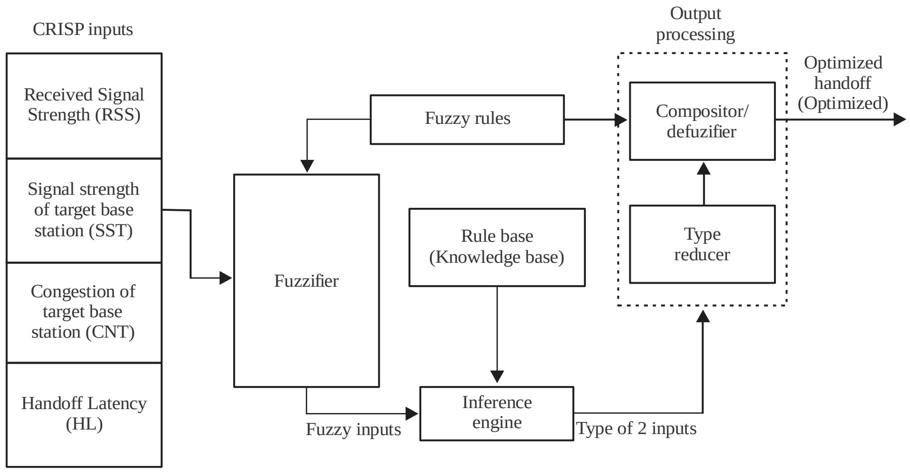

Fig. 2: Conceptual system architecture

Defuzzifier segment: This segment transforms the fuzzy set to a crisp output. The deffuzifier can be perform in several different ways.

Design methodology of fuzzy control systems: The key elements of designing a fuzzy logic controller includes:

- Defining the input and output variables (linguistic variables)
- Deciding on the fuzzy partition of the inputs and output spaces and choosing the membership functions for the input and output linguistic variables
- Deciding on the types and derivation of fuzzy control rules
- Designing the inference mechanism which includes a fuzzy implication and a computational operator and the interpretation of sentence connectives
- Choosing defuzzification operator

Model design: A system is a set of interrelating parts, created for some particular purpose. Essential activities in system design include developing system-level technical requirements and top-level system designs and assessing the design's ability to meet the system requirements.

The system design involves setting of system specification to be adhered to during system implementation.

Vertical Handoff Decision Algorithm (VHDAs): Generally, to determine handoff prediction, any one of Vertical Handoff Decision Algorithms (VHDAs) is needed to be applied in order to ensure predictable and explainable solution. Several VHDAs have been proposed, due to the complexity of the Handoff decision process for wirelessly accessed networks[3]. In his work, Nkansah-Gyekye[3] discussed several vertical handoff algorithms that had been proposed to aid in solving the complexities associated with handoff decision process. Of the algorithms, so, discussed, we have adapted two to define a new algorithm for this work. These two algorithms are multi criteria (VHDAs) and computational intelligence (VHDAs) to come up with what we called Adaptive Intelligence Multi-Factored Algorithm (AIMFA).

Adaptive Intelligence Multi-Factored Algorithm (AIMFA): In this work, we have proposed a new algorithm or approach for achieving and Optimal Handoff Decision (OHD). We consider the Adaptive Intelligence Multi-Factored Algorithm (AIMFA). The AIMFA adapts computational intelligence techniques and multi criteria algorithm to achieve a more optimal Handoff Decision (OHD), the computational intelligence-based handoff decision algorithms choose an access network for vertical handoff by applying a computational intelligence technique such as Fuzzy Logic (FL) and also the multiple criteria VHD algorithms make handoff decisions based on several handoff criteria such as received signal strength, signal strength from the target base station, handoff latency and congestion of the target base station which the two algorithm collectively form an adaptive intelligence algorithm for efficient optimized algorithm.

Rule base: Rules describes the relationship between the input and output linguistic variable which is constructed by their linguistic term.

The general form of a fuzzy rule is defined as a conditional statement. The fuzzy rules are defined using the standard form in the equation below:

$$R^l: \text{IF } x_1 \text{ is } \tilde{F}_1^l \text{ and, ..., } x_p \text{ is } \tilde{F}_p^l \text{ then } y \text{ is } \tilde{G}_1^l$$

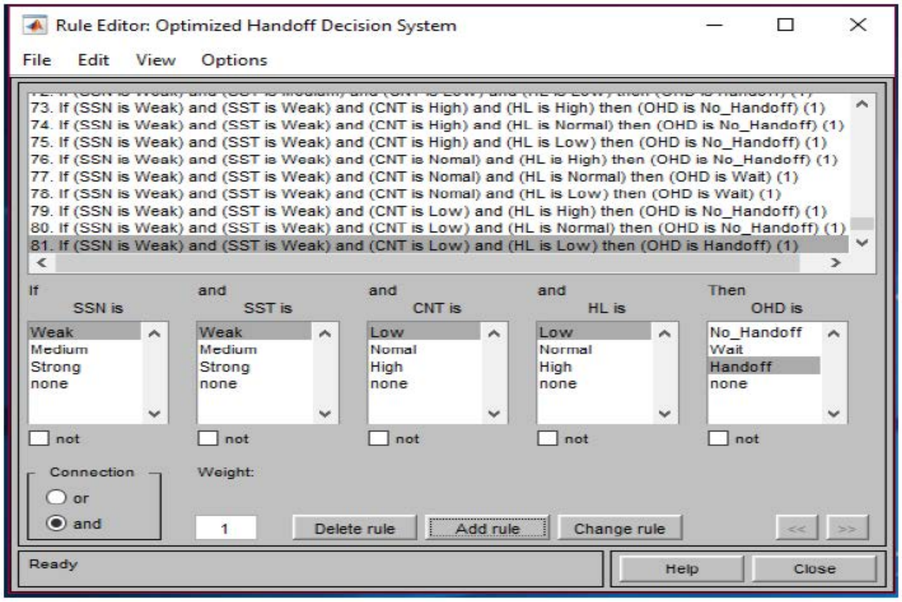

Fig. 3: Fuzzy rule editor

where 1 = 1, ... , M. We have (4) input variables and each of these variables have (3) sets each. From combinational logic, we understand that a truth table of inputs contains 2^N rows, one for each possible value of the inputs. From the 4 input variables, the maximum possible number of rules to be used in defining our rule base is given as $3^4 = 81$. As stated earlier, the rule is a collection of IF-THEN statements. IF-THEN rules is shown in Table 1.

The variables are HG: HIGH, NOR: NORMAL, LW: LOW, HO: HANDOFF, WT: WAIT, NH: NO HANDOFF.

To implement the rules in Table 1, we used the MATLAB Type-2 fuzzy logic toolbox to achieve all the steps needed to actualize this project implementation which is shown in the rule editor window (Fig. 3).

Data collection and analysis: Based on the complexities of the Handoff Decision Process (HDP), many Vertical Handoff Decision Algorithms (VHDAs) have been proposed[3] to facilitate a more optimal handoff decision and seamless communication in Next Generation Wireless Networks (NGWN). Two of these algorithms; the Multi-Criteria VHDA and the computational intelligence VHDAs have been adapted to achieve the aim and objectives of outlined for this work. The computational intelligence algorithm are data dependent and require a lot of data to effectively model the problem specification and determining the solution space.

Artificial Neural Networks (ANN) and fuzzy logic are two typical examples of the computational intelligence algorithms that requires a great deal of data, collected over a period of time, to be modeled efficiently.

Table 1: Sample rule base

Rule No.	RSS	SST	CNT	HL	OHD
1.	Strong	Strong	High	High	No handoff
2.	Strong	Strong	High	Normal	Wait
3.	Strong	Strong	High	Low	Wait
4.	Strong	Strong	Normal	High	No handoff
5.	Strong	Strong	Normal	Normal	Handoff
6.	Strong	Strong	Normal	Low	Handoff
7.	Strong	Strong	Low	High	Wait
8.	Strong	Strong	Low	Normal	Handoff
9.	Strong	Strong	Low	Low	Handoff
10.	Medium	Strong	High	Normal	Wait
11.	Medium	Strong	High	Low	Wait
12.	Medium	Strong	Normal	High	No handoff
13.	Medium	Strong	Normal	Normal	Handoff
14.	Medium	Strong	Normal	Low	Handoff
15.	Medium	Strong	Low	High	Wait
16.	Medium	Strong	Low	Normal	Handoff
17.	Medium	Strong	Low	Low	Handoff
18.	Medium	Medium	High	High	No handoff
19.	Medium	Weak	Low	Low	Wait
20.	Weak	Strong	High	High	No handoff
21.	Weak	Strong	High	Normal	Wait
22.	Weak	Strong	High	Low	Wait
23.	Weak	Strong	Normal	High	No handoff
24.	Weak	Strong	Normal	Normal	Handoff
25.	Weak	Strong	Normal	Low	Handoff
26.	Weak	Strong	Low	High	No handoff
27.	Weak	Strong	Low	Normal	Handoff
28.	Weak	Strong	Low	Low	Handoff

Naturally, abilities of man are limited in sieving through large volumes of noisy data and finding a useful and meaning trends from these data. However, this challenge can be eliminated by applying these computational intelligence algorithms to the data.

In this research paper, large amount of data have been collected over three weeks (21 days) of recorded

Table 2: Call drop troubleshooting (12282012 1226)

			Channel code names		
Date/Start time	Base station code name	Cell code name	CR33A: Channel Activation attempts	Available channel resources (Capacity)	Required channel resources (Capacity)
12/24/2012 00:00:00	HAKBS32	LABEL = AK0004A, Cell Index =0, CGI = 62120021C2714	833	82.943	95.436
12/24/2012 00:00:00	HAKBS32	LABEL = AK0010C, Cell Index = 5, CGI = 62120021C753A	1005	113.043	113.043
12/24/2012 00:00:00	HAKBS32	LABEL = AK0010B, Cell Index = 4, CGI = 62120021C4E2A	1533	78.01	78.01
12/24/2012 00:00:00	HAKBS32	LABEL = AK0010A, Cell Index = 3, CGI = 62120021C271A	1072	69.41	69.41
12/24/2012 00:00:00	HAKBS32	LABEL = AK0049C, Cell Index = 20, CGI = 62120021C7561	1002	71.028	74.208
12/24/2012 00:00:00	HAKBS32	LABEL = AK0049B, Cell Index = 19, CGI = 62120021C4E51	2155	80.004	80.004
12/24/2012 00:00:00	HAKBS32	LABEL = AK0049A, Cell Index = 18, CGI = 62120021C2741	1255	75.09	75.09
12/24/2012 00:00:00	HAKBS32	LABEL = AK0059C, Cell Index = 23, CGI = 62120021C756B	664	14.657	17.633
12/24/2012 00:00:00	HAKBS32	LABEL = AK0059B, Cell Index = 22, CGI = 62120021C4E5B	1223	16.14	18.671
12/24/2012 00:00:00	HAKBS32	LABEL = AK0059A, Cell Index = 21, CGI = 62120021C274B	1201	22.86	26.683

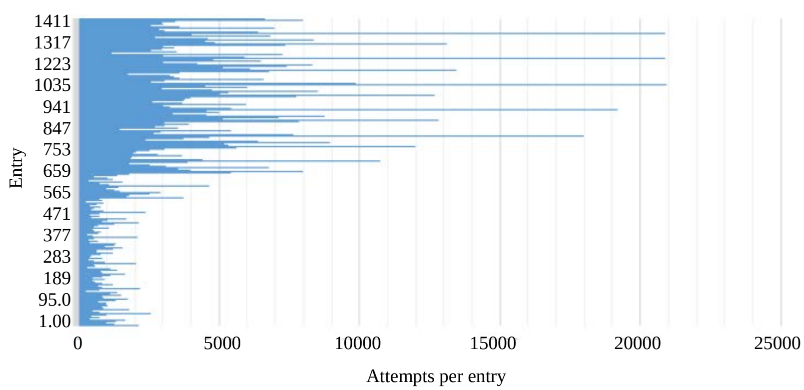

Fig. 4: Channel activation attempts

network data from one of the well-known mobile service providers in Nigeria called Airtel. The collected data had the following records and their code names as listed below:

- 13,392 records for call drop troubleshooting for several cells and channels (12282012 1226) (Table 2) and Fig. 4
- 24 records for Queries made for attempted handover success/Failure rate (12282012 1206)
- 124 records for handoff outgoing success/Failure (12282012 1219)
- 1,052 records of outgoing handover P2P (12242012 1402)

Table 3 and 4 illustrate segments of the different category of data collected and adapted for this research paper. Figure 5 illustrates the success against the failure rates for the handoff considered in a particular cell. Figure 5 shows that as long as the capacity of the cell is not exceeded, the success rates of the cell are high.

Model formation: Cellular handover or cellular handoff is relatively straightforward. Practically, it is not an easy

Table 3: Handoff outgoing rates (12282012 1219)

Date/Start time	Base station code name	Cell code name	Channel code names Number of outgoing internal inter-cell handoff requests	Number of outgoing internal inter-cell handoff commands	Number of unsuccessful outgoing internal inter-cell handoffs	HH-OG handoff success rate (%)
12/27/2012 20:00:00	HAKBS32	LABEL = AK0004A, Cell Index = 0, CGI = 62120021C2714	278	278	9	96.762
12/27/2012 20:00:00	HAKBS32	LABEL = AK0010C, Cell Index = 5, CGI = 62120021C753A	475	475	8	98.315
12/27/2012 20:00:00	HAKBS32	LABEL = AK0010B, Cell Index = 4, CGI = 62120021C4E2A	176	176	8	90.825
12/27/2012 20:00:00	HAKBS32	LABEL = AK0010A, Cell Index = 3, CGI = 62120021C271A	368	368	8	97.831
12/27/2012 20:00:00	HAKBS32	LABEL = AK0049C, Cell Index = 20, CGI = 62120021C7561	158	157	4	92.307
12/27/2012 20:00:00	HAKBS32	LABEL = AK0049B, Cell Index = 19, CGI = 62120021C4E51	77	77	1	94.395
12/27/2012 20:00:00	HAKBS32	LABEL = AK0049A, Cell Index = 18, CGI = 62120021C2741	198	196	8	92.808
12/27/2012 20:00:00	HAKBS32	LABEL = AK0059C, Cell Index = 23, CGI = 62120021C756B	831	831	41	95.072
12/27/2012 20:00:00	HAKBS32	LABEL = AK0059B, Cell Index = 22, CGI = 62120021C4E5B	331	331	12	95.971
12/27/2012 20:00:00	HAKBS32	LABEL = AK0059A, Cell Index = 21, CGI = 62120021C274B	673	673	12	98.013

Table 4: Wireless signal categorization

Signal strength (dBm)	Signal quality evaluation	Recommended usage
-30	Maximum signal strength. The mobile terminal (user) is <200 m from the base station (Access point)	Best for any data needs
-50	Excellent signal strength	-
-60	Good reliable signal strength	-
-67	Reliable signal strength	This is the minimum for any data or mobile service depending on a reliable connection and signal strength such as voice over Wi-Fi and non-HD video streaming
-70	Fairly strong wireless signal	For minimal browsing and emailing
-80	Unreliable signal strength	Not suitable for most wireless network services
-90	Very low signal strength	The chances of connection to this signal is very low

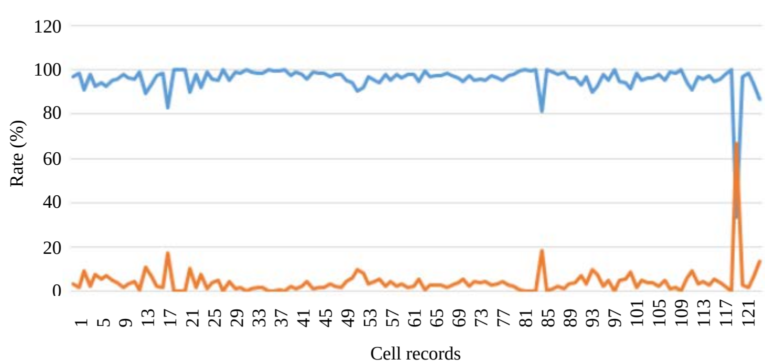

Fig. 5: Success against the failure rate

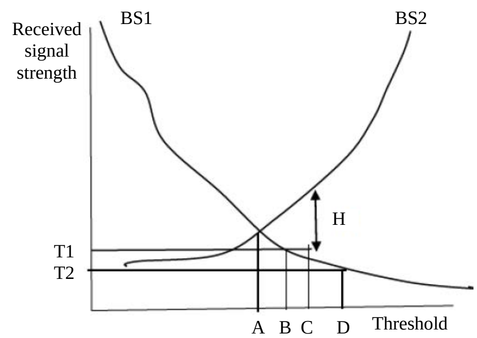

Fig. 6: Conventional handoff based on RSS

process to implement. The cellular network needs to decide when handover or handoff is necessary and to which cell. Again, when handover occurs, it is necessary to re-route the call to the relevant base station along with changing the communication between the mobile and the base station to a new channel. All of this requires to be undertaken without any noticeable interruption to the call. However, the process is quite complicated in early systems calls were often lost if the process did not work correctly. There are different types of conventional models which are used to initiate handoff mobile communication, one of such is the RSS handoff algorithm.

Using conventional method: Ideally, the conventional models, signal strength-based measurements are considered due to its simplicity and effective performance. The conventional handoff decision compares the Received Signal Strength (RSS) from the serving base station with that from one of the target base station, using a constant handoff threshold (also called handoff margin). However, the fluctuations of signal strength cause ping-pong effect. Some of the main signal strength metrics used to support handoff decisions are: Relative signal strength, Relative signal strength with threshold, Relative signal strength with hysteresis, Relative signal strength with threshold and hysteresis. Figure 6 shows a conventional method of handling of handoff.

The conventional RSS based handoff method selects the Base station (BS) with strongest received signal at all times. All the above techniques initiate handoff before point D which is called "Receiver Threshold". Receiver threshold is the minimum acceptable RSS for call continuation (T2 in figure 1). If RSS is dropped below receiver threshold the ongoing call is dropped. This method is observed many unnecessary handoffs even when the signal strength of the current BS is still at an acceptable level which results poor quality of service (QOS) of the whole system. This problem can be minimized using soft computing techniques for handoff decisions such as fuzzy logic.

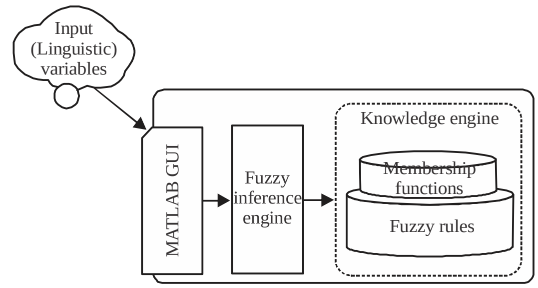

Fig. 7: Conceptual architecture of the FIS

Using fuzzy logic system (Interval type 2): We have adapted and modified T2FLS based on[9] depicted in Fig. 7. Figure 8 illustrate interval type-2 fuzzy model. The components that makes up the interval type-2 Model used in this work are discussed below.

Interval type 2 fuzzification module: this module maps the crisp input (for determining optimized handoff decision) to an interval type-2 intuitionistic fuzzy set using the Gaussian membership function.

Inference engine: This module evaluates the rules in a rule base against interval type-2 intuitionistic fuzzy set gotten from fuzzification to produce another Interval type-2 intuitionistic fuzzy set.

Composition/defuzzification module: The output of interval fuzzy intuitionistic Set-Sugeno is computed by the composition of membership output and non-membership output functions.

Knowledge base: This is a database of rules (rules are generated from expert's knowledge) to be used by the inference engine.

Membership function: This is a mathematical equation that helps the fuzzification module convert crisp input into fuzzy set.

Design architecture: The conceptual system architecture used for this work is based on the fuzzy inference system that basically consist of the MATLAB graphical user interface that provides the platform for defining the fuzzy rules and membership function. The conceptual architecture illustrated below consists of the knowledge engine, knowledge base which is made of the database model and the fuzzy logic model and the user interface. The knowledge engine consists of structured and unstructured data but in this work structured data (Received signal strength, signal strength of target BS, congestion of target BS and handoff latency) are employed in the design of the system. Figure 8 illustrates the conceptual architecture used in this work.

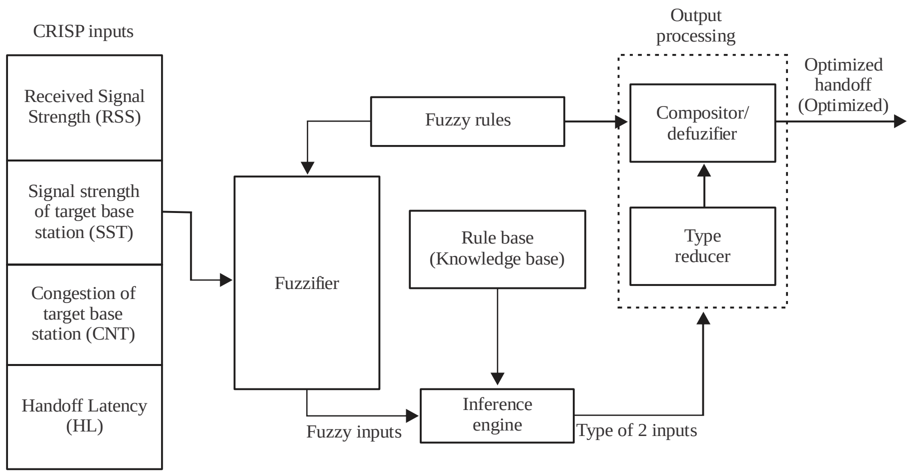

Fig. 8 Interval type-2 model

Design steps: The following are the steps used to design the fuzzy logic of our proposed system:

- Assign linguistic labels RSS, SST, CNT, HL and OHD variables
- Define rules for the rule base and obtain a set of firing rules for each range of inputs based on the linguistic labels and membership functions of input variables
- Convert the membership interval to intuitionistic set for the rules that fired using the equations above
- Obtain the non-zero minimum of the fired rules with their consequence from the composed rules
- Perform inference mechanism using Mamdani's method on the linguistic labels
- Composition of the membership and non-membership with the results (of step 5) to obtain the crisp input

Although Type-2 Fuzzy Logic systems (T2 FLS) have the potential to provide better performance than a type-1 FLS, using an interval type 2 which approach allows us to incorporate uncertainty about the non-membership function into fuzzy set which can be closely related to how the human mind actually reasons. Due to the well-known complexity of using a general T2FLS, a special type of T2FLS is used to compute this work. For a Type 1 Fuzzy Logic Set, we have that A = $\{(x, \mu_A(x))|x\in X, 0\ll\mu_A(x)\leq 1$ (Fig. 9).

To achieve uniform possibilities and accommodate the uncertainties associated with the fuzzy type 1, this paper have adopted Interval type 2 fuzzy logic set for the design.

Interval type 2 fuzzification: Fuzzification is carried out by mapping a numeric input vector $x\in X$ into an IT2IFS which activates the inference engine. This involves feeding the input parameters into the horizontal axis and projecting the upper and lower boundary of membership to determine the degree of membership. These values are then transformed into non-membership functions by simple mathematical equations as shown below. A mathematical representation of these is shown in below: Given $\mu_{\tilde{A}} = (\overline{\mu}, \underline{\mu})$ as the degree of membership for a particular input, then the Interval Fuzzy set is given as follows:

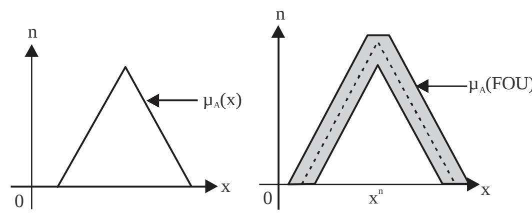

Fig. 9(a, b): Fuzzy logic set, (a) Type 1 fuzzy sets type and (b) 2 Fuzzy sets

$$\mu_{\tilde{A}} = \underline{\mu} \tag{1}$$

$$v_{\tilde{A}} = 1-\overline{\mu} \tag{2}$$

where, $v_{\tilde{A}}$ is the degree of non-membership[15] Fig. 10 shows non membership function of interval type 2 fuzzy system.

We have identified some three factors, as presented in the literatures that we have reviewed, that should be considered before handoff is initiated. We have added a fourth factor to the already established three and these four factors, we have normalized to fuzzy linguistics variable which is defined on both input and output parameter as follows:

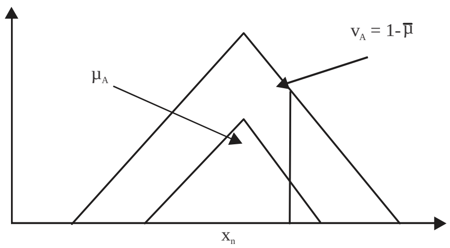

Fig. 10: Interval fuzzy set with membership and non-membership function

- Received Signal Strength (RSS) measured in percentage: {Strong, medium, low}
- Signal strength of target base station (SSN) (%): {Strong, normal, low}
- Congestion of target base station (CNT) (%): {High, normal, low}
- Handoff Latency (HL) measured in seconds: {High, medium, low}

Fuzzy set membership function: The fuzzy logic membership function which is also known as a characteristic function[3] defines the fuzzy set and presents a graphical representation of each participating linguistic variables and linguistic terms[16]. Umoren *et al*.[16] it associates a degree of membership of each of the elements of the domain to the corresponding fuzzy set and illustrates a weighting connection that exist with each of the inputs that are processed, define functional overlap between inputs, and determine their influence on the fuzzy output sets of the final output conclusion[16].

Fuzzy set membership functions can be of any shape or type, but they must satisfy certain constraints as defined below:

- The range of a MF must be in the interval [0, 1]
- For each $x \in X$, $\mu A(x)$ must be unique

The most common forms of MFs are those that are normal and convex. Generally, there are five common shapes of Membership Functions (MF): Triangular MF, Trapezoidal MF, Gaussian MF, Generalized MF and Sigmoidal MF.

For this research, we employ the Gaussian membership function. A Gaussian MF is specified by two parameters s and c as thus:

$$\text{gaussmf}\left(x;\sigma,c\right) = e^{\left(-\left(\frac{x-c}{\sigma}\right)^2\right)} \tag{3}$$

The Gaussian Membership Function (MF) is popular for specifying fuzzy sets in complex systems because it has the advantage of being smooth and differentiable at all points[3].

Using the two point σ, c which it depends on to define a single variable, the Gaussian Membership function is illustrated as:

$$f\left(x\right) = e^{\frac{-1}{2}\left(\frac{x-c}{\sigma}\right)^2},\ \sigma \in [\sigma_1,\ \sigma_2] \text{ and } c \in [c_1,\ c_2] \tag{4}$$

$$\bar{\mu}_{\tilde{A}im}(x_i) = \exp\left(-\frac{xi - c_{im}}{2\bar{\sigma}^2_{2,\,im}}\right),\ \bar{\mu}_{\tilde{A}}(x) = N(c,\ \sigma_2;\ c) \tag{5}$$

$$\underline{\mu}_{\tilde{A}im}(x_i) = \exp\left(-\frac{xi - c_{im}}{2\underline{\sigma}^2_{2,\,im}}\right),\ \underline{\mu}_{\tilde{A}}(x) = N(c,\ \sigma_1;\ c) \tag{6}$$

Here, c is the center (median) of the membership function and s is the width (standard deviation) of the membership function and x is the input vector.

The variables $\bar{\sigma}_{2,\,im}$ and $\bar{\sigma}_{1,\,im}$ are premise parameters that define the degree of membership of each element to the fuzzy set Ã and FOUs of the IT2IFS. MFs are defined and evaluated for all the input and output linguistic variables. IT2F sets are explored in the antecedents' parts and each MF of the antecedent part is represented using an upper and a lower MFs, denoted by $\bar{\mu}\tilde{A}(x)$ and $\underline{\mu}\tilde{A}(x)$ where each node output indicates the lower and upper interval[16]. The Gaussian MF is illustrated in Fig. 11a, b of type1 and 2 fuzzy logic system.

Membership function definition: This study employs the Gaussian MFs owing to smoothness and its ability to concisely accommodate the notation range of the input variable. Individual range of inputs and output variables is outlined to relate with a fuzzy set that has the same name as the range[3]. The work identified four Linguistic input variables and defined three fuzzy sets for these input variables as well as three fuzzy sets for the output variables. Table 4 and 5 present a summary of the linguistic universe of discourse.

Input variables analysis: From the data set obtained from Airtel, we discover trends that determined the handoff success or failure rates which resulted in the number call drops recorded. The data for all the cells and channels indicated that handoff success is largely dependent on the congestion (capacity) of the cells. As long as the resources of the cells or channel are not used up, the handoff success rate is high. From the facts gathered from our data, we have defined two linguistic variables: signal strength of the target base station (SST) and congestion of target base station (CNT), for this, we analyzed records on Call Drops, we have considered records on call drops, handoff failure, handoff success, handoff request and attempts rates, handoff success rates and capacity of the target based station. From the

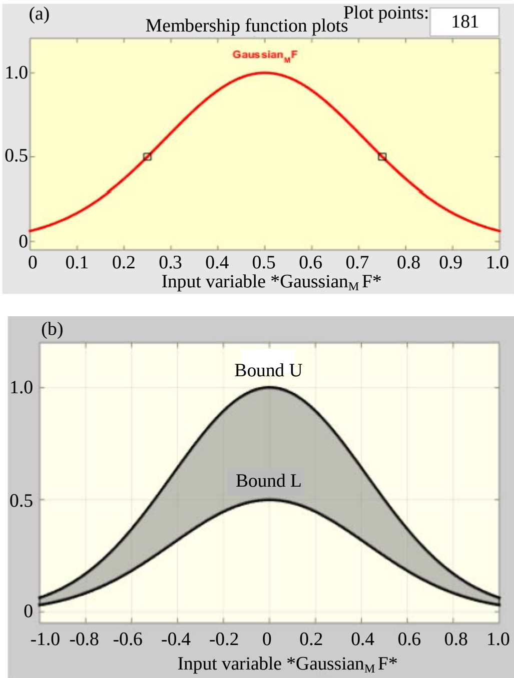

Fig. 11(a, b): (a) Gaussian MF for Type-1 FIS and (b) Gaussian MF for type-2 FIS

Table 5: Input variable

	Received Signal Strength (RSS) (dBm)		
Input V1	Low	High	Symbol
Linguistic term			
Linguistic range			
Strong	-50	-30	STRG
Medium	-70	-50	MD
Weak	-90	-70	WK
Input V2	Signal Strength of Target base station (SST) (dBm)		
Strong	-50	-30	STRG
Medium	-70	-50	MD
Weak	-90	-70	WK
Input V3	Congestion of Target Base Station (CNT) (%)		
High	70	100	HG
Normal	35	70	NOR
Low	0	35	LW
Input V4	Handoff Latency (HL) (milliseconds)		
High	200	300	HG
Normal	100	200	NOR
Low	0	100	LW
OUTPUT	Optimized Handoff Decision (OHD)		
Handoff	0.70	1.00	HO
Wait	0.35	0.70	WT
No handoff	0	0.35	NH

literature reviewed for this work, we have added Network Latency (NL) as one of our linguistic variables.

Conventionally, wireless signal Strength is measured in decibel mill watts (dBm) and represented using negative values. Wireless signal strength is categorized as follows:

Membership and non-membership function evaluation: Membership and non-membership function for Received Signal Strength (RSS):

$$\mu_{WK}(x, [-70,-50], [-90,-70] = e^{\frac{-1}{2}\left(\frac{x-[-70,-50]}{[-90,-70]}\right)^2} = [\bar{\mu}_{\tilde{A}im}, \underline{\mu}] \qquad (7)$$
$$\mu_{WK} = \underline{\mu_{WK}} \text{ and } v_{WK} = 1-\bar{\mu}_w$$

$$\mu_{MD}(, [-70,-50], [-70.-50]) = e^{\frac{-1}{2}\left(\frac{x-[-70,-50]}{[-70,-50]}\right)^2} \qquad (8)$$
$$\mu_{MD} = \underline{\mu_{MD}} \text{ and } v_{MD} = 1-\bar{\mu}_{MD}$$

$$\mu_{STRG}(, [-70,-50], [-50,-30]) = e^{\frac{-1}{2}\left(\frac{x-[-70,-50]}{[-50,-30]}\right)^2} \qquad (9)$$
$$\mu_{STRG} = \underline{\mu_{STRG}} \text{ and } v_{STRG} = 1-\bar{\mu}_{STRG}$$

Membership and non-membership function for Signal Strength of Target Base Station (SST):

$$\mu_{WK}(x, [-70,-50], [-90,-70] = e^{\frac{-1}{2}\left(\frac{x-[-70,-50]}{[-90,-70]}\right)^2} = [\bar{\mu}_{\tilde{A}im}, \underline{\mu}] \qquad (10)$$
$$\mu_{WK} = \underline{\mu_{WK}} \text{ and } v_{WK} = 1-\bar{\mu}_w$$

$$\mu_{MD}(, [-70,-50], [-70.-50]) = e^{\frac{-1}{2}\left(\frac{x-[-70,-50]}{[-70,-50]}\right)^2} \qquad (11)$$
$$\mu_{MD} = \underline{\mu_{MD}} \text{ and } v_{MD} = 1-\bar{\mu}_{MD}$$

$$\mu_{STRG}(, [-70,-50], [-50,-30]) = e^{\frac{-1}{2}\left(\frac{x-[-70,-50]}{[-50,-30]}\right)^2} \qquad (12)$$
$$\mu_{STRG} = \underline{\mu_{STRG}} \text{ and } v_{STRG} = 1-\bar{\mu}_{STRG}$$

Membership and non-membership function for congestion of target base Station (CNT):

$$\mu_{LW}(x, [35, 70], [0, 35] = = e^{\frac{-1}{2}\left(\frac{x-[35,70]}{[35,70}\right)^2} \qquad (13)$$
$$\mu_{L} = \underline{\mu_{LW}} \text{ and } v_{LW} = 1-\bar{\mu}_{LW}$$

$$\mu_{NOR}(x, [35, 70], [35, 70]) = e^{\frac{-1}{2}\left(\frac{x-[35,70]}{[35,70}\right)^2} \qquad (14)$$
$$\mu_{NOR} = \underline{\mu_{NOR}} \text{ and } v_{NOR} = 1-\bar{\mu}_{NOR}$$

$$\mu_{HG}(x, [35, 70], [70, 100]) = e^{\frac{-1}{2}\left(\frac{x-[70,100]}{35,70}\right)^2} \qquad (15)$$
$$\mu_{HG} = \underline{\mu_{HG}} \text{ and } v_{HG} = 1-\bar{\mu}_{HG}$$

Membership and non-membership function for Handoff Latency (HL):

Table 6: Fuzzy inputs universe of discourse

Input variables and their universe of discourse				
RSS (dBm)	SST (dBm)	Congestion (%)	HL (msec)	OHD
[-90, -30]	[-90, -30]	[0, 100]	[0, 300]	[0, 1]

$$\mu_{LW}(x, [0, 100], [0, 100]) = e^{\frac{-1}{2}\left(\frac{x-[0,100]}{[0,100]}\right)^2}$$
$$\mu_{LW} = \underline{\mu_{LW}} \text{ and } v_{LW} = 1-\bar{\mu}_{LW} \tag{16}$$

$$\mu_{NOR}(x, [0, 100], [100, 200]) = e^{\frac{-1}{2}\left(\frac{x-[100,200]}{[0,100]}\right)^2}$$
$$\mu_{NOR} = \underline{\mu_{NOR}} \text{ and } v_{NOR} = 1-\bar{\mu}_{NOR} \tag{17}$$

$$\mu_{STRG}(x, [0, 100], [200, 300]) = e^{\frac{-1}{2}\left(\frac{x-[200,300]}{[0,100]}\right)^2}$$
$$\mu_{STRG} = \underline{\mu_{STRG}} \text{ and } v_{STRG} = 1-\bar{\mu}_{STRG} \tag{18}$$

From Table 6, the linguistic variables have been presented for this work. Each range of input and output variables is defined to associate with a fuzzy set with the same variable as the range. Adopting our variables for RSS and SST from Nkansah-Gyekye[3], the paper defined RSS and SST measured in dBm. The outcome range for output variable as well as the Optimized Handoff Decision (OHD) is defined from 0 to 1 with the highest membership of the sets "No Handoff" and "Handoff" at 0 and 1, respectively. Figure 11a, b shows Graphic Representation of the Membership Functions.

Results evaluation: Result evaluation is an organized and objective assessment of an on-going or completed project. The purpose is to determine the relevance level of achievement of project objectives, development effectiveness, efficiency, impact and sustainability. This research work adopted a fuzzy logic system that consist of a rule viewer that is used for varying of different input in order parameters determine the how the output will varies based on different instigation, Fig. 12 shows a rule viewer for the optimized handoff decision system.

From Fig. 12, the input variables, RSS is set at -60 dBm which portrays a medium signal strength, SST is set at -60 dBm (Medium, signal strength), CNT is set at 50% (Normal congestion) and handoff latency is set at 150 milliseconds (Normal HL) and just as the rules define, our output which is the Optimized Handoff Decision (OHD) is set at 0.5 and according to our defined rules means wait.

By the output wait, the system indicates that the current base station or current cell serving the user or mobile station should hold and search for other base station or other cells within the same base station for better communication resources. The OHD output

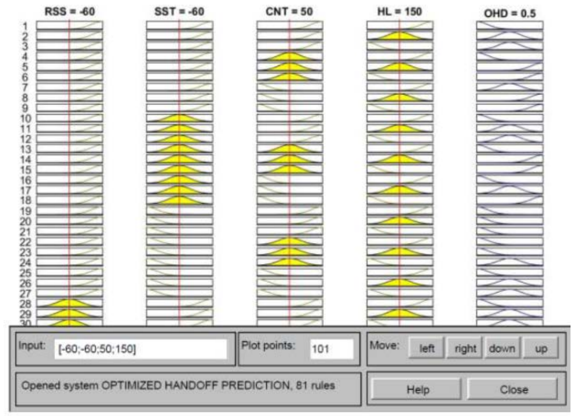

Fig. 12: OHD contributing variables and OHD output

variable varies and indicates Handoff Decisions such "Handoff" or No "Handoff" depending on how the input parameters are varied based on the defined rules.

RESULTS AND DISCUSSION

Membership function plots: Using the linguistic variables which are factors identified to have the potential of influencing the handoff in 4G wireless networks we designed a predictor using the MATLAB IDE. From the linguistic variables, we defined four linguistic variables for the predictor using the Sugeno algorithm. Figure 13a-d illustrate the membership functions showing the ranges and bounds (upper and lower) for each defined variable used in the system[17].

Surface plots: Surface plots in fuzzy logic is use depicts 3D representation of each individual variables how it varies in respect to output. Figure 14a shows a surface plot for RSS (Received Signal Strength) against SST (Signal Strength of the Target), the surface plot of RSS against SST shows that when there is an increase in received signal strength and signal from the target base station, the OHD decision factor will initiate a wait command since there is high signal, so, it will be difficult for handoff to occur and this help solve ping pong effect.

Again Fig. 14b shows a surface plot for RSS (Received Signal Strength) against CNT (Congestion of Target Base Station), the surface plot of RSS against CNT shows that when there is an increase in Received signal strength and the congestion in the Target base station is low, the OHD decision factor will initiate a No handoff command since there is high signal and there is no congestion in the target base station it will be difficult for handoff to occur and this help in seamless connection.

Also Fig. 14c shows a surface plot for RSS (Received Signal Strength) against HL (Handoff Latency), the

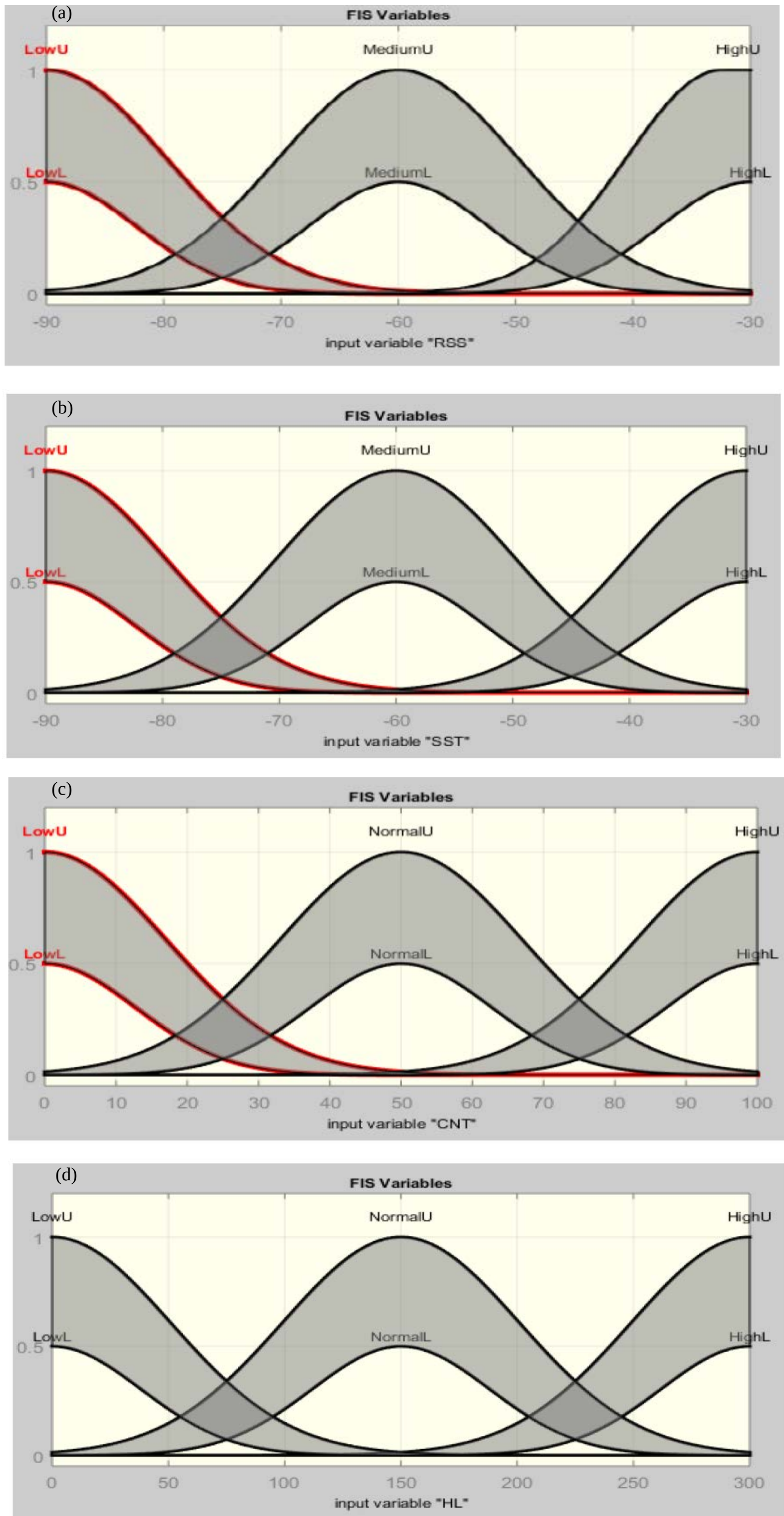

Fig. 13(a-d): (a) Membership function for RSS, (b) Membership function for SST, (c) Membership function for CNT and (d) Membership function for HL

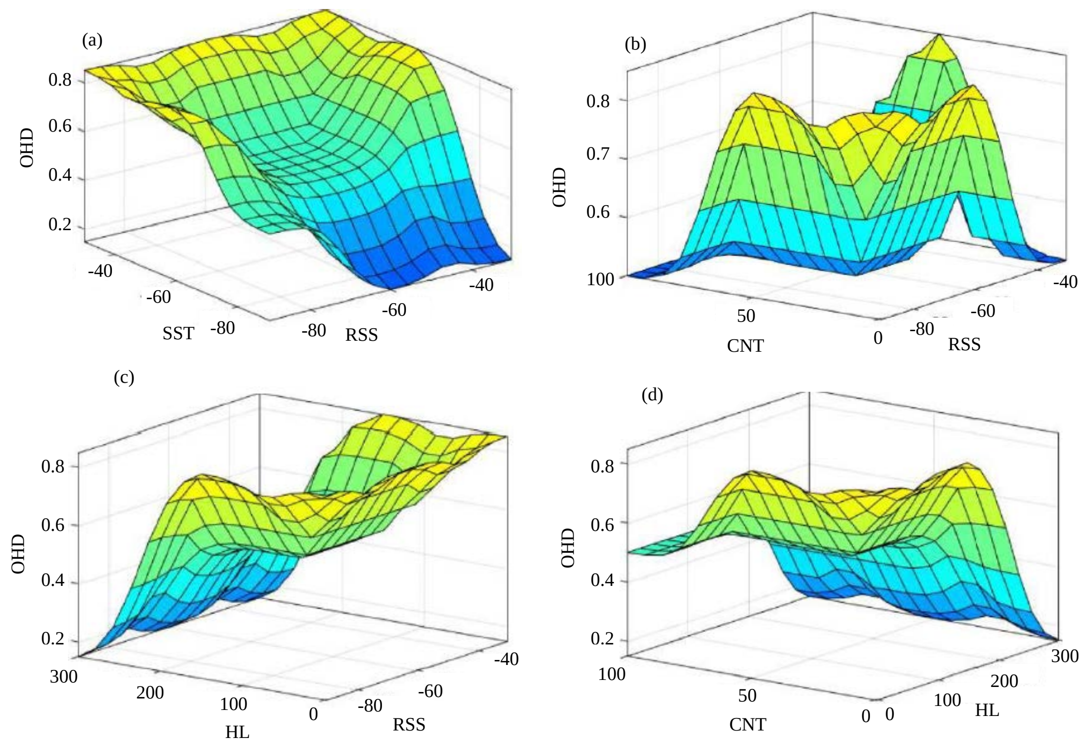

Fig. 14(a-d): (a) Surface plot for SST against RSS, (b) Surface plot for RSS against CNT, (c) Surface plot for SSN against HL and (d) Surface plot for HL against CNT

surface plot of RSS against HL shows that when there is a delay in mobile station trying to move from one particular cell of the base station to another cell and the received signal strength is low, the OHD decision factor will initiate a " Handoff" command since the Signal is low and the latency is low, it will handoff to the target base station.

Furthermore, Fig. 14d shows a surface plot for HL (Handoff Latency) against CNT (Congestion), the surface plot of HL against CNT shows that when there is a delay in mobile station trying to move from one particular cell of the base station to another cell and the congestion in a target cell is high, the OHD decision factor will initiate a "Wait" command since the CNT in the target base station is high and the latency is low, it will wait for the cell to be free up before handoff to the target base station[18].

Comparative performance analysis of results: This research work develops a FL Model for the evaluation of handoff prediction in 4G wireless network. Four linguistic variables (Received signal strength, signal of the target base station, congestion of the target base station and handoff latency) are used as input parameters while the optimized handoff decision is the output parameter. The results are evaluated using both Triangular and Gaussian MFs. Below shows the tested inputs handoff parameters with their expected OHD. In order to test the output accuracy of our model, combinations of samples of the input parameters are taken and fed into the evaluation system and the result is presented in Table 7 it is observed that the output OHD values are a reflection of the input parameters based on the fuzzy system rules which are built considering the network handoffs. We calculate the overall OHD of the 4G from the output OHD vector of the fuzzy system. This is achieved by calculating the average and the standard deviation for the application as shown in Table 8 and 9.

The graph of fuzzy control of OHD results based on triangular MF is shown in Fig. 15a. Figure 15b presents the graph of fuzzy control of OHD results based on Gaussian MF. Figure 15 compares the performance of fuzzy control of OHD in 4G wireless network based on Triangular and Gaussian MFs. Results in Fig. 15 shows that, at input condition 11, where we have weak RSS (Received Signal Strength) of -90 dBm, weak SST(Signal Strength of Target Base station) of -90 dBm and high CNT (congestion of target base station) of 100% and high HL (Handoff Latency) of 300 (msec), low OHD is achieved with a low performance of 13% possibility based on triangular MF which means no handoff and low OHD with approximately 15% possibility when Gaussian MF is applied which means no handoff. This result shows

Table 7: Tested input handoff parameter with their expected output

Tested input handoff parameter with their expected output

Inputs				Output			
RSS (dbm)	SST (dBm)	CNT (%)	HL (msec)	Evaluated OHD triangular	Evaluated OHD triangular	Evaluated OHD Gaussian	OHD level Gaussian
-60	-60	50	150	0.5	WT	0.5	WT
-38	-78	45	236	0.164	NH	0.4	WT
-79	-39	100	139	0.5	WT	0.5	WT
-45	-30	78	90	0.5	WT	0.56	WT
-79	-59	34	120	0.806	HO	0.678	HO
-55	-67	86	56	0.5	WT	0.505	WT
-89	-78	23	97	0.806	HO	0.44	WT
-56	-49	79	145	0.5	WT	0.529	WT
-46	-30	35	300	0.5	WT	0.326	NH
-49	-67	24	120	0.5	WT	0.58	WT
-90	-90	100	300	0.13	NH	0.15	NH
-30	-38	56	156	0.5	WT	0.809	HO
-30	-38	37.1	141	0.5	WT	0.755	HO

Table 8: Statistics of handoff prediction with their results

Statistics of handoff prediction

	Optimized handoff triangular MF			Optimized handoff Guassian MF		
Variables	NH	WT	HO	NH	WT	HO
Mean (%)	37.20	50.00	80.60	32.60	51.43	74.73
SD (%)	34.22	0.00	0.00	12.45	4.28	6.58

Table 9: Overall statistics of optimized handoff prediction

Overall statistics of optimized handoff prediction

Variables	Triangular MF	Gaussian MF
Mean (%)	55.93	52.92
SD (%)	20	4

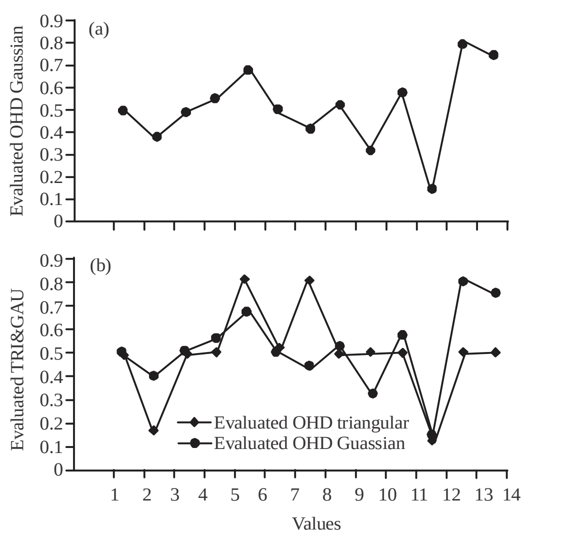

Fig. 15(a, b): (a) OHD level Guassian and (b) OHD level TRI & GAU

the effect of low signal transmission within a base station and also the gaussian membership function outperforms triangular membership function by 2%. Again, at input condition 5, we select weak RSS of -79 dBm, medium SST of -59 dBm and Low CNT of 34 msec and normal HL of 120%. We achieve OHD with approximately 81% possibility using triangular MF and OHD of 67.8% possibility with Gaussian MF. This result indicates a fair system performance with the level of quality of service. Moreover, at input condition 10, we select strong RSS of -49 dBm, medium SST of -67 dBm and low CNT of 24 msec and normal HL of 120 %. We achieve OHD which is WT (handoff) with approximately 50% possibility using triangular MF and OHD of 50.8% possibility with Gaussian MF, this result excellent system performance with service quality. However, it is observed that the input conditions have varying level of influences on the output based on the two membership functions used, in particular it can be seen that Gaussian membership function helps eliminate unnecessary handoff, unlike the triangular membership function[19].

CONCLUSION

Generally, the demand for better and seamless wireless communication is a basic requirement in today's fast paced world of Information and Communication Technology (ICT). Information has become the highest traded commodity in our world today. Modern businesses, scientific exploration institutions, governments and private individuals depend largely on daily information that must be accessed in real time. Most times this information needs to be access at different coverage and geographical areas with this constant movement from one coverage area to another arises the need for prompt and optimal handoff of communication service resources, to meet this need, demand is placed for the development of a more efficient Vertical Handoff Decision Algorithms (VHDAs). Progressively, various handoff decision algorithm has been proposed progressively but they have been numerous challenges encounter during handoff initiation such as the number of parameters use for handoff decision, approaches, employed in handoff decision and the ability to handle uncertainties especially when face with a lot of data associated in handoff, this challenges can lead to call drops, congestion and ping pong effects, that collectively give rise to un-seamless connection. The demand for Quality of Service (QoS) provisioning, seamless connection and handling uncertainties, call drops as well as congestion control required development of an optimal Vertical Handoff Decision Algorithms (VHDAs) to address these conditions. This research paper adopts computational intelligence approach using type 2 fuzzy knowledge based system with capacity of handling uncertainties. The work is highly proficient for optimal handoff decision algorithm to aid shrink the problems experienced by network providers in Nigeria such as ping pong effect and call drops issues towards efficient service delivery[20].

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REFERENCES

01. Tso, F.P., J. Teng, W. Jia and D. Xuan, 2010. Mobility: A double-edged sword for HSPA networks; a large-scale test on Hong Kong mobile HSPA networks. Proceedings of the 11th ACM International Symposium on Mobile Ad Hoc Networking and Computing, September 20-24, 2010, ACM, Chicago, Illinois, pp: 81-90.
02. Jhamta, S.K., 2013. 4G user acceptance technology prediction using grey prediction algorithm. Int. J. Comput. Sci. Eng. Technol., 4: 1377-1382.
03. Nkansah-Gyekye, Y., 2010. An intelligent vertical handoff decision algorithm in next generation wireless networks. Ph.D. Thesis, University of the Western Cape, Cape Town, South Africa.
04. Javed, U., D. Han, R. Caceres, J. Pang, S. Seshan and A. Varshavsky, 2012. Predicting handoffs in 3G networks. ACM SIGOPS Operating Syst. Rev., 45: 65-70.
05. Sati, D.C., 2012. Application of soft computing techniques for handoff management in wireless cellular networks. Int. J. Eng. Manage. Res. (IJEMR.), 2: 1-6.
06. Shen, Y., N. Xi, Q. Pei, J. Ma and Y. Niu, 2012. The wireless vertical handoff decision algorithm with parameter prediction. Proceedings of the 2012 4th International Conference on Intelligent Networking and Collaborative Systems, September 19-21, 2012, IEEE, Bucharest, Romania, pp: 185-192.
07. Miyim, A.M., M. Ismail, R. Nordin and M.T. Ismail, 2013. Technique for cross-layer vertical handover prediction in 4G wireless networks. Procedia Technol., 11: 114-121.
08. Umoren, I. and O. Owolabi, 2014. Handover manageability and performance modeling in mobile communications networks. Comput. Inf. Syst. Dev. Inf. Allied Res. J., 5: 27-42.
09. Mendel, J.M., 2007. Advances in type-2 fuzzy sets and systems. Inf. Sci., 177: 84-110.
10. Madaan, J. and I. Kashyap, 2016. Vertical handoff decision algorithm based on PRSS and dwell time. Int. J. Comput. Network Inf. Secur., 8: 31-42.
11. Vallati, C., E. Mingozzi and C. Benedetto, 2016. Efficient handoff based on link quality prediction for video streaming in urban transport systems. Wirel. Commun. Mob. Comput., 16: 2298-2314.
12. Qiao, Y., Y. Cheng, J. Yang, J. Liu and N. Kato, 2016. A mobility analytical framework for big mobile data in densely populated area. IEEE. Trans. Veh. Technol., 66: 1443-1455.
13. Sasikala, E., R. Radha, S. Sharanya and M. Gayathri, 2018. Artificial neural networks with vertical handoff prediction based on user behaviour. Pak. J. Biotechnol., 15: 89-93.
14. Misra, Y. and H.R. Kamath, 2012. A review on application of fuzzy logic in increasing of efficiency of industrial process. Int. J. Latest Trends Eng. Technol. (IJLTET.), 1: 109-113.
15. Naim, S. and H. Hagras, 2011. Type-2 fuzzy logic in multi-criteria group decision making with intuitionistic evaluation. Proceedings of the 11th Annual Workshop on Computational Intelligence, September 7-9, 2011, The University of Manchester, Manchester, England, pp: 1-6.
16. Umoren, I., K. Udonyah and E. Isong, 2019. A computational intelligence framework for length of stay prediction in emergency healthcare services department. Proceedings of the 2019 14th International Conference on Computer Science & Education (ICCSE), August 19-21, 2019, IEEE, Toronto, Canada, pp: 539-549.

17. Garg1, D. and D. Nagpal, 2016. Vehicular handover approach based on LTE in urban road scenario. Int. J. Res. Applied Sci. Eng. Technol., 4: 862-869.
18. Eyoh, I., R. John and G. De Maere, 2016. Interval type-2 intuitionistic fuzzy logic system for non-linear system prediction. Proceedings of the 2016 IEEE International Conference on Systems, Man and Cybernetics (SMC), October 9-12, 2016, IEEE, Budapest, Hungary, pp: 001063-001068.
19. Zhu, S., S. Setia, S. Jajodia and P. Ning, 2004. An interleaved hop-by-hop authentication scheme for filtering of injected false data in sensor networks. Proceedings of the IEEE Symposium on Security and Privacy, May 12, 2004, IEEE, Berkeley, California, pp: 259-271.
20. Lunden, P., J. Aijanen, K. Aho and T. Ristaniemi, 2008. Performance of VoIP over HSDPA in mobility scenarios. Proceedings of the VTC Spring 2008-IEEE Vehicular Technology Conference, May 11-14, 2008, IEEE, Singapore, pp: 2046-2050.