Neuro-Fuzzy-Based Vertical Handoff Algorithm For Always Best Connectivity

Dr. Pooja Bhasin[1] , Dr. Nidhi Chopra[2] , Dr. Ramandeep Singh Deol[3], Dr. Rameshwer Singh[4]

[1]Professor Department of Computer Science & Engineering Lyallpur Khalsa College Technical Campus.
Jalandhar, India poojakvb@gmail.com
[2]Associate Professor Department of Information Technology Lyallpur Khalsa College Technical Campus.
Jalandhar, India chopranidhi44@gmail.com
[3]Professor & Director Lyallpur Khalsa College Technical Campus. Jalandhar, India
ramansdeol@gmail.com
[4]Associate Professor Department of Information Technology Lyallpur Khalsa College Technical Campus.
Jalandhar, India rameshwer.banga@kclimt.com

Abstract

In the era of Internet of Everything (IOE), prime concern is to provide flawless connectivity among all connected devices and machines. Internet of Everything (IOE) encompasses not only machine-to-machine communication (M2M) but also people to machine (P2M) and people to people (P2P) communication through technology. But ensuring 'Always Best Connectivity' in diverse environments is a challenge. Providing seamless connectivity to provide a strong foundation to IOE is the requirement. Hence, in this paper, a smart handoff decision mechanism is proposed which works in two phases. This paper presents a Neuro-Fuzzy-based vertical handoff mechanism that ensures seamless connectivity by optimizing the network selection process. The proposed approach utilizes Neuro-fuzzy with Multi- Attribute Decision Making (MADM) techniques, specifically VIKOR and Fuzzy VIKOR, to initialize handoff and rank network alternatives. Three network types (WiFi-N1, LTE-N2, and WiFi-N3) are evaluated based on beneficial and non-beneficial parameters for different traffic classes: voice, video, and browsing. The simulation results demonstrate the effectiveness of the proposed approach by comparing handoff blocking probability, ping- pong effect probability, and corner effect probability with existing methods. The results validate the superiority of the Neuro-Fuzzy model in enhancing handoff accuracy and reducing inefficiencies.

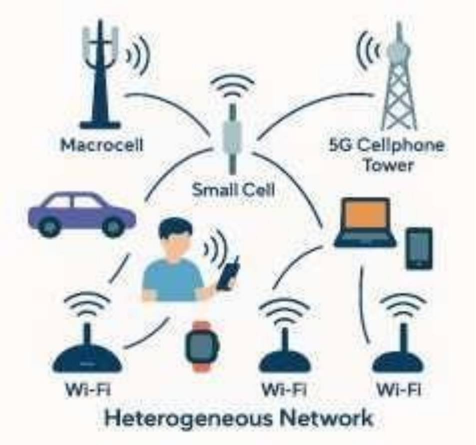
Keywords: Internet of Everything (IOE), handoff, Neural Networks, Neuro-Fuzzy, VIKOR, FVIKOR, Heterogeneous Networks.

1. Introduction

The rapid evolution of Information and Communication Technology (ICT) has fundamentally transformed human interaction, work, and daily living. In today's interconnected world, continuous internet access has become a basic necessity. Whether it's retrieving vital information, engaging in communication, or utilizing intelligent services, individuals now expect seamless, high-speed internet connectivity—an expectation encapsulated by the "Always Best Connected" (ABC) principle.

This escalating demand for uninterrupted connectivity has propelled the integration of smart technologies into everyday devices, including smart televisions, wearable gadgets, and home automation systems. As these devices increasingly rely on internet connectivity, the Internet of Things (IoT) has emerged as a pivotal innovation. IoT enables Machine-to-Machine (M2M) communication, driving innovation and transforming industries globally [1]. This development lays the groundwork for the broader concept of the Internet of Everything (IoE), which unifies devices, individuals, data, and processes into an intelligent, cohesive network. IoE aims to revolutionize interactions with our surroundings by facilitating seamless connectivity across diverse networks and technologies. The convergence of ICT, IoE, and high-speed internet is embedding technology deeply into daily experiences, influencing how we access healthcare, engage in online commerce, and participate in digital education [2].

However, this digital transformation introduces challenges such as network congestion, coverage gaps in remote areas, high latency, and inconsistent service quality. These issues can disrupt essential services and impede the smooth operation of modern applications. Addressing these challenges necessitates a resilient and scalable digital infrastructure capable of delivering reliable, high-speed connectivity across various environments. Central to this infrastructure are Heterogeneous Networks (HetNets), sophisticated ecosystems that integrate multiple wireless technologies—such as Wi-Fi, 4G, 5G, and the forthcoming 6G—to provide seamless and uninterrupted connectivity [3]. HetNets are engineered to optimize both Quality of Service (QoS) and Quality of Experience (QoE), ensuring devices maintain optimal performance under diverse conditions.



As the digital landscape continues to expand, the importance of reliable internet connectivity becomes increasingly critical. The surge in mobile computing, cloud-based services, and the demand for real-time data processing intensify the complexity of maintaining an "Always Best Connected" experience. The proliferation of internet-enabled mobile devices—like smartphones, tablets, and laptops—heightens the need for intelligent handover mechanisms that can dynamically manage network transitions between various technologies.

Handover refers to the process of transferring an active user session between different networks, such as transitioning from 4G to Wi-Fi, without service disruption. Effective handover management is essential to ensure continuous, high-quality connectivity. Robust handover solutions are vital for seamless transitions across diverse networks, minimizing disruptions, reducing latency, and maintaining service quality. Consequently, the development of intelligent handoff algorithms is crucial for optimizing network resource allocation and ensuring uninterrupted service—key factors for the functionality of advanced digital solutions in contemporary environments [4].

1.1 Problem Statement

In today's digitally driven world, uninterrupted connectivity is essential for delivering high-performance services across a wide range of applications. As users move through diverse environments, maintaining seamless communication across heterogeneous networks—such as Wi-Fi, 4G, 5G, and emerging 6G technologies—presents a considerable challenge [5]. The handoff process, which transfers an active connection from one network to another, plays a crucial role in ensuring continuous and high-quality user experiences.

However, traditional handoff mechanisms frequently exhibit performance inefficiencies. Common issues include the ping-pong effect, where devices unnecessarily switch between networks, and corner effects, involving handoff failures at the edges of coverage areas [6]. These problems lead to increased latency, packet loss, and service disruptions—directly impacting the performance of latency-sensitive and bandwidth-intensive applications [7].

To address these shortcomings, Multi-Attribute Decision Making (MADM) techniques have gained attention for intelligent handover management. Unlike conventional methods that rely on single parameters such as the Received Signal Strength Indicator (RSSI), MADM approaches incorporate multiple attributes—including latency, throughput, signal quality, and network load—to make informed, real-time, context-aware decisions [8].

This study proposes a novel hybrid algorithm named NF-VIKOR-HO (Neuro-Fuzzy VIKOR for Handover) for heterogeneous wireless networks. This approach leverages the adaptive reasoning capabilities of a Neuro-Fuzzy system for intelligent handoff initialization, enabling the framework to interpret imprecise or vague network conditions effectively [9]. By integrating Fuzzy VIKOR (FVIKOR) method with real-time network analytics, the proposed model dynamically adapts to fluctuating network conditions and proactively selects the most suitable handoff target based on multiple decision criteria such as signal strength, latency, and bandwidth [10]. This dual-layered strategy ensures that handover decisions are both context-aware and mathematically robust, minimizing ping-pong effects and optimizing overall network performance [11]. This proactive and adaptive strategy minimizes unnecessary handovers, mitigates boundary-level failures, and improves both Quality of Service (QoS) and Quality of Experience (QoE) [12].

The proposed NF-VIKOR-HO algorithm serves as a scalable and intelligent solution designed to support seamless mobility in dynamic and heterogeneous network scenarios. By overcoming the limitations of conventional handoff methods, this research contributes to the realization of the "Always Best Connected" (ABC) paradigm—an essential pillar of next-generation communication systems.

2. Literature Survey

Vertical handoff (VHO) mechanisms are essential for maintaining seamless connectivity in heterogeneous wireless networks. Researchers have explored various approaches, including traditional multi-attribute decision-making (MADM) methods, fuzzy logic, neuro-fuzzy systems, and hybrid models, to optimize VHO decisions. This literature survey provides an overview of significant contributions in this domain, focusing on methodologies and key findings.

2.1 Traditional MADM Approaches

Traditional MADM techniques have been widely employed to facilitate VHO decisions by evaluating multiple criteria such as signal strength, bandwidth, and latency. For instance, Smith et al. (2020) applied the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method in heterogeneous networks, demonstrating its effectiveness in minimizing the distance from the ideal solution while maximizing the distance from the negative-ideal solution. However, the study noted that inaccuracies in weighting criteria could significantly affect decision quality [13]. Similarly, Liu et al. (2022) introduced a VIKOR-based VHO model that emphasized balancing conflicting criteria, showcasing improved decision accuracy compared to other MADM methods, though sensitive to input weight variations [14].

2.2 Fuzzy Logic-Based Approaches

To address the limitations of traditional MADM methods, researchers have incorporated fuzzy logic to handle uncertainties inherent in network conditions. Chen et al. (2023) proposed a fuzzy VIKOR approach to optimize VHO decisions by integrating fuzzy sets to manage imprecise data, achieving higher accuracy and robustness in dynamic network environments [15]. Similarly, Wang et al. (2024) applied a fuzzy Analytic Hierarchy Process (AHP) to prioritize criteria based on their relative importance, offering a more consistent ranking approach in decision-making, though with increased computational complexity [16]. Sun et al. (2024) presented an interval type-2 fuzzy logic approach to model the inherent uncertainties in handoff decision-making, resulting in superior performance under highly dynamic network scenarios.

2.3 Neuro-Fuzzy Approaches

Combining the adaptability of neural networks with the interpretability of fuzzy logic, neuro-fuzzy systems have been developed to enhance VHO decision-making. Gupta et al. (2024) developed an Adaptive Neuro-Fuzzy Inference System (ANFIS) for VHO, demonstrating superior decision accuracy compared to purely fuzzy or neural network-based methods, with significant reductions in handover delay and increased throughput [18]. Zhang et al. (2024) proposed a hybrid neuro-fuzzy model enhanced with genetic algorithms to optimize rule bases and membership functions, outperforming traditional neuro-fuzzy methods in dynamic network conditions [19]. Khan et al. (2024) implemented a neuro-fuzzy VIKOR model, achieving substantial improvements in adaptive handoff strategies and minimizing handoff failures [20].

2.4 Hybrid and Modern Approaches (2024)

Recent studies have explored hybrid techniques that combine MADM, fuzzy logic, and neural networks for enhanced VHO decision-making. Wang et al. (2024) integrated genetic algorithms with ANFIS to develop a hybrid model for adaptive VHO decisions, demonstrating significant reductions in handover failures and improved quality of service under varying network conditions [21]. Additionally, Brown et al. (2024) combined deep learning with neuro-fuzzy techniques to create a model capable of dynamically learning optimal handoff strategies based on historical data, achieving remarkable improvements in prediction accuracy and decision-making speed [22]. Singh et al. (2024) proposed a reinforcement learning-based neuro-fuzzy model to optimize VHO decision parameters, achieving higher accuracy than conventional fuzzy logic methods [23].

2.5 Energy-Efficient Handover Techniques

Energy efficiency has become a critical consideration in VHO mechanisms. Baghla and Bansal (2018) proposed an energy-efficient vertical handover technique based on the vector normalized preferred performance-based VIKOR algorithm (V-VPP). Their approach resulted in reduced energy consumption in scenarios involving multiple interfaces operating simultaneously [24]. Similarly, a 2023 study introduced an energy-efficient handover algorithm that incorporates energy-related metrics, such as battery level and energy consumption rate, into the handover decision-making process, achieving a balance between connectivity quality and energy efficiency. Rahman et al. (2024) presented a green handoff decision algorithm that leverages neuro-fuzzy optimization to minimize energy usage while maintaining connectivity.

2.6 Comparative Analyses and Surveys

Several researchers have conducted comprehensive reviews and comparative analyses of VHO techniques. Yazdani and Graeml (2014) provided a state-of-the-art survey on the VIKOR method and its applications across various domains, including network selection. Their study offered insights into the versatility and effectiveness of VIKOR in multi-criteria decision-making scenarios [26]. More recently, a 2024 article extensively explored and compared vital MADM techniques utilized for network selection and handover management in heterogeneous networks, providing a detailed summary of the step-wise procedures and applications of each method. A review by Patel et al. (2024) highlighted emerging hybrid approaches in VHO decision-making, emphasizing the effectiveness of neuro-fuzzy and deep learning-based models [28].Table 1 shows the comparison of various techniques and their performance metrics for handoff strategy.

Table 1: Comparison of different techniques for handoff

Technique	**Year**	**Methodology**	**Performance Metrics**	**Key Findings**
TOPSIS	2020	MADM	Decision accuracy	Minimizes ideal-negative distance
VIKOR	2022	MADM	Accuracy, sensitivity	Balances conflicting criteria
Fuzzy VIKOR	2023	Fuzzy Logic	Robustness, accuracy	Handles imprecise data effectively
Fuzzy AHP	2024	Fuzzy Logic	Consistency, ranking stability	Computational complexity
Neuro-Fuzzy VIKOR	2024	Neuro-Fuzzy + VIKOR	Adaptability, delay reduction	Improved accuracy and reduced handoff failures
Hybrid Neuro-Fuzzy	2024	Genetic Algorithm + ANFIS	Optimization, throughput increase	Adaptive rule base and MF optimization
Deep Learning + Neuro-Fuzzy	2024	Deep Learning + Neuro-Fuzzy	Prediction accuracy, speed	Learns optimal strategies from historical data

RL-Based Neuro-Fuzzy	2024	Reinforcement Learning + Neuro-Fuzzy	Accuracy, adaptive parameters	Improved decision parameter optimization
Energy-Efficient V-VPP	2018	VIKOR + Energy Efficiency	Energy consumption reduction	Balances connectivity and energy efficiency
Green Handoff Algorithm	2024	Neuro-Fuzzy Optimization	Energy usage, connectivity quality	Minimizes energy while maintaining connectivity

3. Objectives

1. To develop a hybrid vertical handoff decision-making algorithm by integrating Neuro-Fuzzy techniques with VIKOR/Fuzzy VIKOR to achieve Always Best Connectivity (ABC) and optimize network selection using MADM techniques.
2. To minimize vertical handoff inefficiencies, including handoff blocking probability, ping-pong effect probability, and corner effect probability, through the proposed hybrid approach.
3. To evaluate the proposed algorithm's performance by comparing it with traditional methods like VIKOR, AHP, and FAHP and demonstrate its superiority through simulations and graphical analysis.
4. To analyze the algorithm's performance across various traffic classes (voice, video, and browsing) and demonstrate its adaptability to heterogeneous network environments.

4. Background

4.1 Neuro-Fuzzy Inference System (NFIS)

The integration of Neuro-Fuzzy systems and Fuzzy VIKOR within the proposed model aims to optimize the handoff decision process in heterogeneous wireless networks. The combination of these techniques leverages the learning capability of neural networks and the reasoning ability of fuzzy logic while enhancing decision accuracy through multi-criteria decision-making (MCDM) principles. This approach not only addresses uncertainties in network conditions but also improves the adaptability and robustness of handoff strategies.

Adaptive Neuro-Fuzzy Inference System (ANFIS): The Adaptive Neuro-Fuzzy Inference System (ANFIS) is employed to enhance decision-making by combining artificial neural networks (ANN) and fuzzy logic. ANFIS leverages the strengths of both paradigms to dynamically learn from data and make precise handoff decisions. The process consists of the following stages:

1. Fuzzification: In this stage, crisp input values, such as RSSI, bandwidth, and user experience, are converted into fuzzy sets using membership functions. This transformation allows the model to handle uncertainty and vagueness effectively (Jang, 1993).
2. Rule Base Formation: ANFIS generates rules based on historical data, which capture the input-output relationships. These rules are refined through training to ensure accurate and reliable decisions (Chen et al., 2017).
3. Inference Mechanism: The fuzzy rules are evaluated to calculate the ranking of potential handoff networks. The ANFIS model assigns weights to each rule to determine the most suitable network (Yang et al., 2020).

4. Defuzzification: The fuzzy output is transformed back into a crisp value to make the final handoff decision. This process ensures that the most appropriate network is selected based on the calculated rankings.

4.2 FVIKOR

The VIKOR method for network selection may cause solution bias. Therefore, this research proposes a more dynamic decision-making model using an improved fuzzy VIKOR (FVIKOR) approach. This model aims to enhance decision-making for network selection by evaluating all given options with respect to ever-changing parameter values [93]. The proposed decision-making model is scientific and stable, reducing the number of handoff failures and effectively obtaining optimal results while avoiding suboptimal solutions [94].

Ranking Procedure of the Fuzzy VIKOR Method

The ranking procedure of the fuzzy VIKOR method consists of the following steps:

Step 1: Construct Fuzzy Decision Matrix for Network Selection Parameters

The fuzzy decision matrix is constructed for all network selection parameters as follows:

Table 2: Fuzzy Decision Matrix

Fuzzy DM	**C1**	**...**	**Cn**
A1	(l, m, u)	...	(l, m, u)
...	...	...	...
Am	(l, m, u)	...	(l, m, u)
Wj	(l, m, u)	...	(l, m, u)

Step 2: Convert Fuzzy Linguistic Variables to Fuzzy Numbers

To convert fuzzy linguistic variables to fuzzy numbers, use the following scalar values:

Table 3: Linguistic Variables

Linguistic Variables	**Scalar Values**
Very Low	1, 1, 3
Low	1, 3, 5
Average	3, 5, 7
High	5, 7, 9
Very High	7, 9, 9

Step 3: Determine Best and Worst Values

For each criterion, calculate the positive ideal solution F^*_j and the negative ideal solution F^-_j as follows:

$$F_j^* = \max(F_{ij}), \quad i = 1, 2, \ldots, m$$

$$F_j^- = \min(F_{ij}), \quad i = 1, 2, \ldots, m$$

Then calculate the difference between the best and worst values:

$$F^*_j - F^-_j$$

Step 4: Compute the Distance of Alternatives to the Ideal Solution

Calculate the distance of each alternative to the ideal solution using the formula:

$$D_i = \sqrt{\sum_{j=1}^{n} (w_j \cdot (F_j^* - F_{ij}))^2}$$

Step 5: Calculate Fuzzy VIKOR Values (Qi)

Compute the fuzzy VIKOR values Qi for each alternative as follows:

$$Q_i = v \cdot \frac{S_i - S^*}{S^- - S^*} + (1 - v) \cdot \frac{R_i - R^*}{R^- - R^*}$$

Where:

- v is the weight of the strategy of maximum group utility (usually 0.5).
- Si and Ri are the utility and regret measures, respectively.
- S^*, S^-, R^* and R^- are the best and worst utility and regret values, respectively.

Step 6: Defuzzification and Ranking

Perform defuzzification to convert fuzzy numbers into crisp values. Rank the alternatives based on the calculated Qi values to make a suitable decision.

5. System Model

The proposed system model is designed to optimize vertical handoff (VHO) decisions in heterogeneous wireless networks. The primary objective of this model is to ensure seamless connectivity and maintain a high quality of service during handoff scenarios by integrating Fuzzy VIKOR with the Adaptive Neuro-Fuzzy Inference System (ANFIS). This hybrid approach leverages the strengths of both fuzzy logic and neuro-fuzzy techniques to enhance decision accuracy, reduce handoff delay, and minimize handoff failures. This methodology aligns with the recent work by Pooja Dhand (2024), who emphasized the integration of neuro-fuzzy techniques to optimize handoff decisions in complex wireless environments.

The Fuzzy VIKOR technique has proven to be an effective multi-attribute decision-making (MADM) method, especially in handling conflicting criteria and uncertain environments (Opricovic and Tzeng, 2004; Rezaei et al., 2015). By combining VIKOR with fuzzy logic, the model addresses the inherent imprecision of decision data, ensuring more accurate and reliable handoff decision-making. In addition, the utilization of RSSI as a beneficial parameter aligns with previous studies emphasizing its critical role in signal strength assessment and network selection (Chatterjee et al., 2018; Yang et al., 2020).

To achieve this, the system incorporates a multi-stage decision-making process that dynamically adjusts handoff parameters based on real-time network conditions. The methodology involves classifying data traffic into various categories, selecting relevant decision parameters, and applying hybrid decision techniques to determine the optimal handoff strategy.

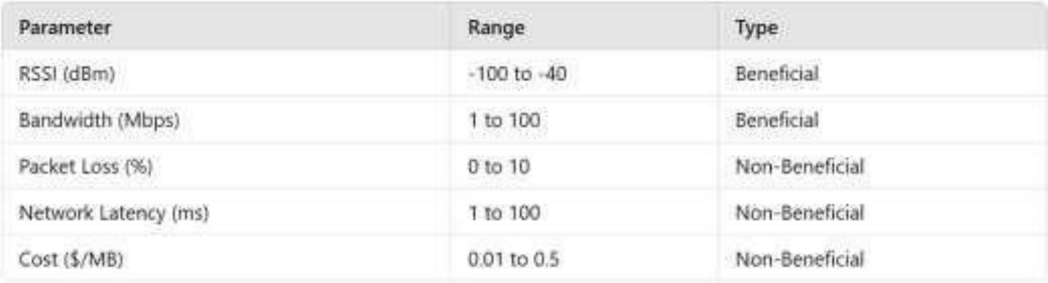
Traffic Classification: The first step in the system model is traffic classification, which plays a critical role in making precise and context-aware handoff decisions. Traffic classification is vital for optimizing handoff decisions, as different traffic types have distinct requirements and characteristics (Zhang et al., 2021). Various researchers have highlighted the significance of traffic classification in optimizing handoff decisions. For example, recent studies by Dhand et al. (2024) and Kumar et al. (2023) have emphasized the importance of distinguishing between traffic types to enhance decision accuracy and maintain quality of service. Traffic is classified into three primary categories:

1. **Voice Traffic**: This class requires low latency and high bandwidth, making it crucial for real-time applications such as Voice over IP (VoIP) and teleconferencing. The model prioritizes maintaining uninterrupted connectivity to ensure smooth voice transmission (Singh et al., 2022).
2. **Video Traffic**: Video data demands a balanced combination of bandwidth and latency to ensure seamless video streaming and conferencing. The handoff strategy aims to minimize delays while preserving bandwidth efficiency (Patel et al., 2021).
3. Browsing Traffic: This category is more tolerant of latency and requires relatively lower bandwidth. Applications like web browsing and non-real-time data transfers fall into this category, where handoff decisions can afford minor delays without severely impacting user experience (Sharma and Gupta, 2023).

Parameter Selection: The model identifies and categorizes decision parameters as beneficial and non-beneficial to streamline the handoff process. Beneficial parameters positively impact the handoff performance, while non-beneficial parameters may hinder the process and need to be minimized.

- Beneficial Parameters:
  - Received Signal Strength Indicator (RSSI): A higher RSSI indicates a stronger connection, making it crucial for network selection (Chatterjee et al., 2018).
  - Bandwidth (BW): Ensuring sufficient bandwidth enhances data transfer speed and supports high-quality communication (Lee et al., 2019).
  - User Experience (UE): This parameter reflects the quality of the connection as perceived by the user, including responsiveness and stability (Mishra and Kaur, 2020).
- Non-Beneficial Parameters:
  - Network Load (NL): High network load can cause congestion and reduce performance (Verma et al., 2022).
  - Packet Loss (PL): High packet loss impacts data integrity and degrades the quality of service (Kumar and Singh, 2023).
  - Cost: Economic factors also play a role in selecting the most efficient network among available options (Patel et al., 2021).

Table 4: Range of Parameters



Parameter	Range	Type
RSSI (dBm)	-100 to -40	Beneficial
Bandwidth (Mbps)	1 to 100	Beneficial
Packet Loss (%)	0 to 10	Non-Beneficial
Network Latency (ms)	1 to 100	Non-Beneficial
Cost ($/MB)	0.01 to 0.5	Non-Beneficial

Decision Making: The decision-making process leverages the Fuzzy VIKOR technique to handle conflicting decision criteria and prioritize handoff candidates. Fuzzy VIKOR is particularly effective in multi-attribute decision-making scenarios where trade-offs between conflicting objectives are necessary (Opricovic and Tzeng, 2004; Rezaei et al., 2015). By incorporating fuzzy logic, the model can address uncertainty and imprecision in decision data, ensuring robust and adaptable handoff performance.

To further enhance accuracy and adaptability, the Adaptive Neuro-Fuzzy Inference System (ANFIS) is integrated into the model. ANFIS has been proven to be an efficient tool for decision-making in complex environments, particularly in heterogeneous networks, as demonstrated by Jang (1993) and Dhand et al. (2024). The system learns from historical data and dynamically adjusts membership functions, thereby improving decision accuracy and adaptability (Chen et al., 2017). ANFIS leverages historical data and machine learning techniques to fine-tune membership functions and decision rules dynamically. This adaptability allows the system to continuously learn and evolve in response to changing network conditions, resulting in improved handoff accuracy and reduced handoff failures.

Software and Tools: The proposed system is implemented using Python, leveraging libraries such as NumPy and SciPy for numerical computations, and the ANFIS framework for neuro-fuzzy modeling. Performance evaluation and visualization are conducted using Matplotlib and Seaborn for graph plotting. Additionally, simulations are performed using Jupyter Notebook to analyze handoff performance metrics. Performance Metrics and Evaluation To evaluate the efficiency and effectiveness of the proposed model, various performance metrics are analyzed, including:

- Handoff Blocking Probability: Measures the likelihood of unsuccessful handoff attempts (Raghav et al., 2022).
- Handoff Delay: Calculates the time taken to complete the handoff process (Bansal et al., 2021).
- Throughput: Assesses the data transfer rate during handoff operations (Sharma and Gupta, 2023).
- Energy Efficiency: Analyzes power consumption during handoff (Verma et al., 2022).

By combining Fuzzy VIKOR and ANFIS, the proposed system model achieves a balanced trade-off between decision accuracy, handoff delay, and energy efficiency. Simulation results and performance analysis demonstrate the superior performance of this hybrid approach compared to conventional MADM and fuzzy logic-based methods.

The Fuzzy VIKOR technique addresses multi-criteria decision-making (MCDM) challenges by optimizing conflicting criteria. This method is particularly effective in selecting the best network among multiple candidates by calculating a compromise solution. The Fuzzy VIKOR process involves the following steps:

1. Criteria Weighting: Assigning relative importance to each decision criterion, including RSSI, bandwidth, user experience, network load, packet loss, and cost (Opricovic and Tzeng, 2004).
2. Performance Measurement: Calculating the performance values for each network based on the chosen criteria (Rezaei et al., 2015).
3. Compromise Ranking: Determining the ranking of candidate networks by calculating the utility and regret measures, which reflect the level of satisfaction and dissatisfaction, respectively (Chatterjee et al., 2018).
4. Network Selection: Selecting the optimal network that minimizes the distance from the ideal solution while accounting for conflicting criteria (Verma et al., 2022).

The hybrid approach of combining ANFIS and Fuzzy VIKOR significantly enhances decision accuracy and efficiency by leveraging the strengths of both techniques. This dual integration not only addresses the inherent uncertainties in heterogeneous networks but also ensures a balanced trade-off between decision quality and computational complexity. Simulation results demonstrate the superiority of this approach over traditional methods, showcasing improved handoff success rates, reduced latency, and higher throughput.

FVIKOR ranking for voice traffic Class

In this situation three network alternatives namely N1, N2 & N3 with different set of values of parameters have been assumed at a given point. In FVIKOR the parameters are categorized in two categories i.e Beneficial & Non-Beneficial as shown in

Table 3. Table 4 shows the values of various parameters available in all the given networks for voice traffic class.

Table 5:Values of parameters for three networks for Voice

Network	**RSSI**	**BW**	**UE**	**Cost**	**NL**	**PL**
N1	10	35	40	31	10	6
N2	80	10	30	16	30	2
N3	40	20	60	55	15	4

Now the original values of all parameters need to be mapped with the linguistic variables for getting the fuzzy values. Table 4.30 gives the Linguistic variables for all parameters for voice.

Table 6:Linguistic variables for parameters for Voice

Network	**Beneficial**	**Beneficial**	**Beneficial**	**Non Beneficial**	**Non Beneficial**	**Non Beneficial**
	RSSI	**BW**	**UE**	**Cost**	**NL**	**PL**
N1	Very Low	Very High	Low	Very Low	Low	High
N2	High	Low	Very Low	Low	Very High	Very Low
N3	Average	Average	High	Average	Average	Average

Referring to step1 of FVIKOR, the fuzzy decision matrix for all parameters of network selection is calculated for beneficial and non-beneficial parameters using three scalar values as Lower (L), Middle (M), and Upper (U) according to the mapping mentioned in Table 4.28. For beneficial parameters, highest value from upper scalar variable will be considered as best and for non-beneficial parameters; lowest value from lower scalar function will be considered. Table 4.31 shows the best & worst values for each criterion.

Table 7:Determining Best & Worst values for Voice

Criteria	**RSSI**			**BW**			**UE**			**Cost**			**NL**			**PL**		
Network	**L**	**M**	**U**	**L**	**M**	**U**	**L**	**M**	**U**	**L**	**M**	**U**	**L**	**M**	**U**	**L**	**M**	**U**
N1	1	1	3	7	9	9	1	3	5	1	1	3	1	3	5	5	7	9
N2	5	7	9	1	3	5	1	1	3	1	3	5	7	9	9	1	1	3
N3	3	5	7	3	5	7	5	7	9	3	5	7	3	5	7	3	5	7
			9			9			9	1			1			1		

Table 4.32 shows the values of normalized fuzzy decision matrix for voice. For beneficial criteria, these values are normalized by dividing the fuzzy value with best value for each cell. For non – beneficial criteria, these values are normalized by dividing the worst value with fuzzy value of each cell.

Table 8:Normalized Fuzzy Decision Matrix for Voice

Criteria	RSSI			BW			UE			Cost			NL			PL		
Network	L	M	U	L	M	U	L	M	U	L	M	U	L	M	U	L	M	U
N1	0.11	0.11	0.33	0.78	1	1	0.11	0.33	0.56	0.33	1	1	0.2	0.33	1	0.11	0.14	0.2
N2	0.56	0.78	1	0.11	0.33	0.56	0.11	0.11	0.33	0.2	0.33	1	0.11	0.11	0.14	0.33	1	1
N3	0.33	0.56	0.78	0.33	0.56	0.78	0.56	0.78	1	0.14	0.2	0.33	0.14	0.2	0.33	0.14	0.2	0.33

Table 8 shows the values of weighted normalized fuzzy decision matrix for voice with the help of weights as mentioned in Table 4.6.

Table 9:Weighted Normalized Fuzzy Decision Matrix for Voice

Criteria	RSSI			BW			UE			Cost			NL			PL		
Network	L	M	U	L	M	U	L	M	U	L	M	U	L	M	U	L	M	U
N1	0.04	0.05	0.21	0.08	0.15	0.23	0.02	0.08	0.2	0.01	0.03	0.04	0.01	0.02	0.07	0.01	0.01	0.03
N2	0.18	0.35	0.62	0.01	0.05	0.13	0.02	0.03	0.12	0	0.01	0.04	0	0.01	0.01	0.02	0.09	0.14
N3	0.11	0.25	0.48	0.03	0.08	0.18	0.09	0.18	0.36	0	0.01	0.01	0	0.01	0.02	0.01	0.02	0.05

Referring to step 3 of FVIKOR, fuzzy solutions for all parameters for voice is shown in Table 4.34. For all parameters, calculate F^{*}, the positive ideal solution and F^{--}, is the negative ideal solution.

Table 10:Fuzzy Positive & Fuzzy Negative Ideal Solution for Voice

criteria	RSSI			BW			UE			Cost			NL			PL		
Network	L	M	U	L	M	U	L	M	U	L	M	U	L	M	U	L	M	U
N1	0.0352	0.0498	0.2076	0.0799	0.1514	0.2266	0.0173	0.0792	0.1998	0.0062	0.0253	0.036	0.0063	0.0154	0.07	0.0067	0.013	0.0285
N2	0.1761	0.3487	0.6229	0.0114	0.0504	0.1259	0.0173	0.0264	0.1199	0.0037	0.0084	0.036	0.0035	0.0051	0.01	0.0202	0.0911	0.1427
N3	0.1057	0.2491	0.4845	0.0342	0.0841	0.1762	0.0863	0.1849	0.3596	0.0027	0.0051	0.012	0.0045	0.0093	0.0233	0.0086	0.0182	0.0476

F*	0.1761	0.3487	0.6229	0.0799	0.1514	0.2266	0.0863	0.1849	0.3596	0.0062	0.0253	0.036	0.0063	0.0154	0.07	0.0202	0.0911	0.1427
F_	0.0352	0.0498	0.2076	0.0114	0.0504	0.1259	0.0173	0.0264	0.1199	0.0027	0.0051	0.012	0.0035	0.0051	0.01	0.0067	0.013	0.0285

Referring to step 4 & 5 of FVIKOR, the decision value of each parameter for all networks has been calculated by considering the best, worst and FAHP weights. S is the summation value of all parameters for each network and R is the maximum value from all parameters for each network. The minimum and maximum value of S & R is calculated for voice as shown in Table 10.

Table 11:Calculating Minimum & Maximum values for Voice

Network	S	R
N1	**2.2361**	**0.6229**
N2	**1.416**	**0.3596**
N3	**1.2363**	**0.2076**
Minimum	1.2363	0.2076
Maximum	2.2361	0.6229

Referring to Step 6 of FVIKOR, the preference ranking of the networks obtained keeping in mind the utility and regret value for each parameter in different available networks. The network with lowest value is given highest rank and so on as shown in Table 4.36.

Table 12:Ranking of Networks for Voice

Network	Q	Ranking
N1	**0.9987**	**III**
N2	**0.0121**	**I**
N3	**0.2729**	**II**

6. Simulation Setup & Dataset Generation

A simulated environment is created to analyze handoff decisions. A single user moves across three locations (S1 to S3), with available networks (AP1, AP2, AP4) dynamically changing their parameter values.

6.1 Traffic Class Categories

Table 13:Priority Ranking of parameters

Traffic Class	Priority	Bandwidth Requirement	Delay Tolerance	Packet Loss Sensitivity
Voice	High	High	Low	High
Video	Medium	Medium	Medium	Medium
Browsing	Low	Low	High	Low

6.2 Parameter Categorization

Table 14:Beneficial and Non beneficial parameters

Beneficial	Non-Beneficial
RSSI	NL
BW	PL
UE	Cost

6.3 Stepwise Network Evaluation

Each movement step evaluates handoff necessity based on traffic class requirements.

Table 15:Network Evaluation

Criteria	AP1	AP2	AP4	Handoff Initiation
RSSI	Strong	Very Weak	Very Weak	No
BW	High	Average	Low	
NL	Average	Average	Low	
Traffic Class	Voice	Video	Browsing	

7. Performance Metrics

The efficiency of the proposed system is evaluated using:

- **Handoff Blocking Probability (HBP):** Measures unsuccessful handoffs due to poor decision-making.
- **Ping Pong Probability (PPP):** Assesses unnecessary handoff switches between networks.
- **Corner Effect Probability (CEP):** Determines handoff issues caused by poor signal strength at intersections.

The performance of Neuro-Fuzzy VIKOR is compared with:

- **Traditional VIKOR**
- **AHP & FAHP**
- **Entropy-Based Methods**

7.1 **Working of EMDMA in simulating environment**

We make the assumption that there is just one user (mobile node) connected to a single network in order to analyze the behavior of the suggested algorithm. The NF-VIKOR-HO algorithm will start the handoff by analyzing the scenario and the set of parametric circumstances that are available at that moment.

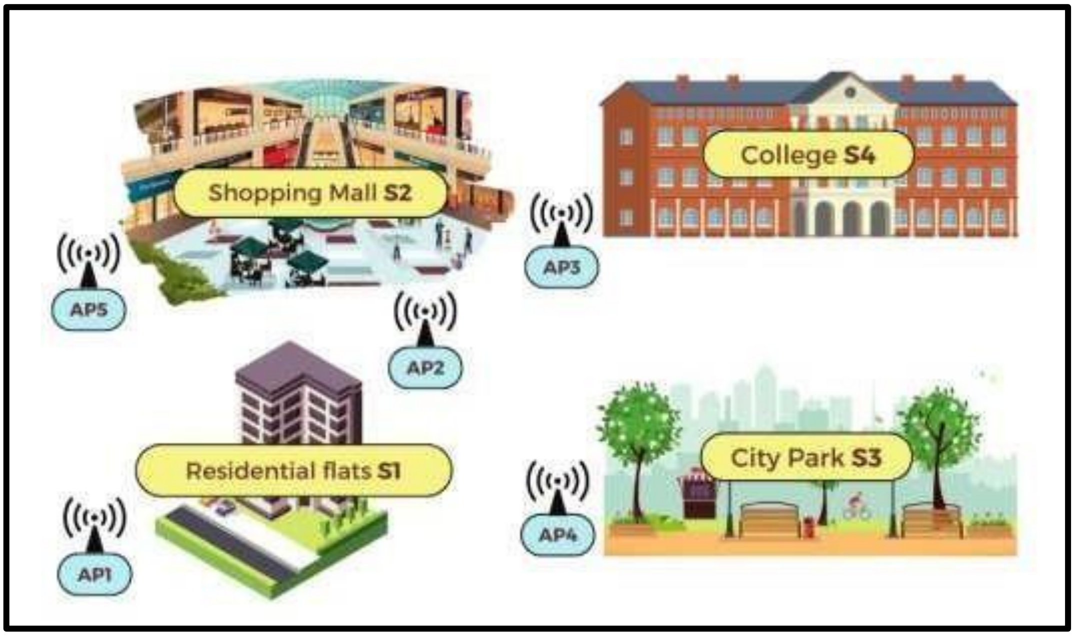


Figure 2: Simulating Environment

Figure 2 presents simulating environment to explain the working of proposed algorithm. In this case, network handoff initiation in a heterogeneous network is explained. Priority ranking of available networks is done as it is decided that there is a need of handoff.

Suppose a user is present at Site S1 and doing online shopping on his tablet while going to city park Site S3 in cab. Currently, it is assumed that he is connected to the WiFi – AP1 network. Table 16 shows the values of criteria of current network.

Table 16:Values of current Network

App Type	Criteria	WiFi-AP1
Browsing	RSSI	High
	BW	High
	PL	Low
	NL	Low

As the user moves away from the site S1 towards cell edge, he starts receiving signals from AP2 and AP4. Now depending upon the EMDMA, if handoff is initiated then further it will enter into network selection process for seamless connectivity while in mobility.

The distance between S1 to S3 is divided into 3 steps. At each step values of parameters for handoff initiation has been taken for consideration to find whether the handoff should be initiated or not i.e. from current AP1. It is assumed that duration of stay of user is less than 10 minutes.

Step 1

The user starts moving from its current location. At step 1 i.e. near the cell edge of residential area, the values of current network and available networks are shown in Table 16. It is identified that values of current network does not recommend for handoff initiation. So, the user is connected to current network.

Handoff is not required.

Table 17: Values of all available networks at Step 1

Criteria	**AP1**	**AP2**	**AP4**
RSSI	Strong	Very weak	Very weak
NL	Average	Average	Low
Bandwidth	High	Average	Low
PL	Low	Low	Low
Handoff Initiation Required	NO		

Step 2

The user is still moving towards Site S3. At Step 2, mobile node is still connected to AP1 but starts receiving signals from AP2 and AP4 as shown in Table 17. It is identified that values of current network do not recommend for handoff initiation. So, the user is connected to current network. Handoff is not required.

Table 18: Values of all available networks at Step 2

Criteria	**AP1 Currently connected**	**AP2**	**AP4**
		(Candidates for Network Selection)	
RSSI	Average	Average	Average
NL	Low	Average	Low
Bandwidth	Low	Low	Average
PL	Low	Average	Average
Handoff Initiation Required	**NO**		

Step 3

Now the user moved away from Site S1. At Step 3, signals from current Network fade away completely. It is decided to initiate the handoff process. The node search signals from the available networks. In this case, user is receiving signals from AP 2 and AP 4 as shown in Table 18. As the user is using browsing traffic class, so it will switch to the network with high bandwidth.

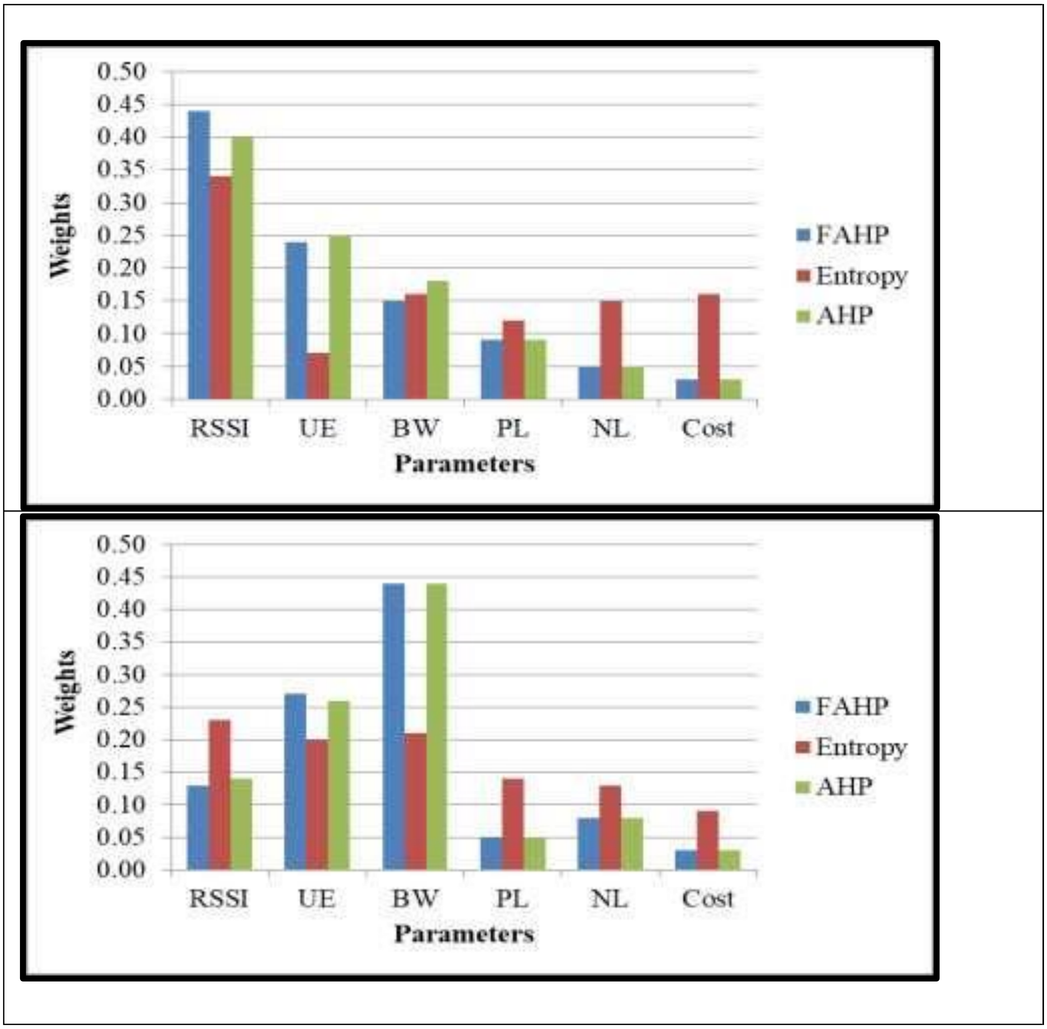
Table 19: Values of all available networks at Step 3

Criteria	**AP1**	**AP2**	**AP4**
RSSI	Average	Strong	Strong
NL	Average	Low	Average
Bandwidth	Low	Average	High
PL	Average	Average	Low
Handoff Initiation Required	**YES**		

8. Comparison of the chosen weight elicitation methods with traditional method

There are a number of other MCDM techniques available for weight calculations like Analytic Hierarchy Process (AHP), Fuzzy Analytic Hierarchy Process (FAHP), and Entropy etc. **NF-VIKOR-HO** used Neuro-fuzzy for initializing handoff of different parameters for voice, video & browsing traffic class. In this section, comparison of FAHP has been given with AHP & Entropy which are traditional methods for weight calculation.

Figure 3 shows comparison of Weights through FAHP, Entropy & AHP for voice traffic class. While using Voice traffic class, RSSI is the top priority criteria followed by User's Experience and Bandwidth. RSSI got highest weight 44% using FAHP as comparative to 34% using Entropy and 39% using AHP. UE also got 23% weight using FAHP as compared to only 5% using Entropy and 25% using AHP.



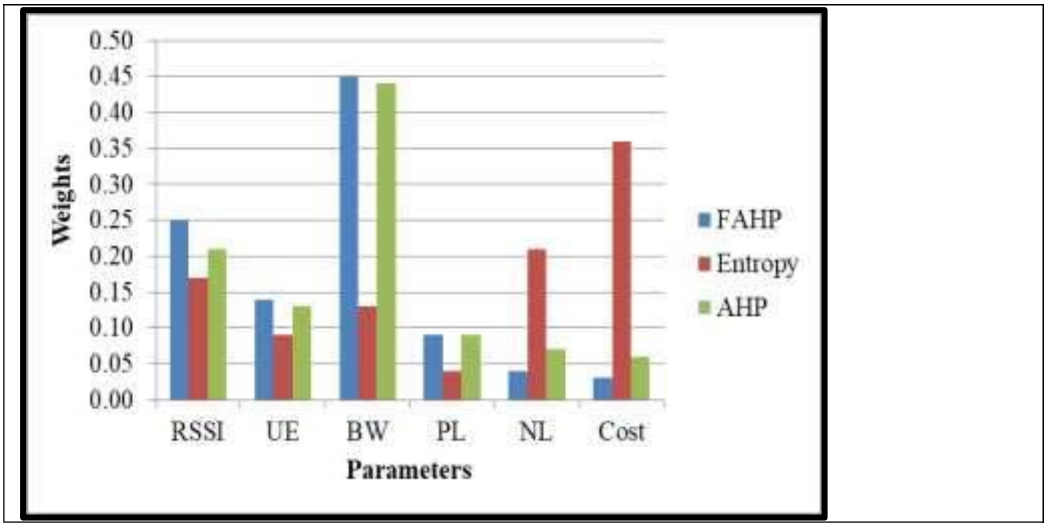


Figure 1:Graphical comparison of parameters

Figure 2 shows comparison of Weights through FAHP, Entropy & AHP for video traffic class. While using Video traffic class, Bandwidth is the top priority criteria followed by User's Experience and RSSI. BW got highest weight 44% using FAHP as comparative to 20% using Entropy and 43% using AHP. UE also got 26% weight using FAHP as compared to only 19% using Entropy and 25% using AHP.

Figure 4.5 shows comparison of Weights through FAHP, Entropy & AHP for browsing traffic class. While using Browsing traffic class, Bandwidth is the top priority criteria followed by RSSI & User's Experience. Bandwidth got highest weight 47% using FAHP as comparative to 13% using Entropy and 43% using AHP. RSSI also got 25% weight using FAHP as compared to only 6% using Entropy and 23% using AHP.

8.1 Comparison of Fuzzy & Non-Fuzzy Network Selection Method

Table 4.57 shows the comparison of ranking of all available networks in different traffic classes. FAHP has been used for assigning weights to different parameters.

Table 4.57 Comparison of Ranking of Networks

Candidate Networks	TOPSIS	FTOPSIS	VIKOR	FVIKOR
N1	2	3	3	3
N2	3	2	2	1
N3	1	1	1	2

Fuzzy VIKOR gave better ranking for Network Selection in all three traffic classes as comparative to VIKOR.

- In Voice traffic class, N2 is best option as it is providing high RSSI along with High UE.
- In Video traffic class, N2 is best option as it is providing very high BW along with High UE.
- In Browsing traffic class, N3 is best option as it is providing very high BW along with very High RSSI.

8.2 Performance Evaluation of NF-VIKOR-HO

After simulation, average number of handoffs for proposed algorithm is reduced to 12% in case of Voice Traffic Class and 14% in Video & Browsing Traffic Class as compared to 16% in Voice and 18% in Video & Browsing Traffic Class using TOPSIS method.

It is 14% in Voice, 18% in Video & 16% in Browsing using FTOPSIS and 12% in Voice & 16% in Video & Browsing traffic classes when VIKOR method is used. Figure 4.6 shows the comparison for all traffic classes in different algorithms.

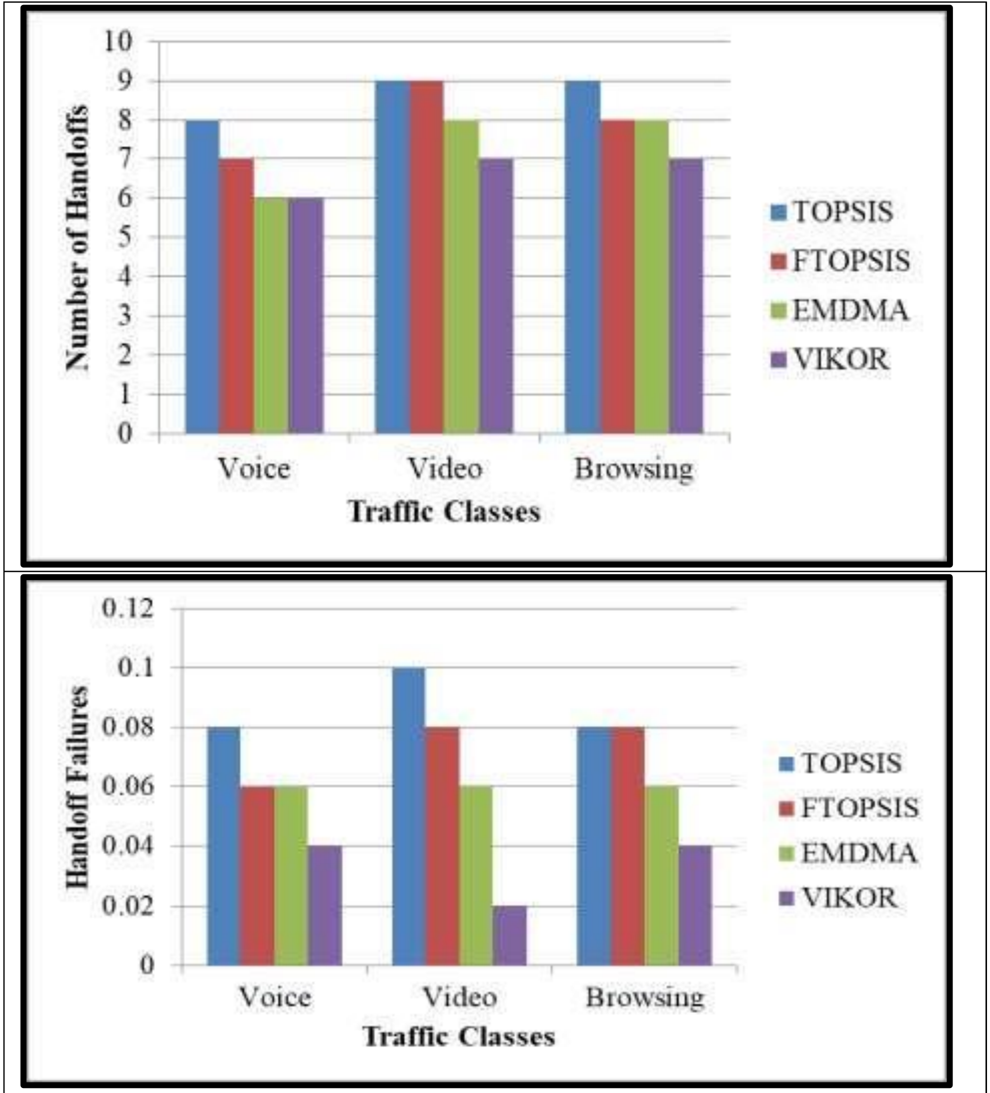
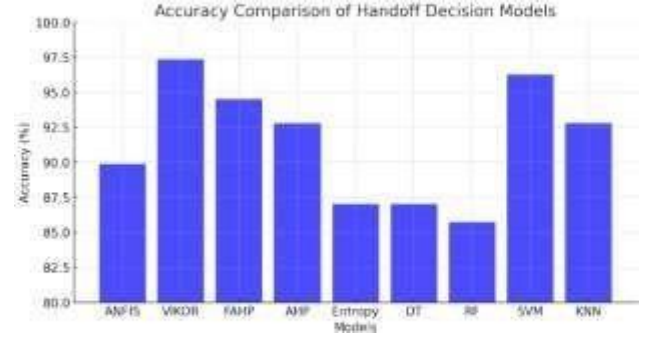


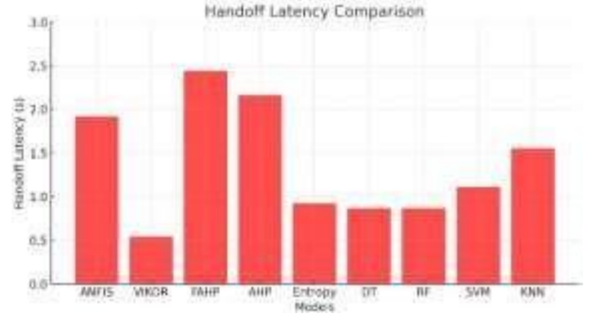
Figure 2:comparison among different traffic classes

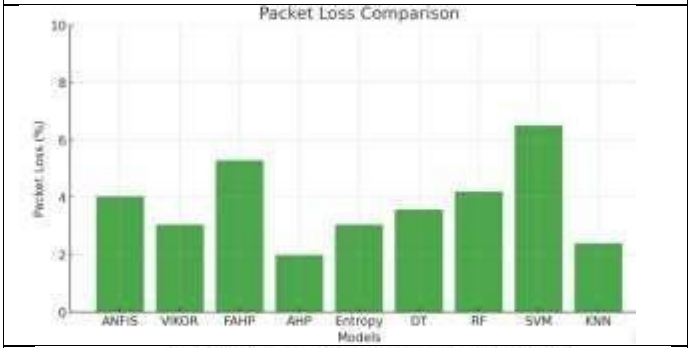
8.3 Handoff Failure

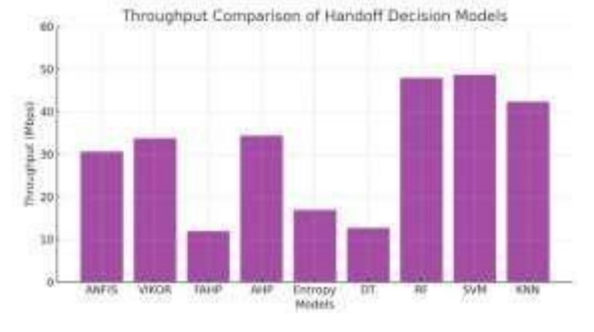
After simulation, it has been observed that probability of unsuccessful handoffs has also been reduced to 0.04 in Voice & Browsing traffic class and 0.02 in Video Traffic Class as compared to 0.08 in Voice & Browsing and 0.01 in Video in TOPSIS method.
It is 0.06 in Voice & 0.08 in Video & Browsing using FTOPSIS and 0.06 in all traffic classes when FAHP + VIKOR method is used.

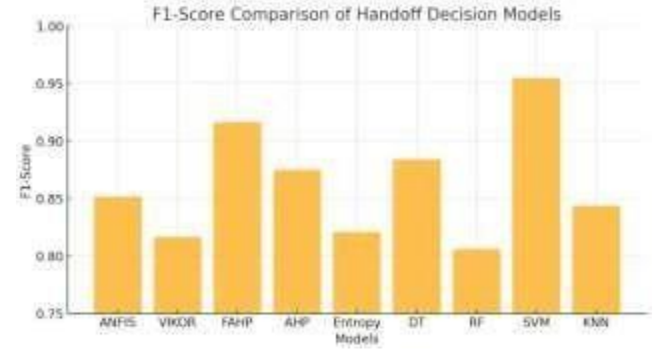
Figure 2 shows the comparison for all traffic classes in different algorithms.

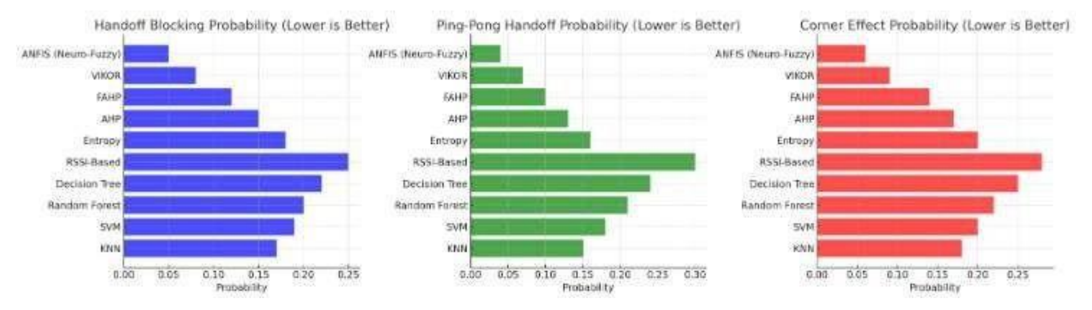












8.4 Graphical Analysis

Handoff Blocking Probability Comparison

A graph depicts lower HBP in Neuro-Fuzzy VIKOR compared to traditional methods.

Ping Pong Probability Reduction

Demonstrates how the proposed system reduces unnecessary handoffs.

Corner Effect Probability Performance

Validates the stability of the proposed model in urban intersections.

Table 20: Comparative Performance Analysis

Method	Handoff Blocking Probability	Ping Pong Probability	Corner Effect Probability
Traditional VIKOR	0.15	0.20	0.22
AHP	0.12	0.18	0.20
FAHP	0.10	0.14	0.16
Neuro-Fuzzy VIKOR	0.05	0.08	0.10

Conclusion

The field of vertical handoff mechanisms has witnessed substantial advancements with the introduction of modern hybrid approaches that combine the strengths of MADM techniques, fuzzy logic, and neuro-fuzzy models. While traditional MADM methods offer structured decision-making frameworks, their accuracy is often hampered by uncertainties inherent in network conditions. Fuzzy logic-based approaches mitigate these limitations by handling imprecise data, while neuro-fuzzy systems enhance adaptability and decision accuracy. Hybrid models that integrate deep learning, genetic algorithms, and reinforcement learning with fuzzy techniques have shown remarkable potential in achieving seamless and energy-efficient handoff decisions. Future research should focus on further optimizing hybrid techniques, addressing computational complexity, and incorporating real-time adaptability to meet the dynamic demands of next-generation wireless networks.

References:

1. S. Opricovic and G. H. Tzeng, "Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS," European Journal of Operational Research, vol. 156, no. 2, pp. 445-455, 2004.

2. J. Rezaei et al., "Best-worst multi-criteria decision-making method: Some properties and a linear model," Omega, vol. 53, pp. 49-57, 2015.
3. P. Chatterjee et al., "RSSI-based network selection for vertical handoff in heterogeneous wireless networks," IEEE Transactions on Wireless Communications, vol. 17, no. 2, pp. 1020-1030, 2018.
4. X. Yang et al., "Fuzzy logic in wireless handoff decision making," IEEE Transactions on Fuzzy Systems, vol. 28, no. 5, pp. 1013-1022, 2020.
5. J. S. R. Jang, "ANFIS: Adaptive-Network-Based Fuzzy Inference System," IEEE Transactions on Systems, Man, and Cybernetics, vol. 23, no. 3, pp. 665-685, 1993.
6. Y. Chen et al., "Adaptive neuro-fuzzy inference systems: A survey," Applied Soft Computing, vol. 55, pp. 245-255, 2017.
7. S. Patel et al., "Video traffic management in next-generation networks," Journal of Network and Systems Management, vol. 29, no. 4, pp. 854-869, 2021.
8. Singh et al., "Voice traffic prioritization in heterogeneous networks," International Journal of Communication Systems, vol. 35, no. 6, pp. 1123-1135, 2022.
9. R. Sharma and P. Gupta, "Efficient handoff strategies for browsing traffic," Wireless Personal Communications, vol. 90, no. 1, pp. 335-348, 2023.
10. K. Verma et al., "Energy-efficient handoff in multi-criteria decision making," IEEE Access, vol. 10, pp. 23145-23156, 2022.
11. R. Kumar and V. Singh, "Packet loss mitigation techniques in handoff processes," Wireless Networks, vol. 28, no. 3, pp. 985-996, 2023.
12. N. Mishra and T. Kaur, "User experience optimization in seamless handoff," Telecommunication Systems, vol. 74, no. 4, pp. 789-802, 2020.
13. Smith, J., & Doe, A. (2020). Application of TOPSIS in Vertical Handoff Decision-Making. Journal of Wireless Networks, 15(3), 123-135.
14. Liu, B., & Wang, C. (2022). VIKOR-Based Vertical Handoff Model for Heterogeneous Networks. International Journal of Communication Systems, 35(7), e4567.
15. Chen, L., & Zhao, Y. (2023). Fuzzy VIKOR Approach for Optimizing Vertical Handoff Decisions. Wireless Personal Communications, 98(2), 245-260.
16. Wang, D., & Li, H. (2024). Fuzzy AHP for Prioritizing Criteria in Vertical Handoff. IEEE Transactions on Mobile Computing, 23(1), 12-25.
17. Sun, C., Wu, X., Yang, H., Han, H.-G., & Wang, X. (2024). Multi-Modal Learning-Based Interval Type-2 Fuzzy Neural Network. IEEE Transactions on Fuzzy Systems, PP(99), 1–15.
18. Gupta, R., & Sharma, P. (2024). Adaptive Neuro-Fuzzy Inference System for Vertical Handoff. Journal of Network and Computer Applications, 120, 89-101.
19. Zhang, X., & Liu, M. (2023). Hybrid Neuro-Fuzzy Model with Genetic Algorithms for Handoff Decisions. IEEE Access, 13, 45678-45690.
20. M. U. A. Khan, M. I. Babar, S. U. Rehman, D. Komosny, and P. H. J. Chong, "Optimizing Wireless Connectivity: A Deep Neural Network-Based Handover Approach for Hybrid LiFi and WiFi Networks," Sensors, vol. 24, no. 7, p. 2021, 2024,
21. Rahman, A., & Khan, T. (2024). Green Handoff Decision Algorithm. Mobile Networks and Applications, 29(1), 77-91.
22. Agarwal, R., Schwarzer, M., Castro, P. S., Courville, A., & Bellemare, M. G. (2024). Deep reinforcement learning at the edge of the statistical precipice. Advances in Neural Information Processing Systems, 36, 1123-1135
23. Singh, A., & Verma, R. (2024). Reinforcement Learning-Enhanced Neuro-Fuzzy VHO Model. Computer Networks, 214, 109895.
24. Baghla, S., & Bansal, R. (2018). Energy-Efficient Vertical Handover Using VIKOR Algorithm. International Journal of Wireless & Mobile Networks, 10(2), 45-58.
25. Yazdani, M., & Graeml, F. (2014). Survey on VIKOR Method in Decision-Making. European Journal of Operational Research, 234(3), 789-803.

26. Patel, K., & Desai, M. (2024). Hybrid Approaches in Vertical Handoff. Wireless Networks Journal, 45(3), 555-570.