Dynamic Load Balancing for Congestion Avoidance using Adaptive Neuro-Fuzzy Inference System in Mobile Communication Network

Original Scientific Paper

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Abstract *– Network congestion is one of the key challenges to mobile communication services. This is because of rapid and constant growth in the mobile subscriber base that has led to an increase in network traffic. The more the network traffic the more economic opportunity from the business perspective for the operators and the challenges it poses on the network. If not followed by network capacity expansion it will defiantly pose a serious network issue like network congestion that leads to call drop and poor Quality of Service (QoS). Many research works adopted handover mechanism as a means of reducing congestion in a network. However, the decision on when to initiate a handover, which cell to receive the Mobile Station (MS) and how to ensure that the QoS requirements are maintained are the paramount research questions that must be resolved. Therefore, a handover process using soft computing in the Adaptive Neuro-Fuzzy Inference System (ANFIS) to ensure balanced traffic load distribution in-network and reduce the probability of congestion is proposed. The study allows simultaneous evaluation of three major network parameters Received Signal Strength (RSS), Received Signal Quality (RxQual) and network traffic using ANFIS to improve system performance. The results show that when the Hysteresis value approaches 6 the handover processes are triggered. The hysteresis value of the concerned MS with neighbouring cells is considered to determine the most suitable cell to handover. This work will be able to achieve dynamic load balancing, congestion avoidance and avoided the 'ping pong' effect that is often an issue with handover with less computation. At the end customer satisfaction will be achieve Quality of experience (QoE).*

Keywords*: ANFIS, GSM, handover mechanism, mobile communication, network congestion*

1. INTRODUCTION

The GSM network, (second generation of mobile communication), over the years has become the bedrock of mobile communication. The GSM network has remained influential in the mobile communication world despite other technological upgrades like Wideband Code Division Multiple Access (WCDMA), Long Term Evolution (LTE) and others. The GSM has been the basics by which other technologies were developed. The success achieved by this system has led to greater commercialization of the mobile communication system and the gush in the number of subscribers scrambling for the limited network resources that must be shared among numerous users. If these hardware system resources and exchange of information are no longer sufficient to handle the available network users it leads to network congestion, call drop, handover failure, network failure etc [1, 2, 3].

Network congestion is one major factor among Received Signal Strength (RSS), coverage area, Received Signal Quality (RxQual), Signal to Noise Ratio (SNR), network failure, and insufficient network infrastructure that lead to call drop. In the rural areas, the call drop mainly is as a result of lack of network coverage while in the urban area it is due to lack of enough network infrastructures to march the ever-increasing network traffic [4, 5]. However, this increase in network traffic has placed a serious burden on the limited network resources. The more the network traffic the more economic opportunity from the business perspective for the network operators and the challenges it poses on technology. This rapid and constant growth in subscriber base if not well followed by network capacity expansion will defiantly pose serious network issues. The main technical challenges due to the increase in network traffic are; the limited network resources, energy utilization and equipment cost [6].

There are many investigations on how to improve the efficiency and effectiveness of the limited network resources. This must be achieved in such a way that the QoS is not compromised. Network expansion is one method that can easily achieve this at the expense of cost. Network operators usually expand their capacity if there are significant increases in the subscriber base to march the expected capacity upgrade and it must be business-oriented from the economic perspective. This usually includes increasing the number of Base Stations (BS) or cell splitting techniques. Cell splitting is a technique of subdividing a congested cell (usually large – macro and micro-cells) into smaller cells (femtocells). Cell splitting is also a technique of combating network congestion. Each cell should have its base station at a reduced antenna height and transmitter power [7, 8, 9, 10]. Although, in cell splitting, the individual cell has a reduced channel as compared to the original large cell, its ability to increase capacity is by a multiplicity of cells separated by geographical distance to utilise the same channel at the same time with minimal or no interference from each other. The new cells have a smaller coverage area and less transmitter power. Therefore, the measure of capacity increase is dependent on the number of channels per unit area [11].

The issues with cell splitting are; (1) the frequency allocation will be repeated which will require the neighbouring cell to be recalibrated to avoid interference; (2) the handover rate will defiantly increase as it is more likely MS will cross to other cells' coverage area more often due to reduction in coverage radius; and (3) it will also lead to increase in energy consumption of the BS. The network topology and the country's law on BS installation can pose a limit to cell splitting [6, 9, 11].

Another technique of reducing the BS power consumption and network congestion for efficient network resource utilization is handover processes. The process of moving from one BS to another, while a call is ongoing, is called handover. Various handover types, techniques and processes are explained in much literature [12, 13, 14, 15].The MS during handover request that a new Traffic Channel (TCH) be assigned to it. The handover is complete if the MS is assigned a new TCH from another BS. If no TCH is available from the neighbouring BS, the handover is blocked which may lead to a call drop. The blocking of the ongoing call from handover is called handover blocking. This handover is used to maximize spectrum utilization of the system. This is initiated when the signal of the serving cell has dropped below the one from the neighbouring cells. Apart from this reason, a handover can also be initiated to balance the network load or load sharing [16, 17].

The decision on when to initiate a handover, which cell to receive the MS and ensure the QoS requirements are maintained are the paramount research questions that must be resolved. Many research works have considered different cell metrics for handover decision which includes SNR, Path-Loss (PL), the distance between the mobile station and the BS, Mobile Velocity (MV), RSS, traffic load and others. The traditional technique is a single criteria handover decision that compares the RSS from the current cell with that from the neighbouring cells. The single criteria do not put into consideration other cell parameters that could affect the handover. The issue with this technique is that the propagation related RSS fluctuation can result in a "ping pong" effect. It is not all neighbouring cells that can accept a call due to congestion or traffic load on the cell which may lead to handover blocking and eventual call drop [18]. However, it can be initiated as a load balancing to easy traffic on the congested cell to cell with less traffic load, hence easing congestion in the network in the process. Therefore, it is important to put into perspective other important cell metrics (RSS, RxQual and number free channel – traffic load) with a technique that can handle imprecision in some metrics for effective and efficient handover.

The main aim of this work is to develop a handover mechanism for dynamic load balancing using soft computing in ANFIS. The study allows simultaneous evaluation of several significant cell metrics to improve system performance in the handover procedure. This system will consider the traffic load (using several free channels) at the serving and neighbouring cell as well as another key handover parameter in RSS and RxQual. Moreover, in ANFIS, the need for human instinct in exploiting the tolerance of imprecision and in handling nonlinear problems cannot be overstressed. A proper handover algorithm should ensure balanced traffic load distribution in-network and reduce the probability of congestion. The "ping pong" effect will be eliminated due to multiple parameters evaluation in the handover decision. The system when implemented will also ensure reduction in energy consumption, balanced traffic load and reduced traffic congestion in the network without any intrusive network.

2. REVIEW OF RELATED WORKS

The following research works on congestion control through handover management in cellular networks have been reported in journal and conference publications.

An adaptive hysteresis based horizontal handoff algorithm for the GSM network was proposed in [19]. The authors developed a model to adaptively determine the hysteresis value (within the range of 20 to 0dB) using two variables; the distance between the MS and the serving BS and the radius of the BS coverage. The handover process is activated once the RSS from any neighbouring BS is more than the RSS from the serving BS plus the hysteresis value. This technique considered primarily the RSS and adjusted the handover hysteresis margin using the separation distance. The result analysis showed that it performed better than the traditional handover technique. However, it has been observed that the technique ignored the traffics on the neighbouring base stations. A handover to a BS with traffic congestion could lead to handover blocking or call drop.

In this paper [20], an algorithm for automatic off-line optimization of handover margins in GSM/General Packet Radio Services (GPRS) networks is proposed. The author adopted a simple load sharing rule on an adjacency basis to deal with spatial load variability in a mobile network. It also applied the discrimination of several periods using differentiated parameters setting to cope with variations of traffics during the day. The variation in handover margin is relative to the difference in blocking probability between the serving BS and the adjacent BSs without consideration to the instantaneous traffics. The analysis achieved a good result as it recorded a reduced call drop rate and were able to carry more traffic even though call quality deteriorated. There is a need to factor into the optimization algorithm one of the key performance indicators to improve the quality of calls.

In [21], an adaptive hysteresis margin and load balancing to manage congestion in a heterogeneous network was proposed. The authors also investigated major challenges of hysteresis margins and load balancing in a mobile network. The author used quality indicators in SNR to vary the handover margins (HM) for the handover technique. For the mobility load balancing, the cell individual offset (CIO) value and the traffic loads on the serving and new BS were used for the load balancing decision. The result analysis showed that the schemes improved the handover success rate and performed well. However, the techniques are computationally intensive.

The use of a soft computing technique that is based on the hybrid of Neural Network (NN) and Fuzzy Logic (FL) for load balancing in mobile communication was proposed in [22]. An artificial intelligence (AI) based on three calculated parameters; the virtual load of the serving BS, the number of unsatisfied users in the serving BS and the overall load state of the target BS, were used to determine the handover hysteresis margin adaptively. The simulation results appear to have a good performance, although some computations were unnecessary. The number of unsatisfied users is the network-wide parameter that should rather be substituted with SNR or still the BS throughput as a performance indicator.

In [23], a handoff decision in the cellular mobile system using NN, direct retry and load sharing technique was proposed. The parameters considered for the best technique are the RSS and traffic intensity of the BS. The NN technique outperformed the other two techniques. The issue with the algorithm is that it automatically blocks the handover of calls with RSS below -100dB. This might lead to a call drop as the RSS deteriorate further below the MS receiver sensitivity.

In [24], a NN approach to GSM traffic congestion prediction was proposed. The authors used real network traffic data to train NN to predict the probability of congestion in a BS. The result of the trained model when tested with new traffic data came close to a real network situation. A very good prediction technique applied but did not offer any solution to congestion management in the network.

In [25], the authors approached congestion management by developing a traffic class prioritization algorithm. The algorithm classified the real network traffic based on the order of importance. Priority Queuing (PQ), Weighted Fair Queuing (WFQ) and the hybrid of the two were developed. The performance evaluation was done based on the traffic served per class. The algorithms achieved a good classification and priority given to the traffic with higher priority. The prioritization algorithm ensures that instead of dropping less priority traffic that the less important traffic should be dropped. How that affect congestion is not stated. A hybrid system of the developed algorithm and handover mechanism for load balancing to achieve better congestion management performance is recommended.

An automatic handover control for distributed load balancing in mobile communication networks was proposed in [26]. The algorithm considered only the available channel in a BS in achieving its load balancing. The algorithm adopted a round-robin queuing method for calls waiting to be assigned a channel based on quantum and time slice variables. The performance evaluation was based on the call blocking rate. It performed very well when compared with a normal system without load balancing. The algorithm was applied regardless of any QoS parameters like RSS; SNR and others.

In [17], the work proposed a fuzzy logic multiple parameter handover algorithms based on RSS, traffic load, SNR and Path Loss (PL) of the serving BS for load balancing. The output of the fuzzy inference system is a handover decision based on the values of the four inputs parameters. This technique cannot be applied in determining the suitability of the target base stations because the requesting MS don't have the SNR and PL parameters used for the algorithm. MS can only measure these parameters from the serving BS. We recommend that the two parameters be removed as an input to the fuzzy controller. The system will perform better if NN is applied to optimize the system.

Some research works proposed techniques for load balancing in 3GPP LTE. An algorithm was developed in [27] to find the appropriate handoff offset value between the congested BS and a potential target BS. In this technique, each eNodeB accumulates measured RSS report from the served MS and the same resource reports from neighbouring BS. If the traffic load of the selected BS exceeds a pre-set threshold, it commences transferring the MS to less loaded target BS. This handover procedure goes on pending when the traffic load of the sending BS becomes less than the overload threshold, or the traffic load of the target eNodeB surpasses a particular threshold. The algorithms are based on hard (traditional) computing which does not exploit the tolerance for exactness of the load balancing technique.

This research seeks to provide a handover mechanism that will utilize multiple criteria to provide congestion management in most mobile communication. The ANFIS will be developed to handle load balancing in the network through a handover mechanism. ANFIS is chosen as the best technique to handle the imprecision in RSS and its ability to handle the on-linear problem. It is important to make a handover decision based on RSS, RxQual and traffic loads in BS as the three major metrics. Relying only on RSS might result in handing over to a network already congested thereby creating an imbalance in the network. Most of the reviewed works depend on one or two-parameter(s) to take handover decisions while a traditional method uses only the RSS.

3. SYSTEM AND PARAMETERS MODELLING

The proposed technique uses five-layer ANFIS with three inputs; –(1) the RSS; (2) the RxQual; and (3) the number of free channels. The problem of network congestion remains a critical issue due to the ever-growing size, speed and demand of mobile networks these days. Steps to congestion avoidance through uneven load distribution in cell cluster using handover process are:

- Locate the most congested Base Transceiver Station (BTS) within a cluster.
- Check the status of the BTS neighbours based on the following parameters; RSS, RxQual and the number of available channels
- Determine the Hysteresis value of the MS using the ANFIS techniques
- Initiate a handover process if the hysteresis value is above the pre-determine hysteresis value called handover hysteresis value (HHV).

Therefore, by determining the hysteresis value of mobile users of a congested BTS within a cluster, it is possible to move users with handover hysteresis value to BTSs with lesser traffic loads or better hysteresis value. Aside from locating a congested BTS, the handover mechanism can also be triggered once an MS reaches hysteresis value irrespective of the traffic load on the serving BTS. This ensures the QoS is not degraded as a result of the insufficient value of the parameters under consideration. This approach can be called dynamic load balancing which leads to more efficient radio resource utilisation [28]

For each channel, RxQual is measured, averaged without including the measurement during the previous period on that channel over the measurement period of length of the slow-associated control channel (SACCH) multi-frame. When the RxQual is accessed over the full-set and sub-set of the frame, eight levels of quality (0 – 7) are defined [29, 30]. This reflects the quality of voice connection where 0 is the best and 7 the worst. Each of these values matches up to an estimated number of bit errors in a burst. Therefore, it is measured based on Bit Error Rate (BER) with an acceptable value of "0 to 5" in a commercial mobile network [31]. RxQual is a part of the network measurement reports (NMR) and a measured metric that indicates the quality of the downlink model.

The RSS may be adopted as a measure in the radio frequency power control and handover process. The Root-Mean-Square (RMS) RSSI at the receiver input shall be measured by the MS and the BSS over a full range of -110dBm to -48dBm with a fixed accuracy of ± 4dB from -110dBm to -70dBm under normal conditions and ± 6dB under both normal and severe conditions over the full range. The RMS RSS at the receiver input shall be measured by MS above -48dBm to -38dBm with a fixed accuracy of ± 9dB under both normal and severe conditions [29],[30]. Hence, the range of RSS levels considered for this research is -120dBm to -30dBm.

It is possible to have excellent RSSI but no connection due to poor RxQual and vice versa. Both QoS parameters must be considered for a successful connection between the receiver and the transmitter. A variance of both quality parameters is significant for connection as a particular measurement characterize one moment which can vary radically over a short time. A stable connection requires consistency of both parameters.

Many factors influence the RSS and RxQual, including but not limited to;

- BTS load
- MS proximity to BTS
- Signal going through a mobile repeater
- Interference from competing signal
- Physical barriers (building, mountain, trees etc)
- Weather condition

Even if you have an excellent RSSI, you may not achieve maximum network speed due to the high volume of mobile users on the BTS (BTS load). The BTS may be congested leading to call drop or degradation in the network connection. Thus, the number of free channels is considered as a parameter for use in scheduling or handover mechanisms for mobility load balancing.

Table 1 is used to generate input/out data for ANFIS modelling using MATLAB. The ranges of these parameters are mostly standards which are classified into four linguistic variables such as 'insufficient', 'medium', 'Good' and 'Strong' to indicate the strengths of these input data for this work [32], [33]. It is a matter of necessity to generate an ideal input/output relationship data since we don't have real measured network input data with corresponding output data (Hysteresis) to use the model and train the ANFIS. Also generated is input/output data sufficiently different from the training data set for model validation and testing. The generated data completely represents the features of the data expected to get from a real cellular network if implemented. Based on the three input data with four linguistic variables, there can only be 64 possible permutations each with a distinct hysteresis value as shown in Table 2. The range of the hysteresis value is 0 to 10. The MATLAB simulated training data in table 3 is generated using Table 1 and 2.

Table 1. Data classification and FIS variables

RSSI(dBm)	RxQual	Free Channel	FIS Variables
RSSI<= -110	5<=RxQual<=7	0<=FC<=200	**Insufficient**
-109<=RSSI<=-91	3<=RxQual<=4	201<=FC<=450	**Medium**
-90<=RSSI<=-75	2<=RxQual<3	451<=FC<=700	**Good**
-74<=RSSI<=-30	0<=RxQual<=1	701<=FC<=1000	**Strong**

Table 2. Sample of 64 permutations for 3 inputs data with 4 linguistic variables

1.	If (RSS is Insuff) and (RxQUAL is Insuff) and (FChannel is Insuff) then (hysteresis is 10)
2.	If (RSS is Insuff) and (RxQUAL is Insuff) and (FChannel is Medium) then (hysteresis is 9.84375)
3.	If (RSS is Insuff) and (RxQUAL is Insuff) and (FChannel is Good) then (hysteresis is 9.375)
4.	If (RSS is Insuff) and (RxQUAL is Insuff) and (FChannel is Strong) then (hysteresis is 8.90625)
5.	If (RSS is Insuff) and (RxQUAL is Medium) and (FChannel is Insuff) then (hysteresis is 9.53125)
6.	If (RSS is Insuff) and (RxQUAL is Medium) and (FChannel is Medium) then (hysteresis is 8.28125)
7.	If (RSS is Insuff) and (RxQUAL is Medium) and (FChannel is Good) then (hysteresis is 7.65625)
8.	If (RSS is Insuff) and (RxQUAL is Medium) and (FChannel is Strong) then (hysteresis is 6.71875)
9.	If (RSS is Insuff) and (RxQUAL is Good) and (FChannel is Insuff) then (hysteresis is 9.0625)
10.	If (RSS is Insuff) and (RxQUAL is Good) and (FChannel is Medium) then (hysteresis is 7.5)
.....	.....
63	If (RSS is Strong) and (RxQUAL is Strong) and (FChannel is Good) then (hysteresis is 0.3125)
64	If (RSS is Strong) and (RxQUAL is Strong) and (FChannel is Strong) then (hysteresis is 0.15625)

Table 3. Sample of 1200 simulated training data

RSS (dBm)	RxQUAL	Free Chanel	Hysteresis
-65	5	815	4.6857
-57	4	505	2.5
-104	6	665	7.9688
-102	6	793	7.0313
-116	5	895	8.9063
-122	3	846	6.7188
-57	7	127	8.75
-99	4	276	4.2188
-92	2	996	2.3438
-37	1	190	4.375
-49	2	754	0.625
-64	2	114	5

4. ANFIS MODEL DEVELOPMENT

ANFIS is a hybrid intelligence system that comprises the artificial neural network (ANN) and Fuzzy Inference System (FIS). The ANFIS was first proposed in [34]. The ANN maps input space to an output space using a set of layered processing units called neurons that are interconnected by synaptic junction in parallel [35]. This is developed by passing raw data from an input layer through to its output layer continuously to produce ANFIS output which is compared with the target output. This computation using the optimization procedure expressed as the sum of the squared difference between the ANFIS output and the target output is used to adapt the synaptic connection (weight) so that ANFIS can learn the pattern of the input data (ie the learning process of ANFIS). The ANFIS in this process learns the pattern of information presented to the network and can predict the output of a new set of raw data presented to it after training [36, 37]. FISs are based on fuzzy logic, the fuzzy rule which can be viewed as computing with the word rather than the numbers and fuzzy reasoning or linguistic variable whose membership is a matter of degree. The use of word computing can be likened to human perception and exploit the tolerance for imprecise raw data using linguistic variables. The integration of the learning ability of ANN and knowledge representation for making a deduction from observation in FIS to form ANFIS offers a superior technique that can dynamically model load balancing through handover mechanism [36, 38]. The ANFIS structure adopted for this work is a 5 layered feed-forward neural network and is implemented as a Takagi and Sugeno (TKS) fuzzy inference system which is more compact and computationally efficient than the Mamdani system [39]. To get the system output, a constant expression is added to the linear combination of the input variables for each rule while the final output is the weighted average. The system is a five-layered architecture with many nodes in each layer. For simplicity, the ANFIS structure is considered with two inputs x and y and output z for the TKS model. The common rule set of if-then rules is as follow;

If x is A1 and y is B1, then f1 = p1x + q1y + r1

If x is A2 and y is B2, then f2 = p2x + q2y + r2

The nodes in the first layer are used to generate membership grades of input variables. Adopted for node function implementation in this work is the Gaussian membership function that varies between 0 and 1.

$$o_{1,i}=\mu A_i(x),\ \text{for } i=1,2$$

$$o_{1,i}=\mu B_{i-2}(y),\ \text{for } i=3,4$$

$$\mu A(x) = \frac{1}{1+x\left|\frac{x-c_i}{a_i}\right|^{2b}} \quad (1)$$

Where x and y are inputs to node I, A and B are linguistic variables (insufficient, low, medium and strong), $o_{1,i}$ and μA_i (x) (orμB_{i-2} (y)) is ith node output and MF of x (or y) in the linguistic variable A_i (or B_{i-2}). The MF shape is determined by the parameter set (a_i,b_i,c_i). The parameters of this layer are called premises parameters. The layer two nodes determine the firing strength of the rule. This is the fixed node in nature whose output is the product of membership functions.

$$w_i= O_{2,1} = \mu A_i(x)\mu B_i(y),i=1,2 \quad (2)$$

Layer three comprises fixed nodes used to determine the ratio of the ith rule's firing strength to the total number of the firing strengths whose output is referred to as normalised firing strength.

$$O_{3,i} = \overline{w} = \frac{w_i}{w_1+w_2}, i = 1,2 \quad (3)$$

Where w_i and $\overline{w}$ are called firing strength and normalised firing strength respectively.

The mapping of the output membership functions (MF) is carried out at the fourth layer (also called the defuzzification layer) by its adaptive nodes

$$\overline{w}_i f_i = O_{4,i} = \overline{w}_i(pix + qiy + ri) \quad (4)$$

Where { pix + qiy + ri} is the parameter set of the layer four adaptive nodes and whose output resulting from the inference of the rules is called consequent parameters.

Lastly, the fifth layer consists of fixed nodes that determine the final/ANFIS output through weighted average.

$$O_{5,i} = \textstyle\sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (5)$$

4.1 HYBRID LEARNING ALGORITHM

The essence of learning in ANFIS is to tune all the adjustable parameters to ensure there are minimal errors between the ANFIS output and the target output. Here, the efficiency of the training is improved by using a combination of the Least-Square Algorithm (LSA) and Back Propagation Gradient Descent Algorithm (BPGDA). There are two steps in a hybrid optimization algorithm which include a forward pass (LSA) and a backward pass [40]. In the forward pass, the premises (antecedent) parameter is fixed while the LSA is used to optimize the consequent parameters.

In the backward pass (backpropagation training algorithm), the consequent parameters are fixed while the gradient descent is used to update the parameters of the premises. These two steps are repeated until optimum premises and consequent parameters are identified for the FIS system. The output of Fig 1 is expressed in equation 6.

$$\begin{aligned} f &= \overline{w}_1 f_1 + \overline{w}_2 f_2 \\ &= \overline{w}_1(p_1x + q_1y + r_1) + \overline{w}_2(p_2x + q_2y + r_2) \\ &= (\overline{w}_1 x)p_1 + (\overline{w}_1 y)q_1 + (\overline{w}_1)r_1 + (\overline{w}_2 x)p_2 \\ &\quad (\overline{w}_2 y)q_2 + (\overline{w}_2 r_2) \end{aligned} \quad (6)$$

4.2. ANFIS CONFIGURATION

As discussed in the above section, the inputs to the ANFIS model are the RSSI, the RxQual and the number of free channels. The inputs data were first changed into linguistic variables each with Gaussian Membership (GM) function. The GM function was used for its smoothness, concise notation and nonzero at all times. These three crisp inputs parameters and four fuzzified variables gave rise to 64 knowledge-based or inference systems. The output of the inference engine is a fuzzy set derived from the application of fuzzy variables on the fuzzy rule. In practical case, the crisp output is what is required. The fuzzy output is, therefore, further defuzzified to produce crisp and quantifiable output which is the hysteresis value that determines the handover decision. The defuzzification technique adopted for the work is the centre-of-gravity (COG) which employs a weighted average.

The ANFIS model in Fig 1 is made up of 158 nodes, 64 linear parameters, 24 nonlinear parameters, 64 fuzzy rules and 88 total numbers of parameters. The total number of training data pairs is 1200, the same as the number of checking data pairs. To achieve good generalisation, it's normal to have the number of training data pairs far more than the total number of parameters. The ratio of the training data pairs to parameters numbers is 1200/88 = 13.6.

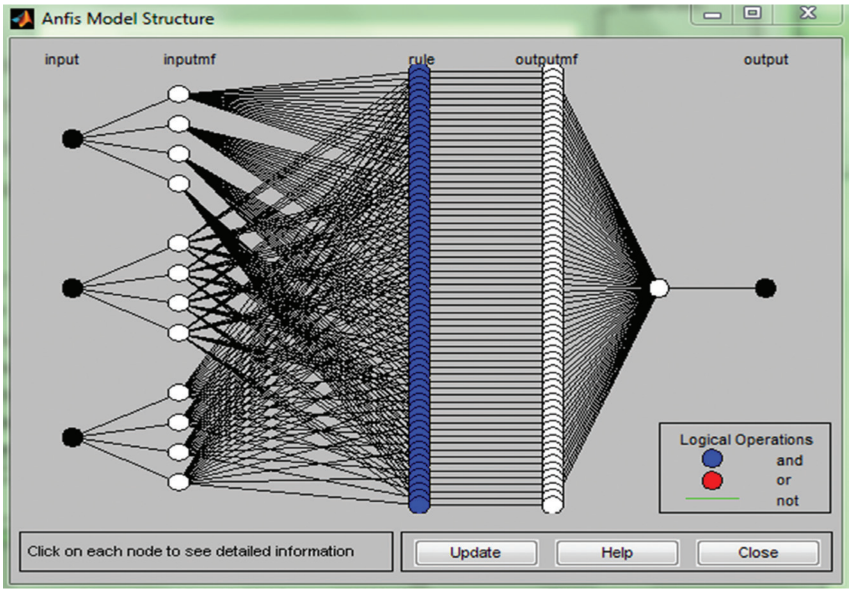

Fig. 1. ANFIS model structure for a dynamic handover decision.

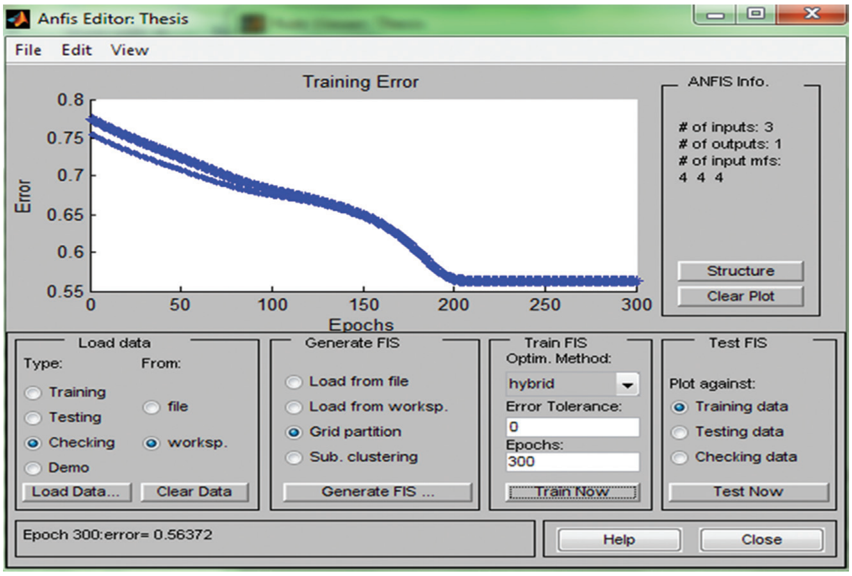

Fig. 2. ANFIS configuration for training FIS for handover decision

5. RESULT AND DISCUSSION

The developed ANFIS model employs the hysteresis value for QoS aware dynamic load balancing through the handover mechanism. The ANFIS was able to correctly predict the checking data output from the checking data input. The plot shows the ANFIS was correctly trained and can dynamically predict the hysteresis value from unknown data (data not used for the training).

Figs 3 to 5 are the 3D surface representation of ANFIS model prediction from a combination of two input variables from RSS, RxQual, and Free Channels. Each surface illustrates the impact of two input variables on the Hysteresis value. In cellular systems, RSS and RxQual are both fundamental quality performance indicators. The ANFIS system increases the hysteresis value as the RSS decreases and RxQual increases in value. It is very difficult to observe an overriding effect of one variable over the other when these are the predominant input metrics as shown in Fig. 3. A closer look at Fig 3 indicates that the RxQual is indeed the most critical factor in determining the hysteresis value.

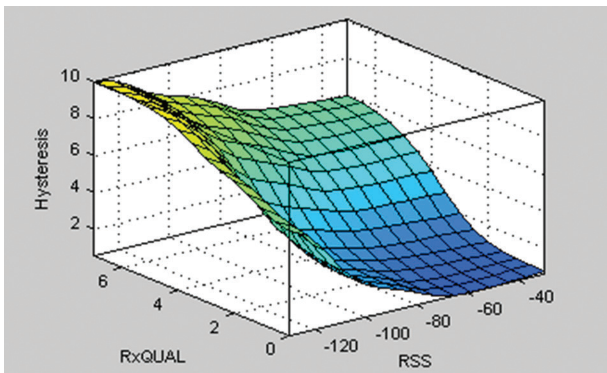

Fig. 3. ANFIS Model 3D Surface – Impact of RSS and RxQual on Hysteresis Value

As the number of free channels in a cellular cell increases, hysteresis value decreases, and vice versa. The number of free channels is not a quality parameter indicator but should be seriously considered in load balancing through the handover mechanism. The RSS has a dominant effect on hysteresis value over several free channels as illustrated in Fig. 4.

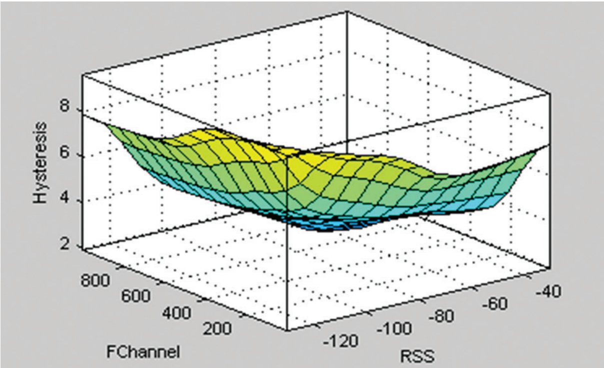

Fig.4. ANFIS Model 3D Surface – Impact of RSS and No. of Free Channel on Hysteresis Value.

Fig. 5. depicts the impact of received signal quality and the number of the free channel on hysteresis value. It can be observed that the RxQual has a more dominant effect over the number of free channels in determining the hysteresis value and subsequently the load balancing.

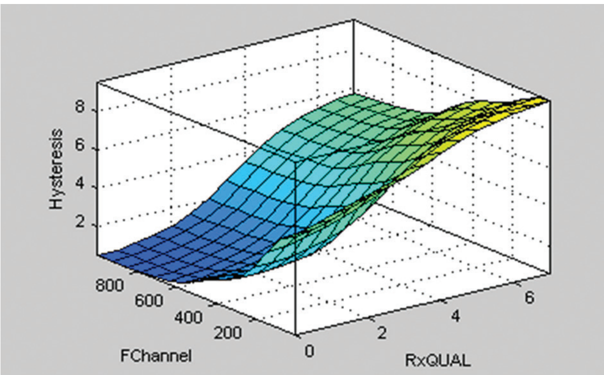

Fig.5. ANFIS Model 3D Surface – Impact of No. of Free Channel and RxQual on Hysteresis Value

Figures 6 to 8 illustrate individual parameter effects on load balancing and congestion avoidance. The blue colours indicate that the network is at the optimum condition concerning the three parameters under consideration. Handover is considered or triggered in the green colour while it is unexpected for MS to hang on to BS at the yellow colour. The yellow colors indicate critical network conditions and no communication can be established in this region. It also indicates that at least two of the parameters under consideration are in a poor state or insufficient for communication. The developed system will not allow the network to reach the yellow region through the handover mechanism.In Fig 6, it took up to -100dB for there to be an appreciable increase in hysteresis value. This is because above -100dB is considered sufficient for effective communication. At -110dB the RSS value becomes insufficient for communication and the load balancing is triggered at hysteresis value six (6) irrespective of other parameter values. The same can be said of received signal quality with a hysteresis value of 6 at RxQual 5 in Fig. 7. By cellular network standard, there should be no communication when RSS and RxQual are -110dB and 5 values respectively. Most mobile receivers have a sensitivity value of -115dB. RxQual value shows the higher impact on hysteresis value as there is an appreciable increase in hysteresis value halfway through the RxQual values. As expected the number of the free channel did not show any appreciable increase in hysteresis value until at 300 free channels from 1000.

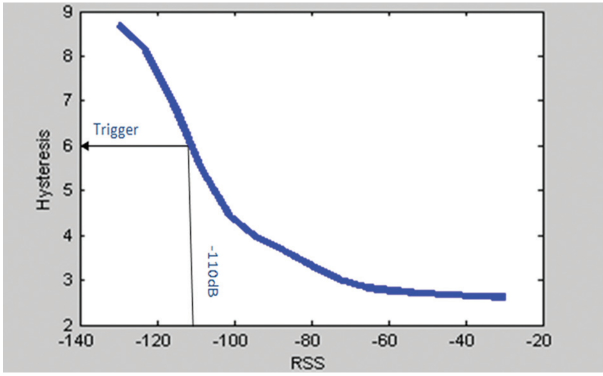

Fig. 6. The effect of RSS on Hysteresis Value

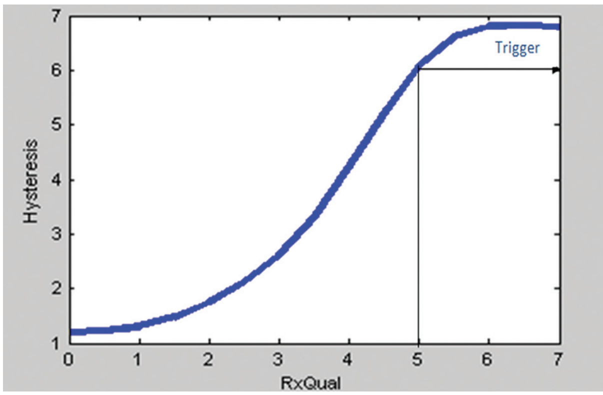

Fig. 7. The effect of RxQual on Hysteresis value

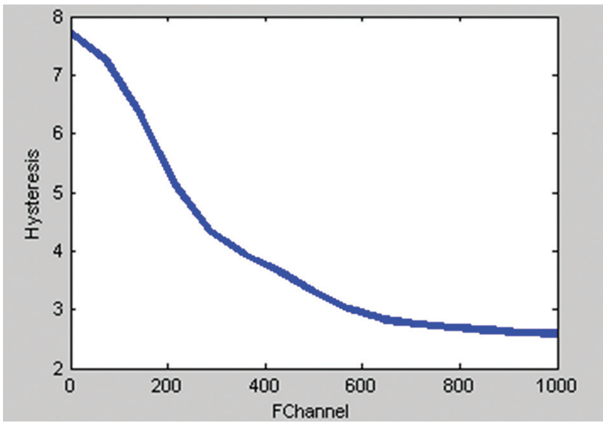

Fig. 8. The effect of numbers of free channels on Hysteresis value

Fig. 9 (a) shows the linear regression between the ANFIS output and the corresponding targets value

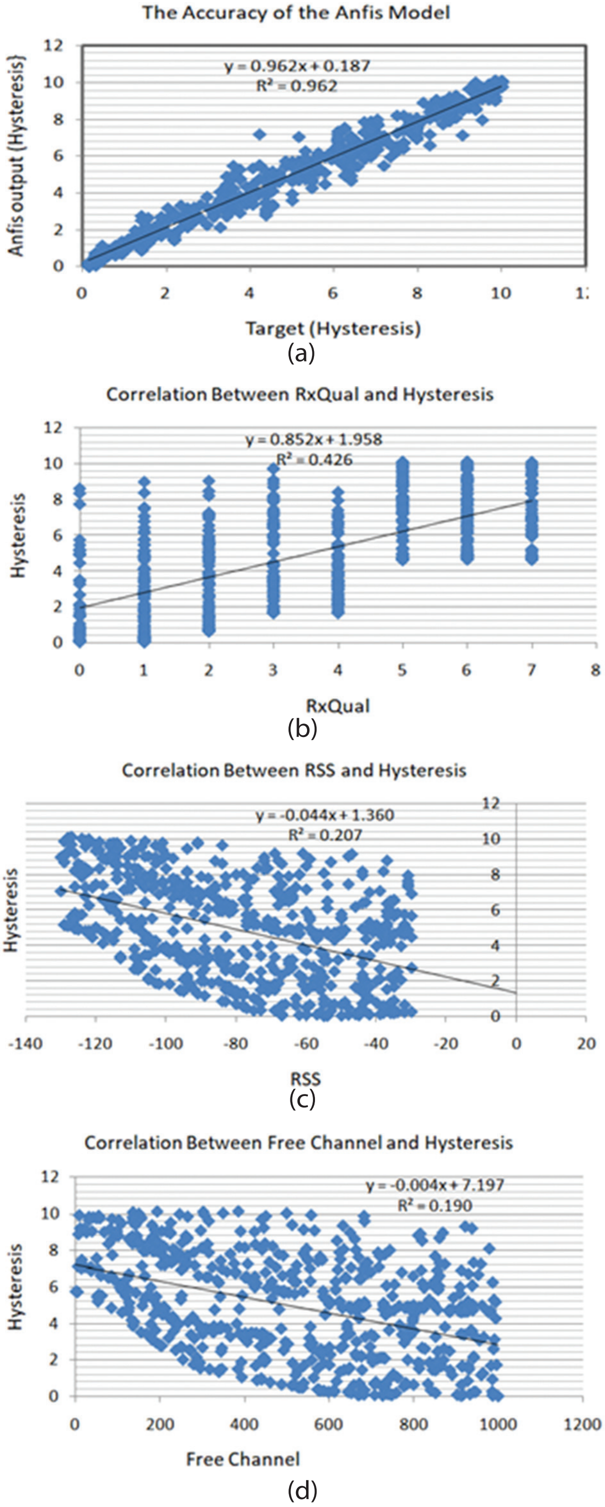

Fig. 9. Regression and Correlation between independents and dependent variables

In summary, these relationships illustrate that RSS and RxQual are the dominant parameters in determining the load balancing process and congestion avoidance, and should be controlled. The number of the free channel did not reflect well when compared with other load balance parameters in determining the hysteresis value. Based on illustration from From table 3 and figs 3 to 8, it can be observed that at Hysteresis value 6 one or two of the independent variables are almost insufficient to maintain good communication and to avoid call drop the handover mechanism should be triggered. In this handover process, the overall hysteresis state of the serving cell and its neighboring cells should be considered. A handover to the cell with a hysteresis value of 5 or less should always be considered. This is important to avoid excessive and ping-pong effects when the neighboring cell is highly loaded or has a hysteresis value of 6 or close. The increase in hysteresis value either sustains or triggers the load balancing process.

6. CONCLUSION

In this paper, ANFIS model prediction for dynamic load balancing and congestion avoidance through the handover mechanism is proposed. As can be seen in the results, the RxQual and RSS play a key role in determining the hysteresis value for load balancing complemented by the number of the free channel which ensures congestion avoidance. The results show that when the Hysteresis value approaches 6 the handover process should be triggered. The hysteresis value of the concern MS with neighboring cells is considered in determining the most suitable cell to handover to using the ANFIS technique, thereby achieving dynamic load balancing and congestion avoidance. Moreover, RSS and RxQual can also be used as the key performance indicators to decide scheduling and mobile assignment in a mobile communication network. Based on the simulation result, it is assumed that the performance of the system when implemented will be close if different from the result obtained in this work. This work was able to achieve dynamic load balancing, congestion avoidance and avoided the 'ping pong' effect that is often an issue with handover. This work also reduces the rate of call drop, call block and energy consumption of the base station associated with the fluctuation (ping pong effect) in conventional handover. Therefore, the subscribers' quality of experience (QoE) would have been enhanced. This work can be furthered by adopting a test-bed setup using a Wireless Network Simulation (WNS) test suite or Emulator.

7. REFERENCE

[1] T. Iliev, T. A Bikov, G. Mihaylov, E. Ivanova, I. Stoyanova, V. Keseev, "Algorithm for Congestion Control in LTE Mobile Network", Software Engineering and Algorithms in Intelligent Systems, Vol. 763, 2018.

[2] S. Kramer, S. Molnar, S. Solymoi, A. Mihaly, "On the Benefit of Multi-Domain Congestion Control in LTE Networks", Proceedings of the IEEE 24th International Workshop on Computer Aided Modeling and Design of Communication Links and Networks, Limassol, Cyprus, 2019, pp. 1-6.

[3] S. Pa, S. Mandale, A. Adiwjaja, “A New Method for Congestion Avoidance in Wireless Mesh Networks”, Proceedings of the 2nd International Conference on Data and Information Science, IOP Conference Series: Journal of Physics, Conference Series 1192, 10-14 October 2019, pp. 1-13.

[4] A. Singh, S. P Singh, U. N. Tripathi, M. Mishra, “Optimizing Call Drops in cellular Network using Artificial Intelligence Based Handover Scheme”, International Journal of Advanced Research in Computer and Communication Engineering, Vol 6, No. 1, 2017.

[5] E. O. Oluwafemi, O. E. Nnonye, U. Okechukwu, A. L. Adewale, “Prediction of Call Drops in GSM Networks using Artificial Neural Network”, Jurnal Teknologi dan Sistem Komputer, Vol 7, No. 1, 2019, pp. 38-46.

[6] C. O. Nnamani, C. L. Anioke, C. I. Ani, M. Anedda, M. Murroni, “Load-Shared Redundant Interface for LTE Access Network”, https://www.researchgate.net/publication/318020116 (Online).

[7] Y. Zaki, T. Potsch, J. Chen, L. Subramanian, C. Gorg, “Adaptive Congestion Control for Unpredictable Cellular Networks”, ACM SIGCOMM Computer Communication Review, Vol. 45, No. 4, 2015, pp. 509-522.

[8] N. S. Khan, M. Umar, K. Anand, S. K Shabia, “Early Prediction of Congestion in GSM based on Area location using Neural Network” International Journal of Advanced Research in Electronics and Communication Engineering, Vol. 5, No. 5, 2016.

[9] S. Alam, A. Mittal, M. G. Siddiqui, T. Qamar, “Capacity Improvement by Cell Splitting Technique in CDMA System over Telecommunication Network”, International Refereed Journal of Engineering and Science, Vol. 2, No. 7, 2013, pp. 1-8.

[10] A. Ozovehe, O. U. Okereke, E. Anene, A. U Usman, “Busy Hour Traffic Congestion Analysis in Mobile Macrocells”, Nigeria Journal of Technology, Vol. 36, No. 4, 2017, pp. 1265-1270.

[11] C. O. Ohaneme, G. N. Onoh, E. N. Ifeagwu, I. Eneh, “Improving Channel Capacity of A Cellular SystemUsing Cell Splitting”, International Journal of Scientific and Engineering Research, Vol. 3, No. 5, 2012, pp. 1-8.

[12] R. Arshad, H. Elsawy, S. Sorour, T.Y Al-Naffouri, M. Alouini, “Handover Management in 5G and beyond”, A Topology Aware Skipping Approach, IEEE Access, Vol. 4, 2016, pp. 9073-9081.

[13] R. A. Saeed, “Performance Comparison of Handover Mechanisms in Mobile Wireless Communication Networks for Broadband Wireless Access Systems”, International Journal of Computer Communication and Informatics, 2020, pp. 25-37.

[14] U. Sehgal, R. Sharma, “An Efficient Communication MCHO Protocol used Cellular Networks Technology”, International Journal of Computer Science and Mobile Computing, Vol. 6, No. 1, 2017, pp. 52-60.

[15] K. Yap, Y. Chong, W. Liu, “Enhanced Handover Mechanism using Mobility Prediction in Wireless Networks”, PLOS ON, Vol. 15, No.1, 2020.

[16] S. Moshe, S. David, “New call blocking versus handoff blocking in cellular networks”, Wireless Networks, Vol. 3, 1997, pp 15-27.

[17] Girma. S. T, Konditi. D. B. O and Ndunga, E. N, Fuzzy Logic Based Traffic Balancing in a GSM Network, Journal of Research in Engineering, Vol. 1, No. 2, 2014, pp. 63-74.

[18] O. A. Jeremiah, A. F. Olasebikan, O. Abidemi, “Handover in Mobile Wireless Communication network – A Review”, International Journal of Advanced Engineering, Management and Science, Vol. 3, No. 9, 2017, pp. 934-940.

[19] S. Neeraja, G. S. B. Rao, A. L. Narayana. “Analysis of Adaptive Hysteresis Based Horizontal Handoff Algorithm for GSM”, International Journal of Innovative research in Electrical, Electronics, Instrumentation and Control Engineering, Vol. 1, No. 9, 2013.

[20] M. Toril, S. Pedraza, R. Ferrer, V. Wille, “Optimization of handover margins in GSM/GPRS networks”, Proceedings of the 57th IEEE Semi-annual Vehicular Technology Conference, Jeju, Korea, 22-25 April 2003.

[21] R. P. Ray, L. Tang, “Hysteresis Margin and Load Balancing for Handover in Heterogeneous Network”, International Journal of Future Computer and Communication, Vol.4, No. 4, 2015

[22] A. A. Ateyero, M. K. Luka, "A Soft Computing Approach to Dynamic Load Balancing in 3GPP LTE", International Journal of Computer Application, Vol. 43, No. 19, 2012.

[23] P. Moungnoul, P. Pinprasert, T. Paungma, "Handoff decision in Cellular Mobile System using Neural Network", 2002, http://www.ecti-thailand.org/assets/papers/300_pub_24.pdf (Online).

[24] M. A. Raheem, O. U. Okereke, "A Neural Network Approach to GSM Traffic Congestion Prediction". American Journal of Engineering Research, Vol. 3, No. 11, 2014, pp. 131-138.

[25] K. O. Omotoye, M. A. Akogbe, O. M. Olaniyi, H. C. Inyiama, "Congestion Management on GSM Networks using Traffic Class Prioritization". International Journal of Engineering Research and Technology, Vol. 3, No. 12, 2014, pp. 174-178.

[26] D. F. A. Ali, F. A. Mustafa, M. O. M. Fdolelsid, "Automatic Handover Control for Distributed Load Balancing in Mobile Communication Network", 2016, Arxiv:1605.01228.

[27] L. Andreas, S. Szymon, J. Thomas, B Irina, "Load Balancing in Downlink LTE Self-Optimizing Networks", Proceedings of the IEEE 71st Vehicular Technology Conference, Taipei, Taiwan, 16 -19 May 2010.

[28] T. G Solomon, B. O. K. Dominic, N. N. Eward, "Fuzzy Logic Based Traffic Balancing in a GSM Network", Journal of Research in engineering, Vol. 1, No. 2, 2014, pp. 63-74.

[29] ETSI Technical Specification, "Digital Cellular Telecommunications System (Phase 2+) (GSM); Universal Mobile Telecommunications System (UMTS), LTE, Service Accessibility (3GPP TS 22.011 version 13.4.0 Release 13), 2016, http://www.etsi.org/standards-search (Online).

[30] ETSI Technical Specification, "Digital Cellular Telecommunications System (Phase 2+); Radio Subsystem Link Control", 3GPP TS 45.008 version 9.4.0 Release 9, 2010, http://www.etsi.org/standards-search (Online).

[31] Radio Frequency Engineering: GSM Radio Parameter Details and Score Evaluation from Drive Test (DT) End, 2015, www.cwnabook.blogspot.com/2015/12/gsm-radio-parameter-details-and-score.html?m=1 (Online)

[32] S. Serkan, T. Nurettin, L. Bunyamin, Analysis of Mobile Coomunication Signals with Frequency Analysis Method, Gazi university Journal of Science, Vol. 25, No. 2, 2012.

[33] GSM/GPRS Modem, "GSM/GPRS Modem, Telemetry and Data Accessories "At + CSQ in dbm", 2011, http://www.gprsmodems.co.uk/images/csq1.pdf.

[34] J R Jang, "ANFIS: Adaptive Network-Based Fuzzy Inference System", IEEE Transactions on Systems, Man and Cybernetics, Vol. 23, No. 3, 1, 1993, pp. 665-685.

[35] L. S. Ezema, C. I. Ani, "Artificial Neural Network Approach to Mobile Location Estimation in GSM Network", International Journal of Electronics and Telecommunications, Vol. 63, No. 1, 2017, pp. 39-44.

[36] A. A Atayero, M. K Luka, "Adaptive Neuro-Fuzzy Inference System for Dynamic Load Balancing in 3GPP LTE", International Journal of Advanced Research in Artificial Intelligence, Vol. 1, No. 1, 2012.

[37] F. Castellanos, N. James, "Average Hourly Wind Speed Forecasting with ANFIS", Proceedings of the 11th Americas Conference on Wind Engineering, San Juan, Puerto Rico, 22-26 June, 2009.

[38] S. Huang, "Cross-Layer Congestion Control with Deep Neural Network in Cellular Networks, KTH Royal Institute of Technology, School of Electrical Engineering and Computer Science, Stockholm, Sweden, 2019.

[39] D. S Reddy, C Chandrasekhar, "Support Vector Regressive Dragonfly Optimized Shift Invariant Deep Neural Learning Based Handover for Seamless Data Delivery in Heterogeneous Network", International Journal of Computer Network and Applications, Vol 7, No. 4, 2020.

[40] V. Vaidhehi, "The Role of Dataset in Training ANFIS System for Course Advisor", Department of Computer Science, Christ University, Bangalore, 2016