

Intelligent Vertical Handover Model based on Neuro-Fuzzy for 4G and 802.11 networks

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Abstract— *This paper introduces an intelligent Vertical Handover (VHO) model that combines the capabilities of Fuzzy Logic and Neural Networks within the Adaptive Neuro-Fuzzy Inference System (ANFIS), based on the Takagi–Sugeno Fuzzy Inference System. The proposed framework, termed IVH_NF, assists User Equipment (UE) in selecting the most suitable network between 4G LTE and IEEE 802.11 WiFi by utilizing multiple input parameters, including Received Signal Strength (RSS), Mobile Speed (MS), Distance (D), and Packet Cost (PC). Simulation results of LTE-to-WiFi handover scenarios show that IVH_NF enhances Quality of Service (QoS) by improving throughput, sustaining acceptable speed and bitrate, minimizing End-to-End Delay (EED), and reducing handover frequency. When compared to existing algorithms, IVH_NF achieves a 58% decrease in EED over RSS-based methods, a 33.3% reduction in handovers compared to prior ANFIS approaches, and a 60% reduction relative to Fuzzy Logic-based models.*

Keywords— *4G LTE, WiFi, Horizontal Handover, Vertical Handover, ANFIS, heterogeneous networks, Fuzzy Logic, Neural Network.*

I. INTRODUCTION

A heterogeneous network, also known as an inter-technology network, refers to the integration of IEEE 802.x family standards and cellular networks working in coordination with the IETF group. These networks vary in characteristics such as coverage area, latency, and cost. To overcome the limitations of individual wireless technologies, integrating them into a Next Generation Wireless Network (NGWN) offers a promising solution [4]. One critical aspect of NGWN is handover (HO), the process of transferring a user equipment (UE) connection from one point of attachment or base station to another. Handover enables seamless connectivity and continuous access to services anytime and anywhere by selecting the optimal network based on Quality of Service (QoS). When the UE switches between cells using the same radio access technology, it is referred to as horizontal handover. In contrast, switching between different radio access technologies in heterogeneous networks is known as vertical handover (VHO). VHO typically involves three main phases: initiation, decision, and execution. Among these, the decision phase remains a key challenge in current research on heterogeneous wireless networks. Numerous VHO decision schemes have been proposed, utilizing different architectures and approaches, including methods based on Received Signal Strength (RSS), cost functions, QoS parameters, and intelligent decision-making models. Traditional methods relying on single parameters like RSS are often inefficient as they fail to consider other vital network metrics. While cost-based schemes offer a more comprehensive approach, they often involve complex calculations, particularly when evaluating parameters such as bandwidth. This creates a growing need for intelligent VHO decision algorithms that can handle multiple decision criteria in a dynamic mobile environment, support various real-time services, and enhance overall QoS performance. One such intelligent method is the Adaptive Neuro-Fuzzy Inference System (ANFIS), introduced by Jang in the early 1990s. ANFIS combines neural networks and the Takagi–Sugeno fuzzy inference system to model nonlinear functions. It enables the tuning of fuzzy system parameters through learning, using a training dataset and optimization techniques such as the backpropagation algorithm or a hybrid approach combining backpropagation with least squares estimation to determine the optimal fuzzy inference rules [5].

II. PROPOSED MODEL: IVH-NF LTE/WiFi

This study proposes an Intelligent Vertical Handover based on a Neuro-Fuzzy model (IVH-NF), which is mathematically designed and implemented in MATLAB. The core of the model relies on the Adaptive Neuro-Fuzzy Inference System (ANFIS), an adaptive technique that combines neural networks and fuzzy logic to optimize the parameters of a Fuzzy Inference System (FIS). ANFIS is trained using a dataset to generate fuzzy membership functions (MFs) and decision rules through a hybrid learning algorithm that combines backpropagation and the least squares method. These generated rules are used to make intelligent handover decisions, selecting the optimal network to ensure the best Quality of Service (QoS). Specifically, IVH-NF aims to improve throughput, reduce unnecessary handovers—thereby minimizing Ping-Pong effects—and decrease End-to-End Delay (EED) in heterogeneous environments involving LTE and WiFi networks. To evaluate the reliability and effectiveness of IVH-NF, a simulation scenario transitioning from LTE to WiFi was developed using Apache NetBeans. The tuned membership rules, generated by the ANFIS model in MATLAB, were exported as a text file and read by the Apache-based simulator. This process allows for reliable VHO decision-making that balances complexity and performance, contributing to the development of more efficient handover mechanisms in next-generation wireless networks.

A. Input parameters

The author selected IVH_NF parameters rather than others due to their importance in decision-making and the focus of previous researchers on them and their repetition in many proposed related schemes.

1. **Mobile Speed (MS):** It is the speed at which UE is moving and it has a larger effect in VHO decision.
2. **Received Signal Strength (RSS):** It reflects the strength of the signal received, there is a need for VHO when RSS of the current network is below the threshold otherwise, doesn't need.
3. **Power Consumption (PC):** It consumed by UE and also attributed to base station equipment. During handoff, frequent interface activation can cause considerable battery drainage. The issue of power saving also arises in network discovery because unnecessary interface activation can increase power consumption.
4. **Distance (D):** It is an interval between a UE and a candidate access point (AP) or base station (eNB).

B. Identify the linguistic variables for the inputs/output

<p>Table 1: Membership function 'RSS' specifications</p> <table border="1"> <tbody> <tr> <td>Range</td> <td>-100 to -20 dBm</td> </tr> <tr> <td>Linguistic variables:</td> <td>Weak, Medium, High</td> </tr> <tr> <td>Weak</td> <td>[5.466 -85.79]</td> </tr> <tr> <td>Medium</td> <td>[6.174 -62.02]</td> </tr> <tr> <td>High</td> <td>[7.655 -38.27]</td> </tr> </tbody> </table>	Range	-100 to -20 dBm	Linguistic variables:	Weak, Medium, High	Weak	[5.466 -85.79]	Medium	[6.174 -62.02]	High	[7.655 -38.27]	<p>Table 1: Membership function 'RSS' specifications</p> <table border="1"> <tbody> <tr> <td>Range</td> <td>0 to 2 watts</td> </tr> <tr> <td>Linguistic variables:</td> <td>Low, Medium, High</td> </tr> <tr> <td>Low</td> <td>[0.1316 0.3345]</td> </tr> <tr> <td>Medium</td> <td>[0.213 0.9398]</td> </tr> <tr> <td>High</td> <td>[0.1639 1.607]</td> </tr> </tbody> </table>	Range	0 to 2 watts	Linguistic variables:	Low, Medium, High	Low	[0.1316 0.3345]	Medium	[0.213 0.9398]	High	[0.1639 1.607]
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MF	Handover (HO)				
Range	[0, 1]				
Linguistic variables	VL	L	M	H	VH
Constant values	0	0.25	0.5	0.75	1

HO is the output of IVH_NF model which is constant type from range [0, 1] with five MFs, as we see in table 5. In order to compare the attributes of different values and different units of measurement it is necessary to use the process of normalization as in equation (1) below:

C. The proposed fuzzy inference system

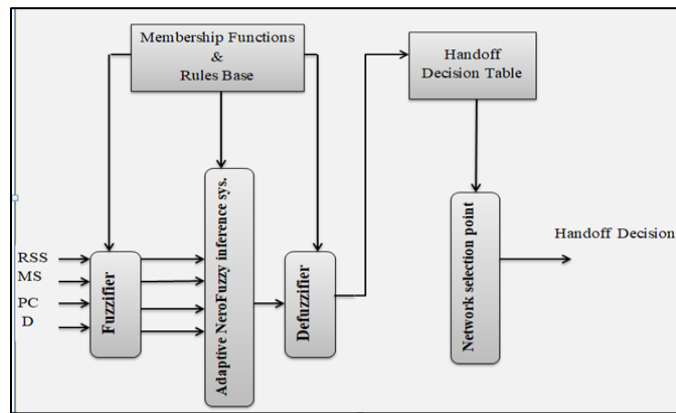


Figure 1: IVH_NF Fuzzy inference system

From Figure 1, the IVH_NF fuzzy inference system is shown to consist of four main blocks. It begins with four crisp inputs—RSS, MS, PC, and D—which are processed in the fuzzification stage, where each crisp input value is transformed into fuzzy linguistic variables. The inference engine then acts as the controller, applying fuzzy logic and leveraging a highly interconnected neural network to map the given inputs into the desired output. Finally, the defuzzification block converts this fuzzy output into a crisp value, denoted as HO.

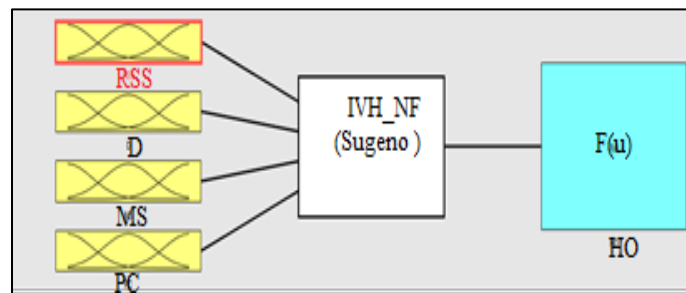
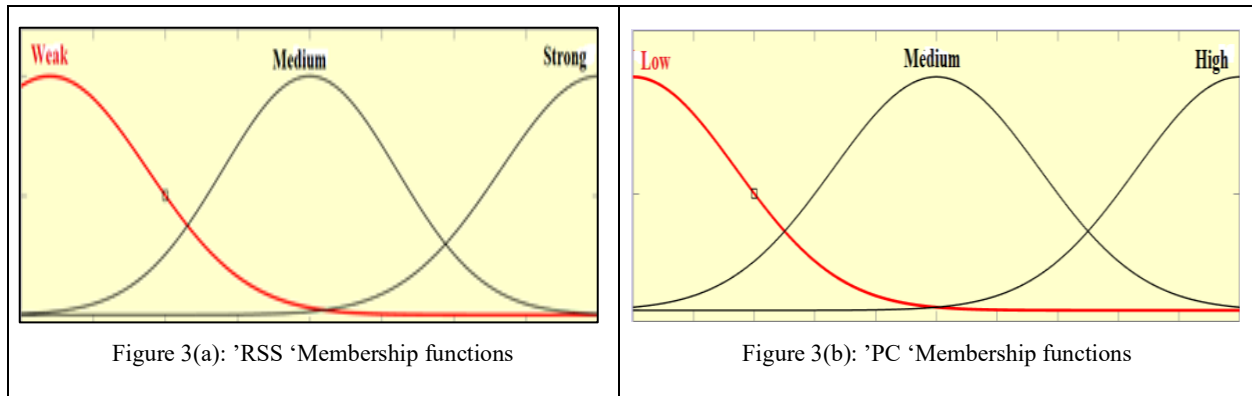


Figure 2: IVH_NF Sugeno FIS controller

The Sugeno model is selected for our proposed system, as illustrated in Figure 2, due to its faster processing time, adaptability, and flexibility compared to the Mamdani system. Unlike Mamdani, which requires computing the centroid of a two-dimensional area—a process that is time-consuming during the defuzzification phase—the Sugeno model employs a weighted sum for data sets, resulting in greater efficiency.

D. Define a set of fuzzy MFs for input parameters

By using the command `genfis1`, Gaussmf type with 3MFs achieves the fit type compared with the others because it achieves least minimum errors (RMSE) during training and testing phase and it's suitable for real-time operation. The ranges of MFs are plotted based on the designer, as in figure3 (a and b) for RSS and PC input parameters.



E. IVH_NF Rule base

Rule Viewer displays one calculation at a time in great detail and allows users interpret the entire fuzzy inference process at once, as we see in figure (4).

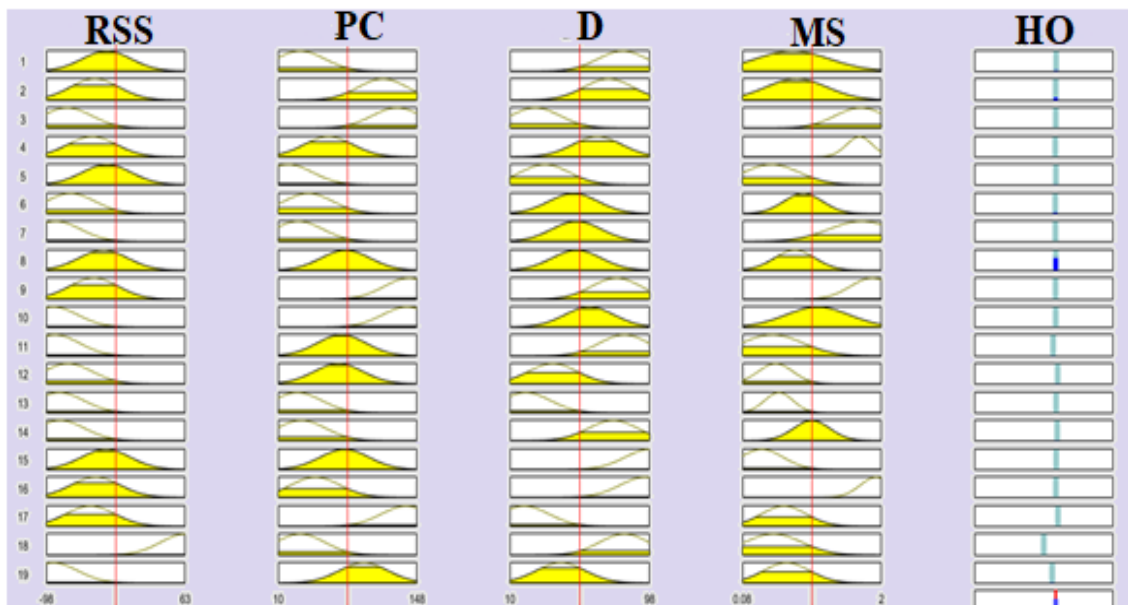


Figure 4: IVH_NF Rule Viewer

$3^4 = 81$ rules base for IVH_NF that comprise all possible relationships among the input and output parameters in IF-THEN rules with the minimum operator are specified using the logical reasoning.

III. IVH_NF EXPERIMENTAL DESIGN

ANFIS is selected to solve the problem of continuous changes in mobile learning environments. IVH_NF structure consists of five layers as we see below.

1) **First Layer:** it consists of twelve adaptive neurons that provides a fuzzification of crisp inputs and the output is the membership value of the input signals, for each node i_n define the inputs (RSS, MS, PC and D) and membership function is given as equation (1):

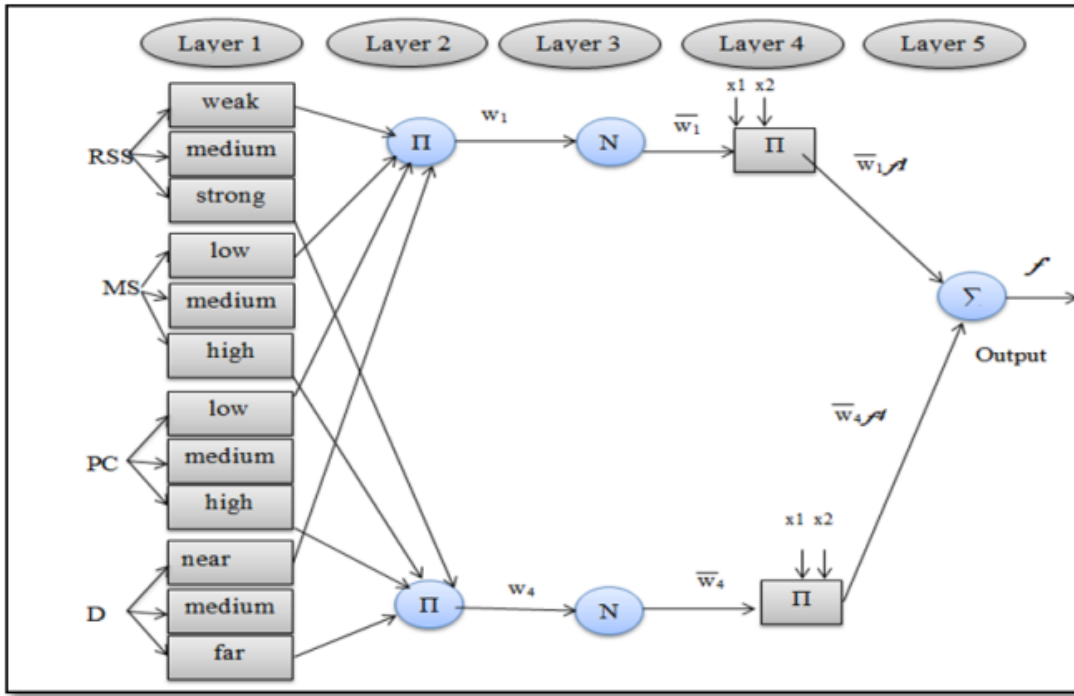


Figure 5: IVH_NF Structure

- 1) $O^1 i_n = \mu A i_n(RSS)$ for $i_n = 1,2,3$;
- 2) $O^1 i_n = \mu B i_{n-3}(MS)$ for $i_n = 4,5,6$;
- 3) $O^1 i_n = \mu C i_{n-6}(PC)$ for $i_n = 7,8,9$;
- 4) $O^1 i_n = \mu D i_{n-9}(D)$ for $i_n = 10,11,12$;

(1)

Where $A i_n, B i_{n-3}, C i_{n-6}, D i_{n-9}$ are the sets of input parameters.

The Gaussian MF is calculated as equation (2):

$$\mu A i_n = \exp \left[-\left(\frac{x - c_n}{a_n} \right)^2 \right] \quad (2)$$

Where $\{a_n$ and $c_n\}$ are the premise parameters which are to be learnt (optimized) in the input layer during adapting or training.

2) *Second layer*: it contains 81 neurons where each one is fixed, it uses fuzzy operators; AND operator to fuzzifier the inputs. The output is the firing strength of the rules in inference engine and define as in equation (3):

$$O^2 i_n = w_i = \mu A i_n(RSS) \cdot \mu B i_{n-3}(MS) \cdot \mu C i_{n-6}(PC) \cdot \mu D i_{n-9}(D) \quad (3)$$

For $i_n=1, \dots, 81$, where w_i is the firing strength and i_n is the number of nodes and rules in this layer.

3) *Third layer*: where the neuron is fixed and responsible for calculating the normalized firing strength by ratio of firing strength for this rule to sum of all firing strength rules as in equation (4):

$$O^3 i_n = \bar{w}_i = \frac{w_i}{\sum w_i} \quad i_n=1,2,3,4 \quad (4)$$

4) *The fourth layer*: it introduces with a defuzzification layer where the neuron is adaptive. The output for each node is the multiplication of normalized firing strength by first-order Sugeno model (first order polynomial) and given by equation (5):

$$O^4 i_n = \overline{w_i} f i_n = \overline{w_i} (p i_n R S S + q i_n M S + t i_n P C + k i_n D + r i_n) \quad (5)$$

Where $p i_n, q i_n, t i_n, k i_n$ and $r i_n$ are the consequent parameters set.

5) *Fifth layer*: a fixed single neuron is representing the output of ANFIS by summation of all incoming signals, as:

$$O^5 i_n = \sum_{i=1}^Q \overline{w_i} f i_n = \frac{\sum_{i=1}^Q w_i f i_n}{\sum_{i=1}^Q w_i} \quad (6)$$

A. Steps for designing IVH_NF Mathematically in MATLAB:

FIS parameters is constructing and implementing using 'ANFIS Editor' tool.

1) *Load data*:

Dataset (201 values) is collected from standard papers [6][7] for training FIS to generate tuned rules which divided into training data (70% which equals 141 values) and testing data (30% which equals 60 values) used for verify the accuracy and the effectiveness for the trained model.

2) *Generate FIS*:

Grid partition is used in our model (where it divides the input data space into rectangular subspace) rather than Subtractive clustering method (which divides data points into clusters based on the membership degree), because it doesn't take any physical meaning or data density repartition which achieve fast learning processes and calculation time optimization. The numbers of MFs equal to $3 \times 3 \times 3$ for the four metrics and constant type for the output (HO), we depend on the value of RMSE and MAE Prediction accuracy calculations for choosing the best fit type for our model which is Gaussian (gaussmf) type due to its lowest value of the RMSE and MAE during validation with the Epoch numbers 10, 25, 50 and 100 and the trapezoidal type is the worst.

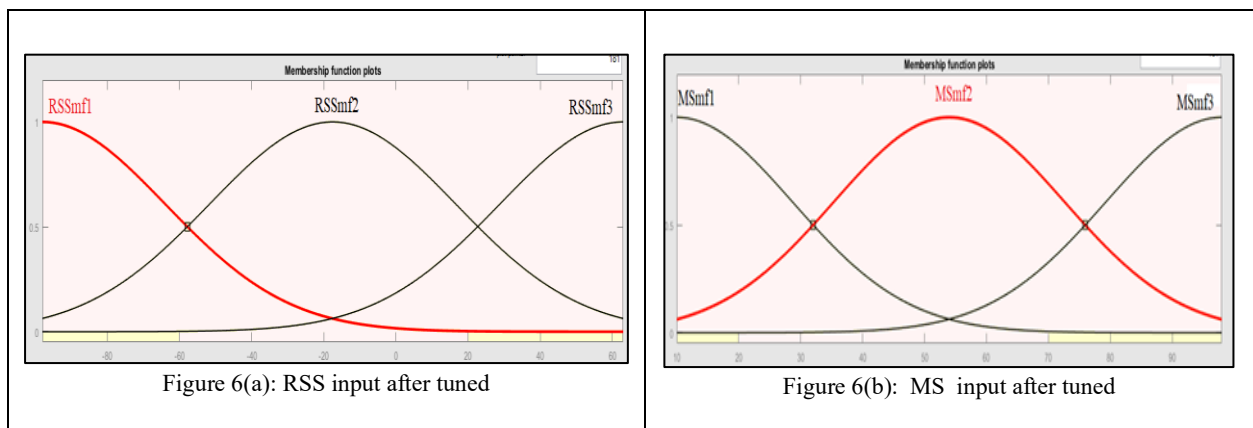
3) *Train FIS*:

To solve the problem of search space, hybrid learning algorithm (combination of back propagation algorithm and least squares method) is chosen.

4) *Test FIS*:

It is essential for enhancing the accuracy and increasing the possibilities to be understood by the system.

In the figures 6(a and b), we notice the linguistic variables for the RSS and MS inputs with their numerical ranges after updated (tuned). In figure7, IVH_NF structure is ready



The *neural network architecture* includes an input layer with four neurons for Mobile Speed (MS), Received Signal Strength (RSS), Power Consumption (PC), and Distance (D), connected to a first hidden layer of eight neurons with

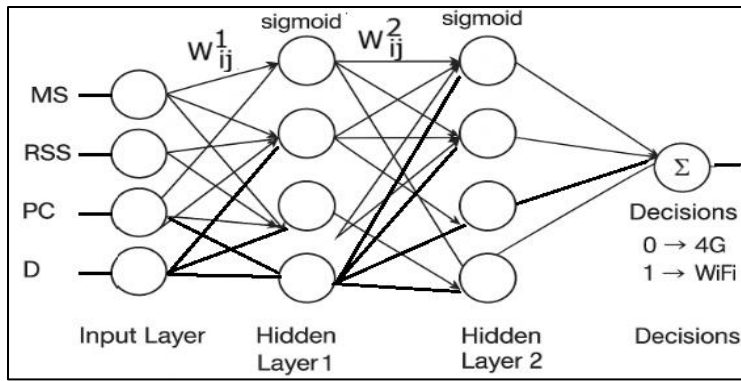


Figure 7: IVH_NF structure after training and testing

sigmoid activation, followed by a second hidden layer of six neurons also using sigmoid activation. The output layer has two neurons representing the decisions $0 \rightarrow 4G$ and $1 \rightarrow WiFi$, with sigmoid activation generating probability distributions. For training, binary_crossentropy is applied when outputs are not mutually exclusive, while softmax with categorical_crossentropy is used if only one option between 4G and WiFi can be true at a time.

$$S = 1 / (1 + e^{-x}) \quad (7)$$

A sigmoid function (S) that takes any real-valued number as input and squashes it into a value between 0 and 1.

IV. RESULT & DISCUSSION

B. Surface viewer of the FIS:

It is a 3D plot surface used for showing the dependency of the HO with two of selected inputs to evaluate the fuzzy logic system using a graphical user interface. In figure 8, it shows that, the handover factor increases (yellow) or decreases (blue) as input factors increase or decrease.

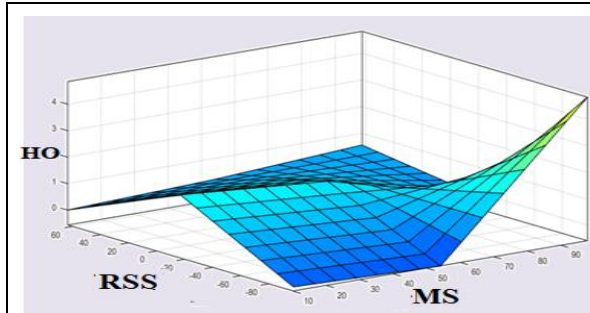


Figure8(a):3-D Surface plot of HO with MS and RSS

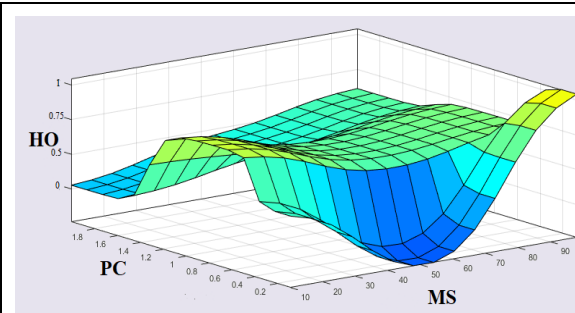


Figure 8(b):3-D Surface plot of HO with MS and PC

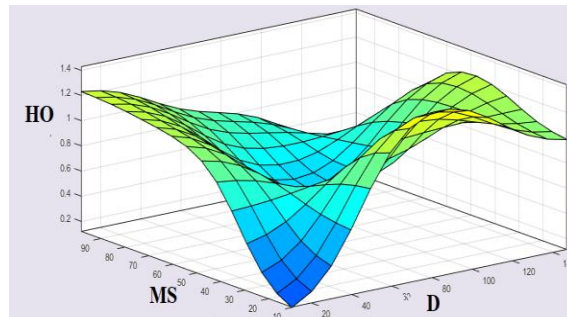


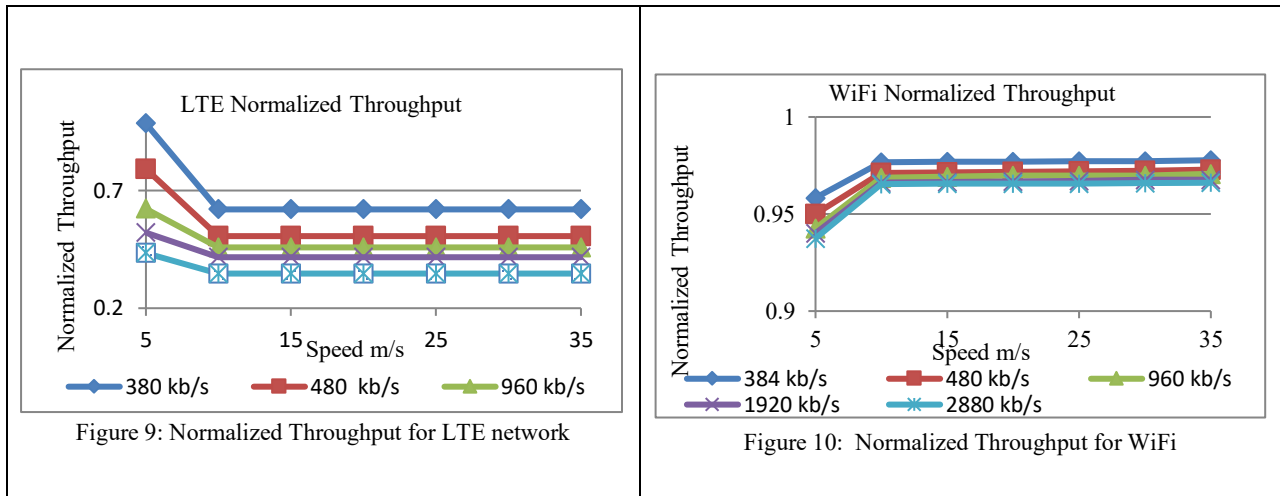
Figure 8(c):3-D Surface plot of HO with D and MS

For example, in figure 8(b), it shows when PC is high and MS is low then the UE will make handoff (blue).

C. LTE to WiFi Scenarios:

1) Throughput:

In Apache NetBeans Simulator we consider the Throughput as function of mobile speed with specific Bitrate for implementing the scenarios.

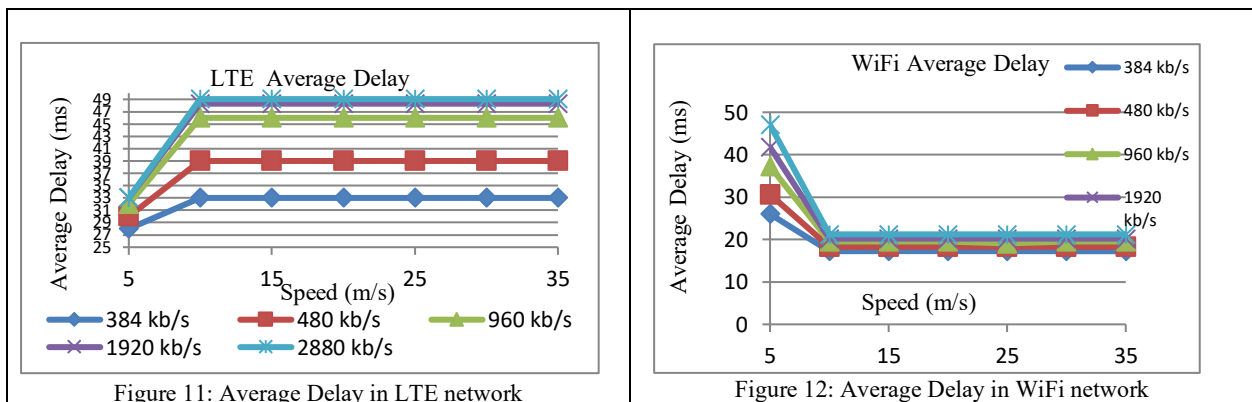


In Figure 9, we observe that throughput decreases as the UE node speed increases from 5 m/s to 10 m/s while leaving the LTE network. Beyond this point, throughput remains relatively stable due to LTE's wide coverage area and enhanced mobility features, which allow the UE to increase its speed without significantly affecting throughput. Furthermore, we conclude that increasing the bitrate values leads to a corresponding increase in throughput.

In Figure 10, when the UE enters the WiFi network, throughput values rise significantly as the UE speed increases from 5 m/s to 10 m/s, followed by a more gradual increase. The UE prefers to remain connected to the WiFi network whenever possible because of its higher bandwidth and lower cost compared with LTE. Similarly, as bitrate values increase, throughput is also observed to increase.

2) Average End to End delay (EED):

The average delay is the total of EED intervals divided by the number of packets received.



The Average End to End delay for LTE packets in figure11 is slightly increases with increasing the values of Bitrate from 384 to 2880 kb/s, due to increasing the speed, the Average EED significantly increases between 5 to 10 m/s after that it is still constant with increasing UE speed.

In figure12, the Average Delay in WiFi network increases with increasing the values of Bitrate on the other side, increasing the UE node speed leads to decrease the Average Delay from 5 to 10 m/s then still constant. We get acceptable values for all UE speed values and application bitrates, which mean the good performance metrics due to the low number of handover occurred times which certainly increase the reliability of the model.

3) Handover Count:

Frequent handovers is a waste of network resources, so that we must keep the number of handovers to be least as possible.

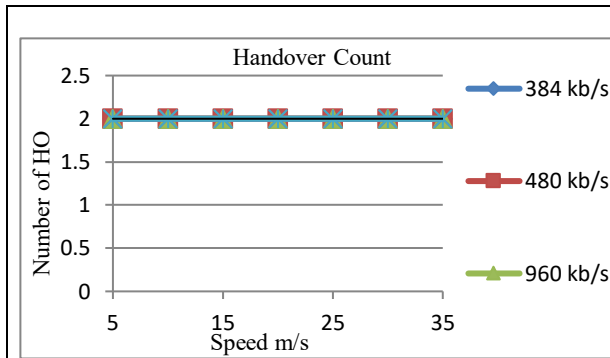


Figure 13: Handover Count in LTE to WiFi Scenario

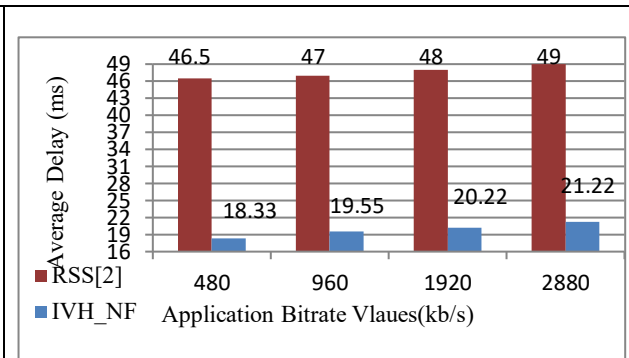


Figure14: Average Delay for IVH_NF and RSS [2]

In the figure 13, changing the UE speed at specific Bitrate for each time isn't effected on the number of HO (equal 2) where it acceptable value that limits Ping-Pong effect and the handover is executed only if needed depending on different inputs criteria.

D. IVH_NF performance Vs. previous models:

1) Average EED Performance:

IVH-NF significantly reduces End-to-End Delay (EED) compared to existing methods. As shown in Figure 14, IVH-NF achieves a 58% reduction in EED compared to RSS [1].

2) Handover Count

IVH-NF demonstrates superior performance in minimizing handover occurrences. As observed in Figure 15, IVH-NF results in the lowest number of handovers when compared to fuzzy logic [3], RSS [8], SNR [9], traditional approaches [10, 11], and ANFIS [2].

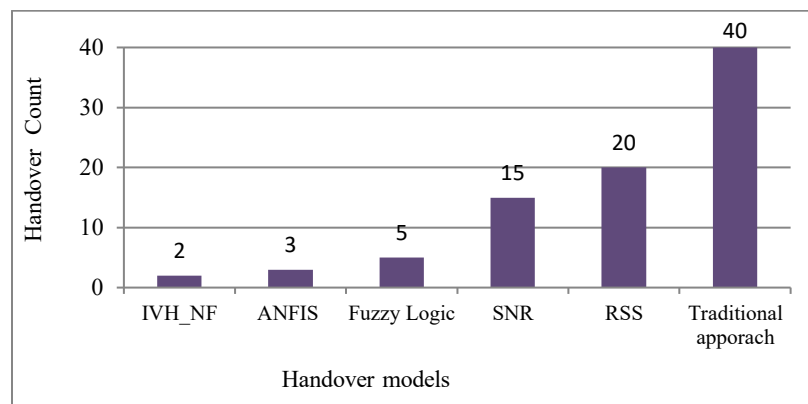


Figure15: Handover Counts for different models

From the figure above, the improvement percentage for IVH_NF is percentage decrease (less count is the best) comparing with the last two intelligent VHO algorithms, Handover Counts in IVH_NF reduced by 33.3% from ANFIS [2] and 60% from FL [3].

V. ADVANTEGES LIMITATIONS AND DRAWBACKS

The proposed approach offers several advantages. It integrates diverse metrics to improve the balance of handover decision-making and delivers notable QoS improvements, with gains of up to 58%. Furthermore, it dynamically adjusts and refines membership functions, which ensures robust performance under varying network conditions. Another important strength is its ability to reduce redundant interface activations, thereby improving energy efficiency and mitigating the Ping-Pong effect.

Despite these advantages, certain limitations remain. The model is highly dependent on the diversity and accuracy of the dataset in order to generalize effectively in unseen environments. In addition, the ranges for static membership functions may require tuning for specific RATs or deployment contexts. The training process can also be computationally intensive, particularly when handling large datasets. Moreover, validation so far has been restricted to simulated and controlled scenarios, which may limit the generalizability of the findings.

Finally, some potential drawbacks should be noted. There is a risk of overfitting unless appropriate cross-validation strategies are employed. The current design is tailored to LTE–WiFi, and extending it to other RAT combinations may necessitate both retraining and model adaptation. In real-time operation, performance may also diminish if key input metrics are missing or experience delays in arrival.

VI. CONCLUSION AND FUTURE WORK

This work introduces a novel multi-criteria vertical handover (VHO) decision-making framework based on ANFIS. It integrates link quality, mobility, energy efficiency, and spatial factors. A key contribution is the incorporation of power consumption for energy-conscious handovers. The framework achieved significant reductions: 58% in end-to-end delay (EED), 33.3% in handovers vs. ANFIS, and 60% vs. traditional fuzzy-logic models. It also enhanced data transmission rates and maintained stable connection quality under varying mobility and bitrate. Adaptability and robustness were confirmed via simulations (MATLAB, Apache NetBeans) and real-world datasets. The study examined UE speed and application bitrate impact on QoS. Compared to existing VHO algorithms, the proposed IVH-NF model demonstrated superior performance by reducing EED, minimizing handovers, improving throughput, extending UE WiFi connection, and lowering costs, proving its efficiency and adaptability for next-gen wireless networks.

Future work will focus on field verification of the model in real-world LTE–WiFi environments to assess its performance under practical interference conditions and dynamic mobility patterns. Another important direction is extending the framework to accommodate 5G and beyond by refining decision parameters and membership functions for 5G NR, WiFi 6/6E, and other emerging radio technologies. In addition, the model can be further enhanced through integration with cutting-edge technologies such as edge computing, AI-driven network controllers, Software-Defined Networking (SDN), and Network Functions Virtualization (NFV). Embedding the model within these structures will enable scalable and low-latency decision-making. By pursuing these developments, the IVH-NF model holds significant potential to evolve into a flexible and advanced vertical handover solution capable of adapting to a wide range of dynamic wireless environments.

ACKNOWLEDGMENTS

I would like to thank my lecturers at AL-QUDS University in Engineering college mainly my supervisor for this project Dr. Rushdi Hamamreh for his guidance, insightful comments and support throughout the contribution of my research work.

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Appendix A — Sample of the dataset structure

In this appendix, we provide a representative sample consisting of the first 10 entries from the dataset used to train and evaluate the proposed Intelligent Vertical Handover Neuro-Fuzzy (IVH-NF) model. The full dataset, which includes a total of 600 entries, can be accessed at: [Google Sheets – IVH_NF Dataset](#)

Table A.1: Sample dataset entries used for IVH-NF model training and evaluation

RSS (dBm)	D(m)	MS (km/h)	PC (W)	HO
-75	90	51	1.3	0.327
-95	55	58	1.1	0
-20	50	58	0.4	0.5
-26	76	51	1	1
-40	80	70	0.7	1
-60	140	20	0.7	0.5
-40	140	70	0.7	0.75
-33	33	87	0.9	1
-80	33	20	0.9	0.25