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HANDOVER OPTIMIZATION IN 5G NETWORKS USING ANFIS

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ABSTRACT

The Corona Virus Disease (COVID-19) pandemic has upended the lives of people all over the world, and people have realized that the demand for new technologies, such as Internet of Things (IoT)-based devices, Vehicle Adhoc Networks (VANETS), and other upcoming technologies is increasing nowadays. These technologies are mostly based on controlling objects from a remote location, and some of them avoid close contact with others. So, a 5G network with more bandwidth is beneficial but the higher frequency signals will have more collisions with obstacles in the air, and thus it tends to reduce its energy more quickly. As a result, 5G networks are segregated into small cells to alleviate this issue but at the same time it is difficult to manage the handover process in small cells. To optimize the handover process, an Adaptive Neuro-Fuzzy Inference System (ANFIS) is adopted in this research. The structure, as well as the input and output variables have been developed, and the rule base mathematical model, which describes all the possible handover scenarios based on these parameters, has been evaluated. A MATLAB simulation was used to test the effectiveness of the proposed handover ANFIS.

Keywords: heterogeneous, handover, ANFIS, 5G

INTRODUCTION

Generally, there are three distinctive use-cases in 5G networks: enhanced Mobile Broadband (eMBB), massive Machine Type Communications (mMTC), and Ultra-Reliable Low Latency Communication (URLLC). Each of them possesses challenging requirements such as imparting wider coverage, increased network capacity, high reliability or providing minimum delay. It is clear that each 5G use-case requires one of a kind handover strategies like Deep Learning Based Localization and HO Optimization, Self-optimization Approach for 4G/5G HetNets Using Weighted Fuzzy Logic Control, Dynamic Fuzzy Q-Learning for Handover Parameters Optimization in 5G multi-tier networks etc, which have an effect on the signaling overhead, power consumption, and handover delay. The implementation of the 5G networks will doubtlessly have an impact on mobile phones compared to preceding generations. 5G allows for a wide variety of connections such as the Internet-of-Things (IoT), Machine-To-Machine (M2M), Device-To-Device (D2D), Vehicle-To-Everything (V2X), and Bluetooth. Collectively, they will influence businesses, governments and customer interactions in the physical world. Connections are significantly developing with time due to the recognized benefits of linking inert devices to the internet by customers, businesses, and governments. Over the next decade, these aforementioned services will be key aspects of the largest device markets in the world. It is anticipated that there will be heaps of hundreds of simultaneous connections deemed essential for the massive deployment of these services in 5G networks. These diverse kinds of connected services will require more system capacity and higher data rates, while parts of them require lower latency. All these have led to the development of the 5G systems.

The required bandwidth for a 5G system is ten instances higher than what is required for the 4G system. This high demand is the key aspect for proposing the use of millimeter waves (mm-waves) given that wider bandwidths are available in these 5G bands. These bands are located between 10 GHz and 300 GHz. The bands of 10 GHz to 86 GHz spectrum have been recommended by the International Telecommunication Union (ITU), numerous industries, and many research centers as the best candidate band for the 5G system. They have also been studied in several research categories. The 28 GHz and 38 GHz are currently the most recommended bands for the 5G system. Meanwhile, other higher mm-wave bands of up to 120 GHz are recommended for the 6G system.

Handover management maintains all active connections for user equipment (UE). Handover is the mechanism of transferring a connection between a UE and a correspondent terminal from one network attachment point to another. Handover decision determines the best access network and decides whether to perform handover or not. Vertical handover takes place between the different attachment points of the different networks and is implemented in heterogeneous networks. The handover process has three steps: system discovery, handover decision, handover execution. Network selection can be initialized either by UE or can be based on measurements performed by the network. UE tends to join the best attachment point, and network selection can be regarded as a decision-making problem. So, the handover problem is solved by the search for an optimal solution. The heterogeneous networks differ in terms of coverage, signal strength, data rate and loss rates. Therefore, there is a relevant scientific problem of developing an effective handover decision algorithm, which is able to adapt dynamically to varying conditions in the wireless environment. Soft-computing techniques i.e. neural net systems, fuzzy controllers, genetic programming and learning rules like deep learning, Q-learning are used in automatic control engineering and are widely applied in telecommunication networks. Employing soft-computing techniques in the 5G network would give greater functionality in traffic handling. Furthermore, soft-computing techniques can be used to support decision making. Thus soft-computing 5G heterogeneous networks can satisfy expected needs and face new technical challenges. Several solutions about soft-computing schemes for handover decisions have been proposed. The Handover Neuro-Fuzzy controller for mobile networks has been taken for further research in this present paper. This paper provides results of further investigation. Therefore, the objective of this paper is to handover optimization using ANFIS or Adaptive Network based Fuzzy Inference System for 5G heterogeneous networks.

RELATED WORK

Handover optimization has several approaches but nowadays soft computing, artificial intelligence and machine learning techniques are more preferable for various optimization. In soft computing different approaches are to be used for handover optimization such as fuzzy logic, Deep Learning, Reinforcement Learning, Q Learning and Neuro-fuzzy logic approach can be used for handover optimization. A fuzzy approach using various parameters for optimization (more information about the problem less will be the error) depending on the number of parameters used. In Self-Optimization Algorithm for 5G Networks Based on Automatic Weight Function there are three parameters used as an input to enhance the Reference Signal Received Power (RSRP) by reducing unreliable handover by maintaining the Handover Control Parameter (HCP), for that they have used an Individualistic Dynamic Handover Parameter Optimization algorithm based on an Automatic Weight Function (IDHPO-AWF) is proposed for 5G networks. This algorithm dynamically appraises the HCPs settings for each individual UE based on UE’s experiences. The algorithm mainly depends on three bounded functions and their automatic weights but that is not sufficient as per requirement. To provide a more flexible way to adjust the HCP the basic three parameters are in Weighted Fuzzy Logic Control, Fuzzy-Logic-Based Handover Algorithm, Neuro-Fuzzy Controller for Handover and these attributes have been enhanced further by ANFIS. Another approach is fuzzy Q-Learning author proposed an algorithm to maintain the call dropping ratio at minimum level and handover ratio so there was no fuzzy rules initially, this algorithm gradually generates new fuzzy rules and gets the required parameters through system learning, so as to reach a balance between the signaling cost caused by handover and the user experience affected by call dropping ratio and another approach is Reinforcement learning (Using a critic information to generate an error and get the desired output when the error is minimum), using centralized reinforcement learning agent to perform an action for handover depending on radio measurement reports from the user equipment.

To reduce latency and increase scalability, the software defined handover model used for Enhanced Mobile Broadband (eMBB) services. In this Markov model with the help of joint consideration of Edge and Core networks and totally removed the handover execution state. As we know that 5G is ultra dense networks and also called heterogeneous networks for that application specific thresholding scheme is used for handover reduction. In thresholding scheme, the author proposed an algorithm which is multi-criteria decision making (MCDM). Another approach for handover optimization is deep learning-based localization, the proposed network consists of feature extractors and dense layers. The model is trained in two parts, the first part serving as an initial weight setting in supervised fashion based on the 3GPP model. The second part is an optimization problem to reduce the number of unnecessary handovers while sustaining a high-quality connection, but this model is complex and difficult to manage there is more chances of layer collision while adjusting the weights.

This paper suggests applying an ANFIS in 5G heterogeneous networks in order to improve the handover process. A rule base and mathematical models of the controller has been considered. The efficiency of the proposed handover ANFIS has been tested by performing the computer simulation.

PROPOSED SYSTEM

Architecture of the ANFIS

A common fuzzy controller consists of four blocks. The fuzzification block converts each crisp input value into a fuzzy one. The fuzzy rule base is a set of “if-then” rules involving linguistic variables. The inference engine computes the fuzzy output taking into account fuzzy inputs and a rule base. The defuzzification block produces a crisp output action.

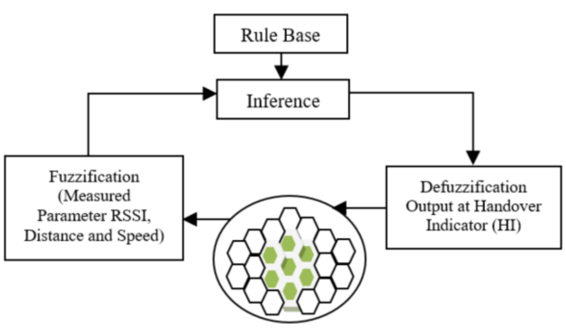

Fig. 1: ANFIS Architecture

The problem of designing a fuzzy-controller for application in telecommunication networks is being considered in self-optimization approach and fuzzy logic-based algorithm these techniques provide better solutions but that can be further optimised so that this paper proposes an architecture of an ANFIS controller as shown in Fig 2 to be used in 5G heterogeneous networks.

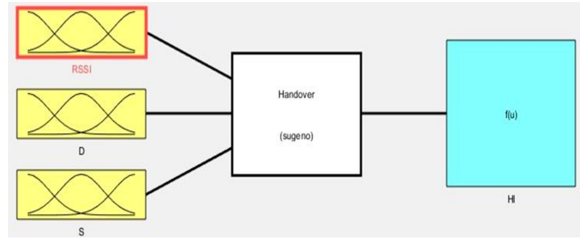

Fig. 2: Handover Fuzzy-controller.

ANFIS uses a hybrid learning algorithm to tune the parameters of a Sugeno-type fuzzy inference system (FIS). The algorithm uses a combination of the least-squares and back-propagation gradient descent methods to model a training data set. ANFIS also validates models using a checking data set to test for overfitting of the training data.

FIS Structure and Parameter Adjustment:

A network-type structure is similar to that of a neural network, which maps inputs through input membership functions and associated parameters, and then through output membership functions and associated parameters to outputs, can be used to interpret the input/output map. The parameters associated with the membership functions changes through the learning process. The computation of these parameters (or their adjustment) is facilitated by a gradient vector. This gradient vector provides a measure of how well the fuzzy inference system is modeling the input/output data for a given set of parameters. When the gradient vector is obtained, any of several optimization routines can be applied in order to adjust the parameters to reduce some error measure. This error measure is usually defined by the sum of the squared difference between actual and desired outputs. anfis uses either back propagation or a combination of least squares estimation and back propagation for membership function parameter estimation.

Model Validation Using Testing and Checking Data Sets.:

Model validation is the process by which the input vectors from input/output data sets on which the FIS was not trained, are presented to the trained FIS model, to see how well the FIS model predicts the corresponding data set output values.

One problem with model validation for models constructed using adaptive techniques is selecting a data set that is both representative of the data the trained model is intended to emulate, yet sufficiently distinct from the training data set so as not to render the validation process trivial. If collected a large amount of data, hopefully this data contains all the necessary representative features, so the process of selecting a data set for checking or testing purposes is made easier. However, if you expect to be presenting noisy measurements to your model, it is possible the training data set does not include all of the representative features that wanted to be model. The testing data set check the generalization capability of the resulting fuzzy inference system. The idea behind using a checking data set for model validation is that after a certain point in the training, the model begins overfitting the training data set. In principle, the model error for the checking data set tends to decrease as the training takes place up to the point that overfitting begins, and then the model error for the checking data suddenly increases. Overfitting is accounted for by testing the FIS trained on the training data against the checking data, and choosing the membership function parameters to be those associated with the minimum checking error if these errors indicate model overfitting. Usually, these training and checking data sets are collected based on observations of the target system and are then stored in separate files.

The proposed ANFIS controller has three input linguistic variables which are received signal strength indicator (RSSI), distance (D) and user's speed (S), its output action is a handover indicator as shown in Table1.1. The RSSI is a measurement value of received carrier's power in the system bandwidth. For defining the various input parameters LOW (L), MEDIUM (M) and HIGH (H) are used.

Table 1.1 Input Parameters

INPUT PARAMETERS	LOW	MEDIUM	HIGH
RSSI (dBm)	-90 to -70	-70 to -60	-50 to -40
Distance(m)	0 to 20	40 to 80	80 to 100
Speed(km/h)	0 to 20	40 to 80	100 to 120

T(RSSI)={Low, Medium, High}

Membership function plots for T(RSSI).

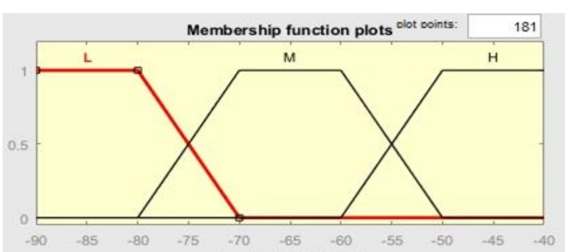

Fig. 3: Membership functions for the linguistic variable RSSI

The distance is an interval between a UE and a user attachment point. For defining the distance terms low, medium, and high are used. The term set of D is:

T(D)= {Low, Medium, High}.

Membership function plots for T(D).

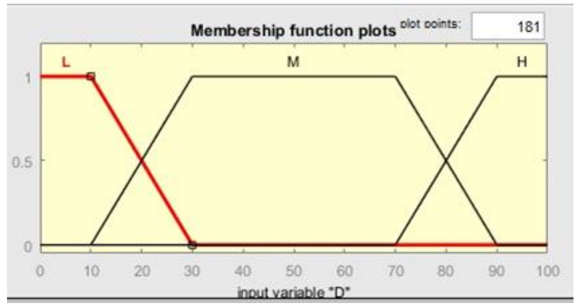

Fig. 4: Membership functions for the linguistic variable D

The user's speed is a rate at which a mobile user changes its position during the communication. For defining the speed terms low, medium, and high are used. The term set of S is:

T(S)={Low, Medium, High}.

Membership function plots for T(S).

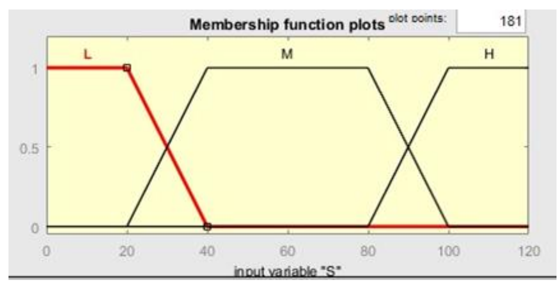

Fig. 5: Membership functions for the linguistic variable S.

For defining the handover indicator (HI) terms very low (VL), low (L), medium (M), high (H) and very high (VH) are used. The corresponding table with its percentage values and corresponding graph is shown in Table 1.2 and Fig 6 respectively. The term set of HI is:

T(HI)= {Very Low, Low, Medium, High, Very High}

Table 1.2 Output Parameters

OUTPUT PARAMETER	VL	L	M	H	VI
HI (%)	0	25	50	75	100

Membership function plots for T(HI)

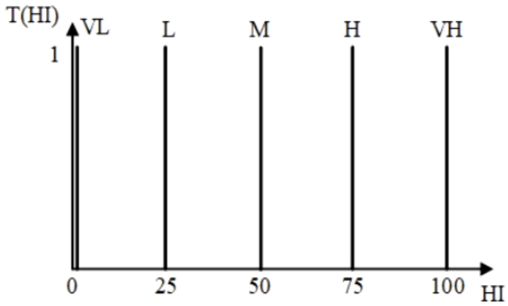

Fig. 6: Membership functions for the linguistic variable HI.

OPERATION OF THE NEURO-FUZZY CONTROLLER

The rule base of the proposed handover neuro-fuzzy controller has 27 if-then rules:

If $a_1 = R_{x1}$ and $a_2=D_{x2}$ and $a_3=S_{x3}$ then $y=f(a_1, a_2, a_3)$

$$x_1 = 1\ldots3;\ x_2 = 1\ldots3;\ x_3 = 1\ldots3.$$

Where, RSSI Parameter denoted with R_{x1}, distance is D_{x2} and speed is denoted with S_{x3} and x1, x2, x3 is number of variables used for particular parameter.

In layer 1 every node produces a membership grade of the linguistic label:

$$z_{1k} = \mu_{Rk}(a_1) \text{ for } k=1, 2, 3;$$
$$z_{1k} = \mu_{Dk-3}(a_2) \text{ for } k=4, 5, 6;$$
$$z_{1k} = \mu_{Sk-6}(a_3) \text{ for } k= 7, 8, 9;$$

therefore, μ_{Rk} is membership function of RSSI, μ_{Dk-3} is membership function of Distance and μ_{Sk-6} is a membership function of Speed and z is used to denote the linguistic variable for each layer.

In layer 2 weights of each membership function are checked:

$$z_{2k} = w_j = \mu_{Rk}(a_1)\cdot\mu_{Dk}(a_2)\cdot\mu_{Sk}(a_3),\ k=1\ldots27.$$

Where, w is denoted with the number of weights of each membership function.

In layer 3 each node's output of is the normalized firing strength:

$$z_{3k} = n_k=w_k/(w_1+\ldots+w_{27}).$$

In layer 4 each node's output is multiplication of the normalized output with a node function:

$$z_{4k}=n_k y_k.$$

In layer 5 the overall output is computed by adding the incoming signals :

$$z_5=n_1y_1 + n_2y_2 +\ldots+ n_{27}y_{27}.$$

THE ANFIS STRUCTURE

The proposed fuzzy handover technique can be optimized using Adaptive Network Fuzzy Inference System (ANFIS) that incorporates a training element into the fuzzy handover technique. Fig 7 shows the handover ANFIS Structure diagram. The proposed ANFIS structure consists of Nine neurons in the first layer provide fuzzification of crisp inputs. Second layer's neurons correspond to fuzzy rules. Third layer's neurons provide the value normalization. The fourth layer has twenty-seven neurons and is a defuzzification layer. The neuron in the fifth layer represents an output of the ANFIS.

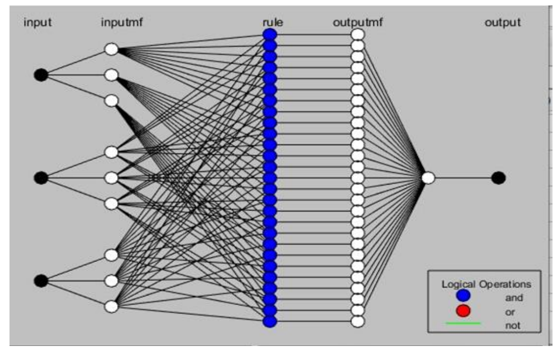

Fig. 7: Handover ANFIS Structure

The simulation process carried out for building ANFIS is shown in Fig 8. Number of inputs and their ranges have been decided based on literature survey and then the rules have been made considering the relationship amongst various inputs taken and the corresponding output. Then the system is trained and tested for a given set of values. Here 50 values of each input have been considered in the given range. ANFIS is generated for the given problem and error is checked, if the error is high then the rule base is changed and the same process is repeated.

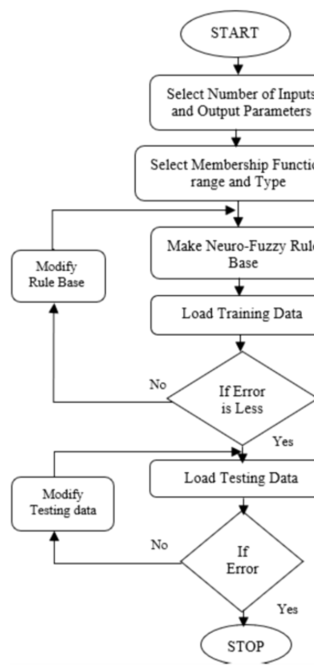

Fig. 8: Flow Chart of ANFIS

SIMULATION

Operability and availability of the proposed handover ANFIS can be confirmed by using the MATLAB software. Fig. 1 shows the fuzzy controller interface. To evaluate the operability of the fuzzy controller the input values are assigned and the simulation is run in order to obtain the output value.

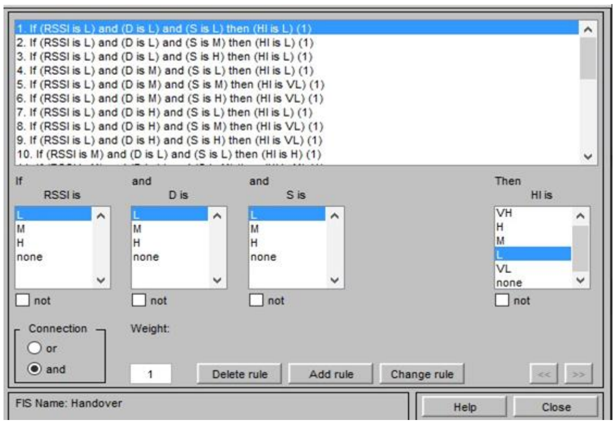

Fig 9 The Rule Base for Handover optimization.

The rule base in the MATLAB interface is shown in Fig 9.

Case A: Let the received signal strength indicator RSSI= -65dBm, the distance D= 60 m, and the user's speed S= 90 km/h. According to Fig 10, we get the handover indicator HI=62.5%.

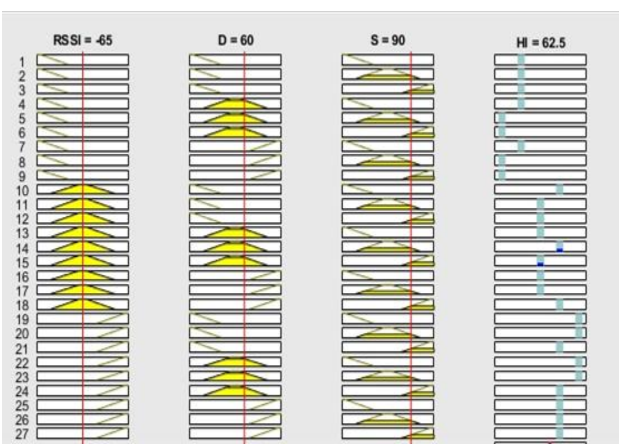

Fig. 10: Handover Rule Base Case A

Case B: Let the received signal strength indicator RSSI = –50dBm, the distance D = 59.6 m, and the user's speed S = 60 km/h. According to Fig 11, we get the handover indicator HI = 93.2%. Similarly substituting different values in RSSI, Distance and user's Speed is checked. Apply all the possible inputs and output combination then load the training data from the workspace after loading the data check for the training error, when the training error is least the modified ANFIS structure and updated rule are generated inputs after all training process. We can have number of cases by changing the input parameter values.

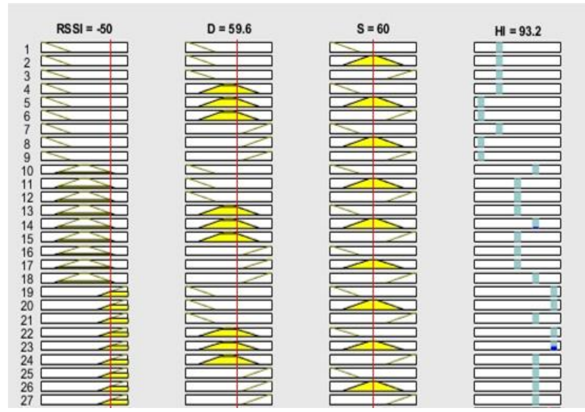

Fig 11 Handover Rule Base Case B.

The number of inputs that appear after training error depending on parameters that are used for handover optimization are shown in the Fig 12-16 for training and testing the data hybrid optimization method is used with 10 epochs.

Fig 12 ANFIS Training Data.

Fig 12 illustrates the ANFIS training data. Desired output values as well as corresponding input values were presented as an array. The training process took 10 iterations and the error is generated as shown in Fig. 14 that is after generate FIS operation.

Fig. 13: Training data before FIS Generate

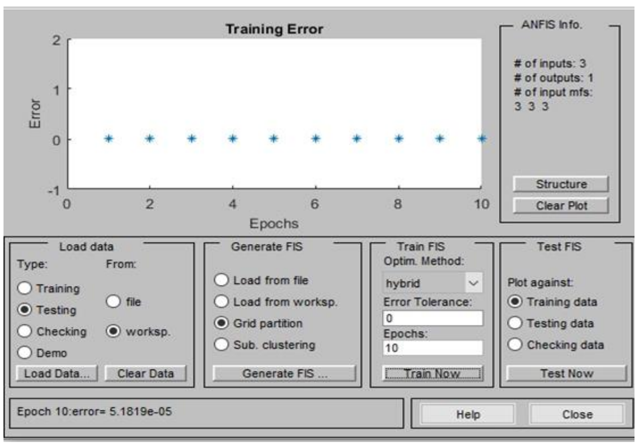

Fig. 14: Training Error after FIS Generate

The Training error is very less as comparative to neuro fuzzy that is because of the proposed rule base that is used to improve the handover process contains maximum information about the problem. The uncertainty is reduced due to this and hence we get less error after training as shown in Fig 14. Same is valid for Testing Error which is also reduced in the proposed methodology as shown in Fig 16 and Fig 17. The same conclusion has been made in Table 3 and same has been shown in Fig 15.

Table 3. Comparison with other techniques

Techniques	Training and Testing Error		Handover Indication
	Before FIS Generate	After FIS Generate	
Neuro Fuzzy[7]	31.1805	_	80.2%
Weighted Fuzzy logic control[2]	_	_	93.2%
ANFIS (Proposed)	**4.8113**	**5.1819E-05**	**96%**

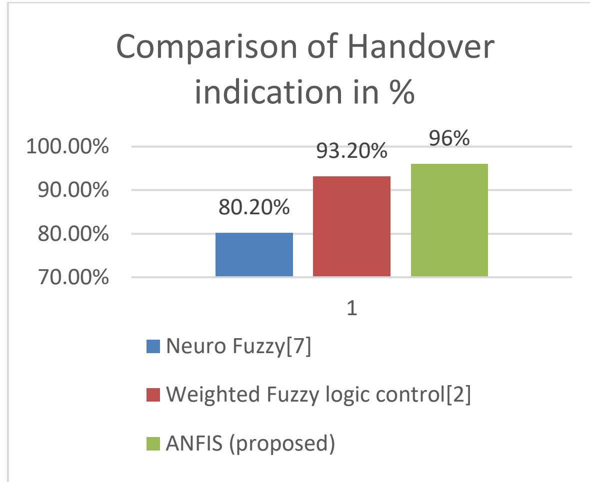

Fig. 15: Comparison of Handover indication

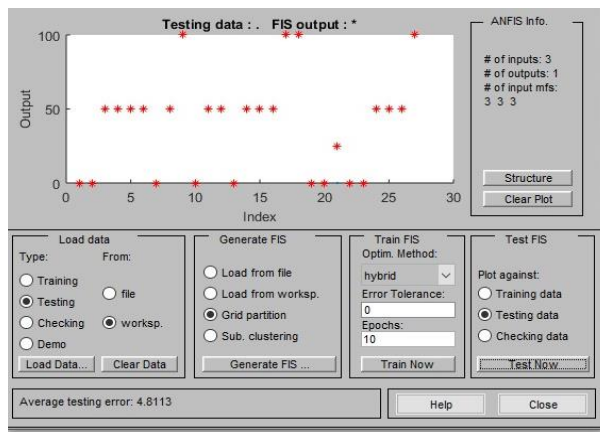

Fig. 16: Testing error before FIS generate

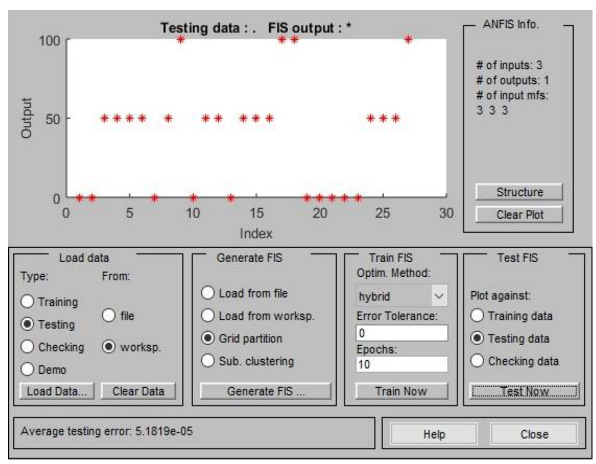

Fig. 17: Testing error after FIS generate

CONCLUSIONS

This paper has proposed a handover mechanism based on fuzzy logic and a neural network for heterogeneous networks. The ANFIS decide whether a candidate network is suitable for the handover operation. However, performing the handover decision in mobile networks may be quite complicated because of criteria, which must be considered. In this paper the fuzzy-controller for heterogeneous 5G networks with several criteria has been developed in order to improve the handover decision operation. The handover ANFIS has been developed by introducing the training process and testing process into the obtained fuzzy controller. Using the adaptive network based fuzzy inference system reduces the rate of handover failure in 5G heterogeneous networks. Since the quality of service depends on the rate of handover failure, it means that the quality of service is enhanced. The simulation results have proved the feasibility of the obtained handover ANFIS application in heterogeneous networks. Moreover, the simulation results have shown the feasibility of the proposed handover ANFIS to adapt membership function graphs. Application of the fuzzy controller reduces the quantity of superfluous handovers. Application of the neural network trains the system to select the best network among available ones. Therefore, the application of the handover ANFIS provides improving of the attachment point selection process and avoiding unnecessary handovers. The Training error is very less as compared to other approaches for the same scenario, which can be verified from the figures 13-14 as well as Table 3. Table 3 shows that the uncertainty of Handover is reduced and an error of 6.1802e-05 after training has been achieved compared to Neuro-Fuzzy Controller for handover operation and Weighted Fuzzy Logic Control respectively.

FUTURE SCOPE

Furthermore, consideration of other parameters of the heterogeneous 5G networks can enhance the proposed handover ANFIS controller. Also, handover mechanisms can be optimized by combining the fuzzy logic and neural network methods with genetic algorithm techniques that provide computation according to the features of mobile devices and networks.

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