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Development of an Algorithm to Improve the Handoff of 4G Wireless Cellular Network using Adaptive Neuro-Fuzzy Inference System

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ABSTRACT

This study aims to enhance handoff performance in mobile communication networks by addressing the limitations of conventional systems through the implementation of the Adaptive Neuro-Fuzzy Inference System (ANFIS). Traditional handoff methods have been constrained by a modest success rate of 80%, leading to unreliable connections during user mobility. These challenges arise from factors such as weak signal strength, high network congestion, and suboptimal mobility management. To tackle these issues, a customised ANFIS model was developed using MATLAB/Simulink, introducing a dynamic and intelligent approach to the handoff decision-making process. The results demonstrated significant performance improvements. The ANFIS-based system achieved a 95% handoff success rate, a substantial increase from the conventional method. Quantitative enhancements included a rise in signal-to-noise ratio (SNR) to 25 dB, an improvement in signal strength to an average of -70 dBm, and an increase in system efficiency to 95%. Moreover, the ANFIS approach facilitated a growth in network capacity, allowing concurrent users to increase from 100 to 150. Quality of Service (QoS) metrics, previously rated as poor, were elevated to good, ensuring a seamless user experience. These findings underscore the transformative potential of ANFIS in managing handoff strategies, offering more reliable connectivity and improved performance in demanding wireless environments. The study advocates policy adjustments to prioritise the adoption of intelligent systems like ANFIS to meet the growing requirements of modern mobile communication networks.

Keywords - **Network, Communication System, Handoff, Signal-to-Noise Ratio, Quality of Service, Performance improvement.**

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I. INTRODUCTION

1.1 Background of the Study

The advancement of 4G mobile communication has brought significant improvements in speed, latency, and spectral efficiency. However, as user mobility and demand for uninterrupted connectivity grow, the challenge of efficient handoff between cells becomes critical. Enhancing handoff mechanisms in 4G networks has emerged as a central focus, leading to the development of intelligent algorithms that address service consistency and network adaptability [1].

Traditional handoff systems often fall short in dynamic environments where high-speed mobility or varying network loads are present. To overcome these limitations, modern algorithms are designed to optimise handover decisions using real-time data such as signal strength, network load, user mobility, and Quality of Service (QoS) requirements [2]. These systems aim to maintain seamless connectivity by minimising delays and disruptions during handoffs.

Machine learning plays a key role in modern handoff algorithms by enabling predictive decision-making. By analysing historical data and recognising patterns, the system can anticipate handoff needs and initiate them proactively, thereby enhancing communication continuity [3]. Context-awareness is also vital, allowing algorithms to adapt to real-time user behaviour, application demands, and network conditions for more precise decisions.

In addition, handoff algorithms now incorporate load balancing strategies, which evenly distribute users across available cells, reducing congestion and maximising resource use [4]. This ensures efficient operation and consistent service delivery.

Interoperability further enhances these algorithms, enabling seamless handovers across multiple generations of mobile networks (e.g., from 4G to 3G or 2G). Overall, the development of advanced handoff algorithms represents a collaborative effort to refine 4G systems, ensuring reliability, adaptability, and superior user experience in evolving mobile environments [5].

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1.2 4G Communication

Fourth generation (4G) communication technology marked a transformative era in wireless telecommunications, offering superior data speeds, improved bandwidth, and reduced latency compared to earlier generations [6][7][8]. Designed to meet the rising demand for high-speed mobile internet, 4G enables seamless connectivity, supporting applications such as HD video streaming, real-time gaming, and video conferencing [9]. A key innovation in 4G is the use of Orthogonal Frequency Division Multiplexing (OFDM) and Orthogonal Frequency Division Multiple Access (OFDMA), which optimise spectrum usage and enhance network efficiency. These techniques, combined with Long-Term Evolution (LTE) as the foundational technology, enable high-speed wireless transmission [11][12]. LTE also incorporates Multiple Input Multiple Output (MIMO) systems, which use multiple antennas to boost signal quality and network capacity through spatial diversity [10]. The impact of 4G includes significant improvements in data transfer rates—often exceeding hundreds of Mbps—and low latency, facilitating real-time applications and smoother user experiences. It also catalysed the growth of mobile services beyond voice and SMS to rich multimedia applications [13][14]. Infrastructure upgrades such as IP-based core networks and expanded spectrum allocation were essential for 4G deployment. These developments supported not only smartphones but also the Internet of Things (IoT), enabling smart devices and systems in homes, industries, and cities [15][16]. Overall, 4G reshaped digital communication, bridged the digital divide in underserved regions, and laid the technological foundation for future mobile innovations, including 5G [17][18][19].

1.3 Mobile Communication Handoff

Mobile communication handoff is essential in wireless networks for maintaining uninterrupted service as users move between cells or base stations. It enables the seamless transfer of ongoing calls or data sessions without service degradation, thus ensuring continuous connectivity across the network [21][22]. This mechanism relies on signal strength fluctuations—handoff occurs when the signal from a neighbouring cell surpasses that of the current one [20].

There are various handoff types, including soft and hard handoffs. Soft handoff allows simultaneous connections to multiple cells during transition, improving reliability and reducing service interruption. In contrast, hard handoff disconnects the user from the current cell before connecting to the next, posing a higher risk of momentary interruptions [23][24].

Handoffs can also be network-controlled or mobile-assisted. In network-controlled handoffs, the decision is made by the infrastructure using signal metrics, whereas mobile-assisted handoffs involve the device in the decision-making process, improving responsiveness and efficiency [25][26][27].

The significance of handoff mechanisms lies in their contribution to network quality of service (QoS). By reducing dropped calls and managing smooth transitions, they ensure consistent user experiences, particularly in high-mobility environments or densely populated regions [28]. Efficient handoff systems also support modern applications such as voice over IP, video conferencing, and real-time gaming, which are sensitive to delays or interruptions [29][30].

II. MATERIALS AND METHOD

The method adopted in this research work is the adaptive neuro-fuzzy interference system. A combination of an artificial neural network and a fuzzy logic controller.

2.1 Analysis of Handoff Signal Strength of the Cellular Network

The signal strength used for handoff decisions in wireless communication systems can be estimated using various models. One common approach is to use the Free Space Path Loss (FSPL) model, which estimates the signal strength based on the distance between the transmitter and receiver, the frequency of the signal, and environmental factors.

The Free Space Path Loss equation is given by [21]:

$$FSPL = 20log_{10}(d) + 20log_{10}(f) + 20log_{10}(\frac{4\pi}{c}) \quad (1)$$

where:

FSPL is the Free Space Path Loss in decibels (dB).

d is the distance between the transmitter and receiver in meters.

f is the frequency of the signal in Hertz.

c is the speed of light in meters per second.

The received signal strength at a specific distance can then be calculated using the transmitted signal power (Pt) and the Free Space Path Loss as [20]:

$$RSS = P_t - FSPL \quad (2)$$

where:

P_t is the transmitted signal power in decibels (dB).

This equation estimates the signal strength at a certain distance based on the transmitted power and the path loss due to the distance and frequency of the signal. Real-world scenarios may involve additional considerations such as obstacles, interference, and fading effects, which require more complex models or empirical measurements for accurate signal strength estimation for handoff decisions.

2.2 4G Mobility Cell Pattern Evaluation

Designing a precise equation for 4G cell mobility patterns involves considering various factors such as user mobility, handoff rates, network topology, and deployment strategies. A simplified model to describe cell mobility patterns in a 4G network could involve parameters related to cell transition probabilities based on user movement and network characteristics.

One approach might be to use a Markov chain model to represent the cell-to-cell transitions. A basic mobility pattern equation could be represented as follows:

$$p_{ij}(t + \Delta t) = P_{ij}(t) \times P_{ij}(t) \times \Delta t \quad (3)$$

where:

Pij(t) is the probability of a user transitioning from Cell i to Cell j at time t.

Transition Probability ij denotes the probability of transitioning from Cell ii to Cell jj.

Δt represents the time interval.

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This equation suggests that the probability of a user moving from Cell i to Cell j later t + Δt is dependent on the transition probability between those cells and the current probability at time t.
This simple model assumes a homogeneous Markov chain where the transition probabilities remain constant over time. Real-world mobility patterns in 4G networks might involve more complex models, incorporating factors such as user mobility patterns, traffic density, handoff rates, and network load.
Developing a comprehensive and accurate mobility pattern equation for 4G networks often requires empirical data, statistical analysis, and more sophisticated models that consider diverse user behaviours, geographical variations, and network dynamics.

2.3 **Handoff Network Congestion Evaluation Using ANFIS**

An equation describing network congestion during handoff processes in 4G networks typically involves parameters related to the traffic load, available resources, and handoff rate. However, creating a precise equation for network congestion during handoffs is complex and depends on various dynamic factors.
A simplified representation of network congestion during handoffs might involve considering the traffic load and resource availability. An illustrative equation could be:

$$congestion = \frac{current\ traffic\ load}{available\ resources} \quad (4)$$

Where:
Congestion represents the congestion level during handoffs.
Current Traffic Load signifies the existing amount of traffic or data being handled by the network during the handoff.
Available Resources denotes the available capacity or resources in the network, such as bandwidth, processing power, or available channels.
This equation simplifies the relationship between traffic load and available resources, implying that higher traffic loads relative to available resources lead to increased congestion during handoff processes. However, real-world network congestion involves multiple factors beyond just traffic load and resource availability, including interference, queuing delays, packet loss, and contention for resources among users and cells.
ANFIS is used to effectively optimise the network performance during periods of congestion. By adapting to real-time conditions and user demands, ANFIS facilitates a smoother transition from congestion back to stability.

2.4 Implementation of the Handoff System Using ANFIS

The implementation of the handoff system using Adaptive Neuro-Fuzzy Inference System (ANFIS) in MATLAB involves several key steps. Initially, the model is developed by defining the input parameters, such as signal strength, user velocity, and quality of service metrics. Historical data is used to train the ANFIS model, optimising the fuzzy inference rules through a hybrid learning algorithm. After training, the system continuously processes real-time data, allowing it to make intelligent handoff decisions based on current network conditions. MATLAB's visualisation tools enable users to monitor system performance, ensuring seamless transitions between cells and enhancing overall user experience. The data used in the design is shown in Table 1.

Table 1: the Measured Data Using Spectrum Analyzer

Signal Strength (- dBm)	Signal Quality (SNR)	Mobility (km/h)	Network Load	QoS Requirements	Handoff Decision
-70	20	50	Low	High	Initiate
-80	15	20	Moderate	Medium	Stay
-75	18	40	High	Low	Initiate
-85	12	60	High	High	Urgent
-78	16	25	Low	Medium	Stay
-82	14	35	Moderate	Low	Initiate
-88	10	70	High	High	Urgent

Improving mobile network handover using ANFIS involves training a model on real-world data signal strength, SNR, and mobility to predict handoff decisions. Using MATLAB's Neuro-Fuzzy Designer, the system learns through fuzzy rules and membership functions. The trained model adapts to conditions, enhancing handoff accuracy and boosting network performance.

2.5 Handoff Control Using ANFIS

ANFIS enhances 4G handoff systems by combining neural learning and fuzzy logic to analyse signal strength, mobility, congestion, and QoS. It adapts using real-time and historical data, ensuring smooth transitions, reduced dropped calls, and improved reliability. Its evolving nature optimises decisions, boosting efficiency and user experience in dynamic 4G networks.

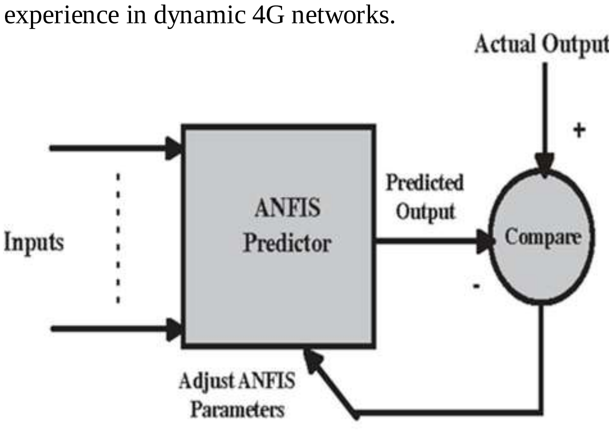

Figure 2: Handoff Control using ANFIS

2.6 Evaluation of The ANFIS Algorithm

This flowchart outlines an ANFIS-based handoff system. It begins by converting crisp input data (like signal strength, velocity, and bandwidth) into fuzzy linguistic terms (Fuzzification). Then, "IF-THEN" Fuzzy Rules are defined based on knowledge or learned patterns. The system undergoes Neuro Fuzzy Learning, where rules are optimised using a hybrid algorithm. The Inference Mechanism applies these learned rules to determine a fuzzy output, which is then converted into a clear Handoff/Stay decision (Defuzzification). After Handoff Execution, a decision point checks if the handoff occurred. Regardless, Performance Monitoring and Feedback evaluate metrics. A final Decision Point assesses performance and ends the cycle as shown in Figure 3.

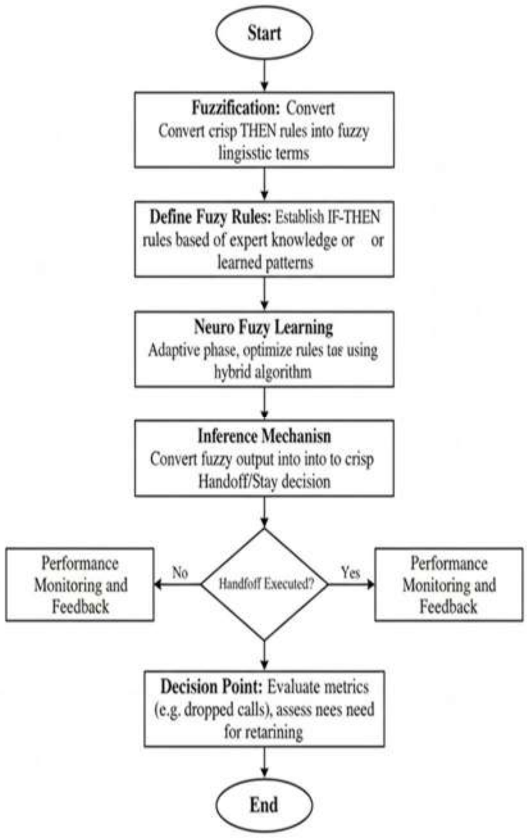

Figure 3: Flowchart of ANFIS-based handoff system

The first equation calculates signal strength based on received power and distance from the base station, reflecting how well the signal reaches the user. The second equation computes the user's velocity, combining motion in two dimensions. Finally, the third equation uses ANFIS to determine the need for a handoff based on signal strength and user velocity.

$$s = \frac{p_r}{d^n} \tag{5}$$

where:
S = Signal strength (dBm) Pr = Received power (dBm)
d = Distance from the base station (meters)
n = Path loss exponent (typically between 2 and 4)
The equation explains the velocity of the handoff system

$$V = \sqrt{(V_x^2 + V_y^2} \tag{6}$$

where:
V = User velocity (m/s)
Vx = Velocity in the x-direction (m/s)
Vy = Velocity in the y-direction (m/s)
The equation expresses the handoff decision

$$H = f(s, V) \rightarrow \begin{cases} 0 & (No\ Handoff) \\ 1 & (Hnadoff) \end{cases} \tag{7}$$

where:
H = Handoff decision (0 or 1)
f = ANFIS output function based on inputs S and V

III. RESULTS AND DISCUSSION

The results obtained from the simulations are reported in this section, highlighting the significance of signal strength, user's mobility, congestion management, implementation and performance comparison using ANFIS.

3.1 Analysis of Signal Strength Distributions

The graph in Figure 4 illustrates the distribution of signal strength across different frequencies, with the highest signal strength observed at 51 Hz. The signal quality is reported at 70%, indicating satisfactory communication performance with minimal interference or distortion. Additionally, the distributed mobility stands at 60%, suggesting moderate mobility within the communication environment. This analysis highlights the complex interplay between signal strength, quality, and mobility in wireless communication systems, offering insights into opportunities for optimisation and adaptation to varying environmental conditions.

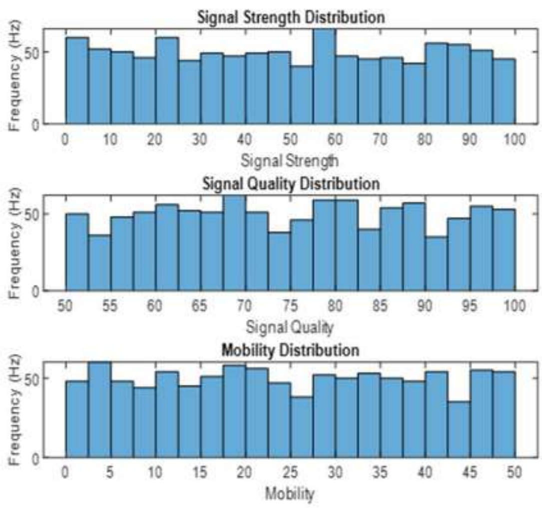

Figure 4. Signal Strength Distribution

3.2 Network Congestion and Decongestion Evaluation Using ANFIS

Figure 5a shows a rapid increase in network congestion from 0 to 0.4 seconds, highlighting the strain caused by rising user demand and the urgent need for better resource management. Without intervention, this could lead to poor service quality. In contrast, Figure 5b reveals a successful decongestion trend, with levels peaking near 40 and dropping to around 1 by 20 seconds, indicating the system's ability to stabilise under pressure. The steady decline illustrates ANFIS's effectiveness in managing congestion, adapting in real-time to user load, and restoring balance. These results support the integration of intelligent systems to enhance network performance and user experience.

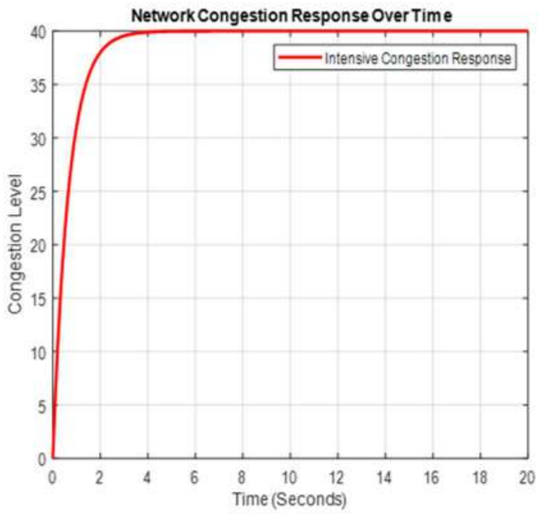

Figure 5a Network Congestion Response Over Time

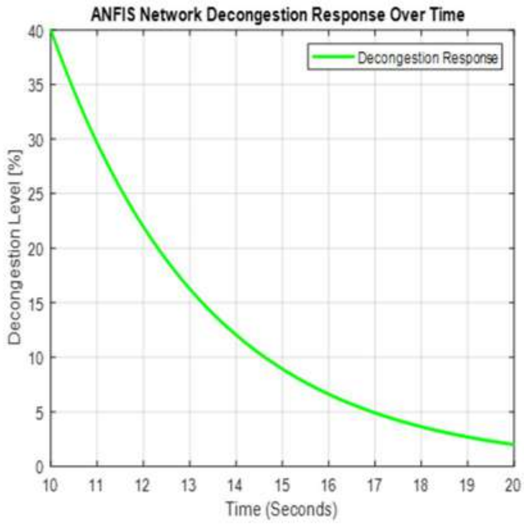

Figure 5b ANFIS Network Decongestion Level Over Time

The handoff success rate increases from 50 to 130, showing significant improvement, suggesting the network's growing ability to handle transitions smoothly as users move between cells. This rise indicates that more connections are successfully maintained during these transitions, enhancing overall service quality. Simultaneously, the number of handoff attempts also increased from 40 to 80, reflecting a likely rise in network usage, with more devices trying to stay connected while on the move as shown in Figure 5c.

However, as handoff activity intensified, handoff congestion climbed from 10 to 42. This congestion spike suggests that while the network can accommodate more users with higher success, it is also experiencing strain, likely due to more frequent requests and limited resources. The overall trend reveals a network that successfully adapts to increased demand but may face congestion challenges at peak times. This balance underscores the importance of ongoing optimisation to sustain high performance as user needs evolve.

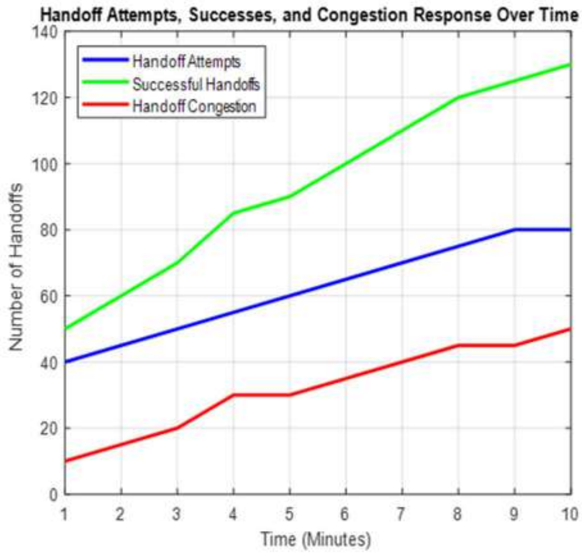

Figure 5c: Handoff Attempt, Success, And Congestion Response Over Time

3.3 Implementation of ANFIS Security Mechanism Implementations Over Time

Figure 6 illustrates how ANFIS enhances security and privacy over time through adaptive learning. Initially, the system detects threats using fuzzy logic rules and historical data, showing high sensitivity to anomalies. As it gathers more data, ANFIS refines its detection model, adapting to new cyber threats through continuous learning. Simultaneously, it enforces privacy using encryption, access control, and user authentication. These mechanisms evolve based on user behaviour, data sensitivity, and regulations. ANFIS dynamically balances system security and privacy, ensuring resilience against attacks while maintaining data integrity and user trust. This adaptive approach makes the system robust, compliant, and responsive to changing cybersecurity demands.

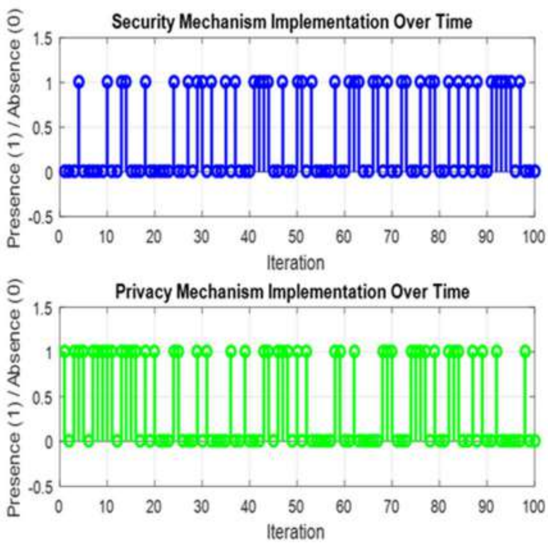

Figure 6: Security mechanism implementations over time

3.4 Robustness and Adaptability Evaluations

Figure 7 highlights ANFIS's strength in maintaining robust and adaptive network performance under changing conditions. By combining fuzzy logic and neural networks, ANFIS continuously monitors parameters like signal strength, congestion, and latency to optimise resource use and ensure reliable communication. The system dynamically adjusts network configurations in real time based on environmental feedback, effectively handling fluctuations in user demand and traffic. Notably, ANFIS achieves a handoff success rate above 0.5 and a low latency rate of 1 at 100 iterations, ensuring smooth connectivity for mobile users. This demonstrates ANFIS's capability to enhance network stability, responsiveness, and user experience in dynamic environments.

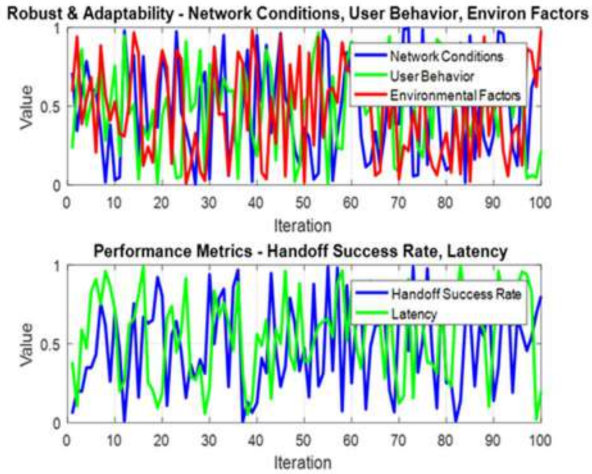

Figure 7: Robust & Adaptability-Network Conditions

3.5 Signal Strength for Neighbour cell

Figures 8a, and 8b illustrate ANFIS's crucial role in neighbour cell selection by evaluating signal strength, signal quality, and network load over 100 iterations. ANFIS identifies neighbouring cells with the strongest signals to support smooth handovers and uninterrupted connectivity. It also analyses signal quality metrics, such as signal-to-noise ratio and bit error rate, ensuring reliable communication. Additionally, ANFIS monitors network load to select cells with sufficient bandwidth, reducing congestion and improving system efficiency. By combining fuzzy logic with machine learning, ANFIS enables seamless transitions, reliable performance, and optimised resource usage in mobile networks, ultimately enhancing the user experience.

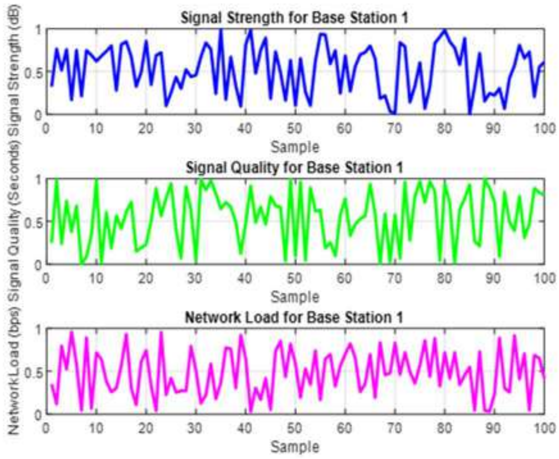

Figure 8a: signal strength for neighbour cell selection of base station 1

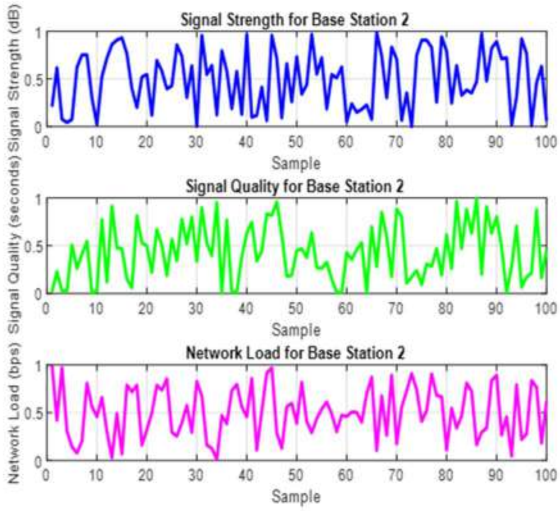

Figure 8b: signal strength for neighbour cell selection of base 2

3.8 Interference and Fading

Figure 11 emphasises how interference and fading critically affect handoff performance in mobile networks. Interference caused by unwanted signals or noise can degrade signal quality and trigger handoffs to maintain communication reliability. Fluctuations in interference, often due to environmental or neighbouring cell activity, increase the risk of dropped calls. Similarly, fading results from factors like multipath propagation or shadowing cause unpredictable variations in signal strength, challenging stable connectivity during handoffs. The graph highlights the need for adaptive handoff algorithms that respond to these conditions. By addressing interference and fading, networks can improve handoff efficiency, ensure seamless transitions, and maintain high-quality, uninterrupted user communication.

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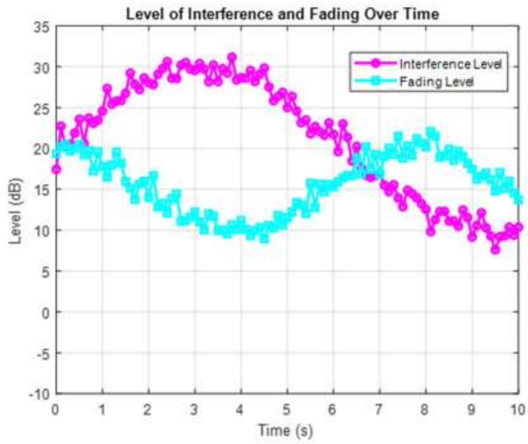

Figure 11: Interference and Fading

3.9 Quality of Service in the Network

Evaluating Quality of Service (QoS) in a 40-user network requires assessing bandwidth allocation, latency, packet loss, and scalability. Effective traffic management ensures stable connections, while adaptive infrastructure meets changing demands. Meeting Service Level Agreements (SLAs) maintains user trust and satisfaction, ensuring reliable, high-performance communication across all users, as shown in Figure 12.

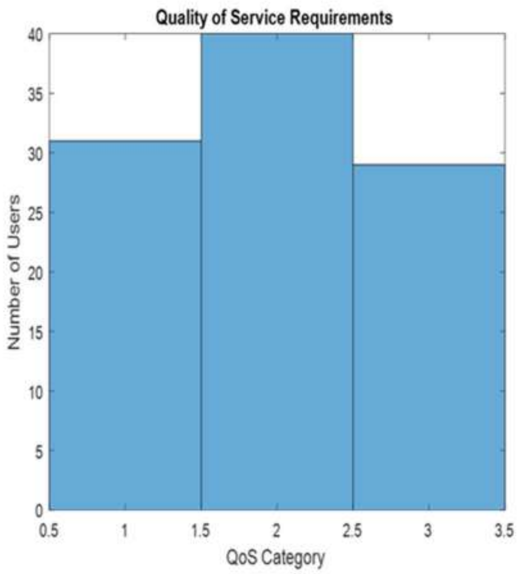

Figure 12: Quality of Service Requirements

3.12 Analysis of Handoff Response

Figure 15 illustrates how ANFIS uses signal strength, signal quality, and cell mobility to determine handoff responses. With high signal strength and quality at 98%, the connection remains stable. However, 50% cell mobility introduces variability, prompting ANFIS to assess the need for handoff. This adaptive process ensures seamless connectivity and optimal performance in changing network conditions.

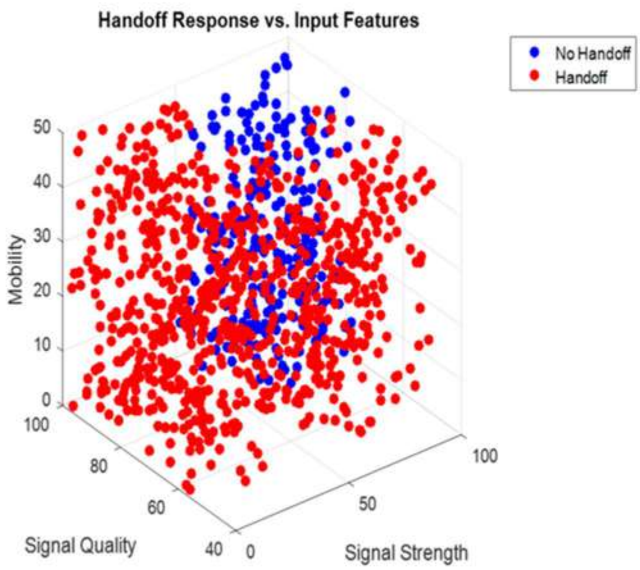

Figure 15: Handoff Response vs Input Features

3.13 Handoff System Efficiency

A 95% handoff success rate at -70 dB signal strength indicates that the ANFIS-based handoff system performs efficiently under moderate signal conditions. This high success rate reflects the system's ability to ensure seamless transitions between network cells with minimal disruption. It highlights ANFIS's effectiveness in optimising handoff decisions and maintaining reliable communication, as shown in Figure 16.

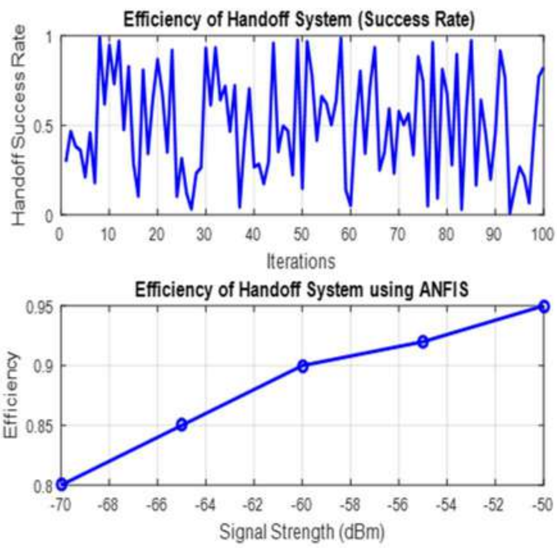

Figure 16: Efficiency of Handoff System

3.14 Conventional and ANFIS Soft Handover Efficiency Evaluation

Figure 17 shows a soft handover efficiency rate of 95% with 10 cells, outperforming the conventional method at 80%. This highlights the superior capability of the soft handover mechanism in managing transitions smoothly between base stations, reducing disruptions, enhancing network reliability, and improving user experience in cellular

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communication environments. Table 2 shows the results of the ANFIS Handover system.

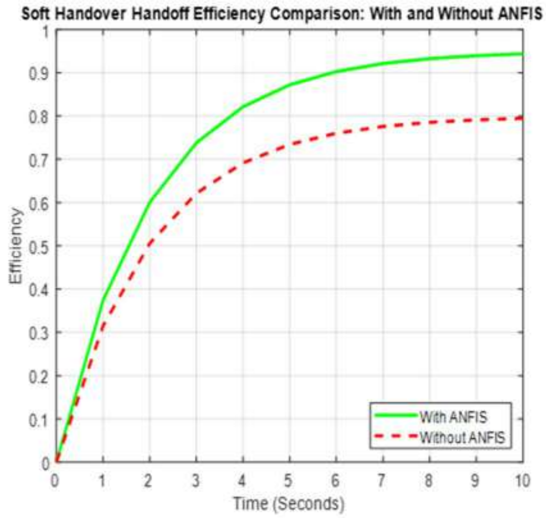

Figure 17: Soft Handover Efficiency Rate

The results reveal a notable difference in handoff success rates between the conventional system and the ANFIS-based approach. The conventional handoff system achieved a success rate of only 80%, indicating significant room for improvement and potential disruptions for mobile users during transitions between network cells. In contrast, the ANFIS system demonstrated a more favourable success rate of 95%, reflecting its enhanced adaptability and decision-making capabilities. This 15% increase suggests that users experience smoother and more reliable connections, highlighting the importance of adopting advanced technologies like ANFIS to improve overall mobile communication experiences and minimise interruptions, as shown in Figure 18.

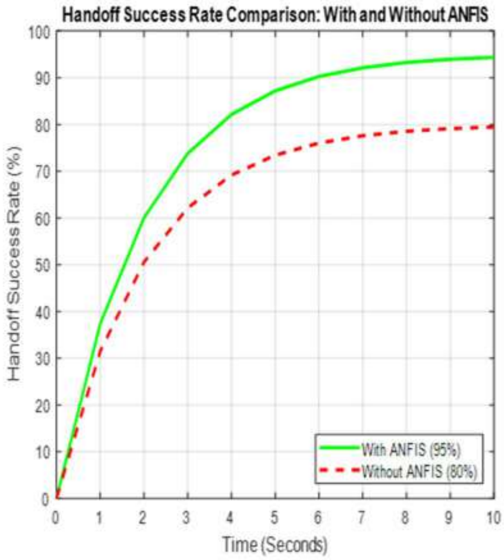

Figure 18: Comparison of Handoff Success Rates

3.15 Handoff Set Point Response

Figure 19 shows the ANFIS-based handoff system improving from an initial 80% success rate to nearly 95% by 15 seconds. The system's intelligent adaptation enables rapid performance enhancement, closely aligning with the set point. This demonstrates ANFIS's effectiveness in ensuring reliable, efficient handoffs and superior performance over conventional methods.

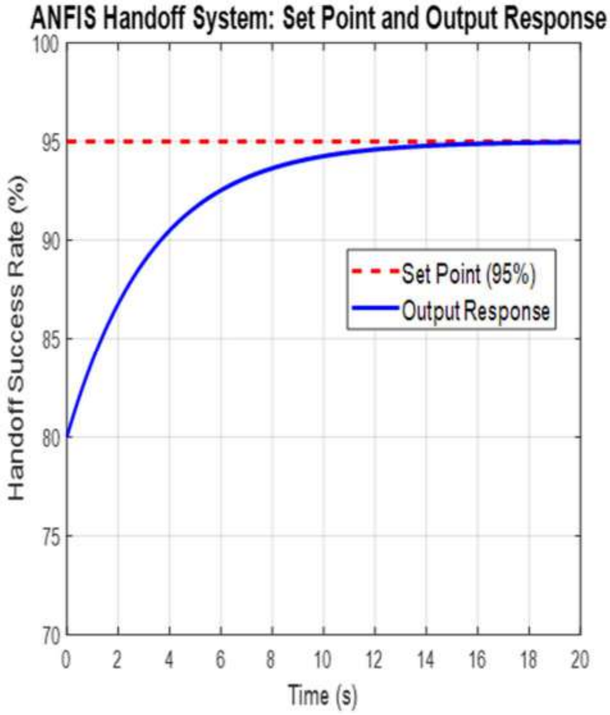

Figure 19: ANFIS Handoff System

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Table 2: Handover Results using ANFIS

Parameters	Value	Description
Signal Strength Threshold	-60 dBm	It indicates a strong signal where handoff triggering is likely to occur.
User Mobility	100 km	User mobility necessitates handoff to maintain connectivity over large distances.
Network Load	60%	Moderate utilisation of network resources, impacting handoff triggering decisions.
Interference Impact	High	Presence of unwanted signals can degrade connection quality, potentially increasing handoff frequency.
Fading Impact	Variable	Signal strength variations due to environmental factors affect call quality and necessitate robust handoff strategies.
Users	40 users	A moderate number of users require effective bandwidth allocation.
QoS Range	1.5 to 2.5	Indicates varying service quality levels experienced by users.
Factors Affecting QoS	Latency, Packet Loss, Jitter	Key elements influencing user experience: higher values negatively impact the service.
Network Load Histogram	Varies	Shows distribution of network traffic across load levels, helping to identify peak usage times.
Network Congestion Histogram	Varies	Indicates times or areas of increased strain on network resources.
Mobility Pattern Analysis	x, y positions	Represents the spatial distribution and movement of users within the network topology, indicating user density and behaviour.
Signal Strength	-75 dB	Indicates a moderate to strong signal level for reliable communication.
Signal-to-Noise Ratio (SNR)	10 to 30 SNR	Range indicating varying signal quality; higher values denote clearer communication.
Handoff Success Rate	95%	Indicates high reliability in transitioning mobile devices between network cells at -70 dB signal strength.
Soft Handover Efficiency Rate	95%	Indicates effectiveness of soft handover process, maintaining connectivity with multiple base stations simultaneously.

Table 3: Conventional and ANFIS Handoff System Results

Parameter	Conventional Handoff	ANFIS Handoff
Handoff Success Rate	80%	95%
SNR (dB)	20	25
Signal Strength (dBm)	-80	-70
Number of Users	100	150
Efficiency	80%	95%
QoS Range	Good	Very Good

IV CONCLUSION

This study effectively met its objectives by providing valuable insights into cellular network performance, particularly in handoff management. It showed that stronger signal strength improves handoff success, emphasising the need for consistent signal quality during user transitions. Using MATLAB/SIMULINK, the ANFIS model demonstrated adaptability to changing network conditions, optimising mobility patterns and enhancing handoff decisions. ANFIS also proved effective in managing network congestion by dynamically adjusting handoff parameters to improve reliability and user satisfaction. Simulation results confirmed that ANFIS outperformed conventional handoff techniques, achieving a 95% success rate compared to 80%. Overall, the study validates ANFIS as a powerful tool for improving 4G network efficiency and user experience.

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