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An Effective Design And Implementation Of Deep Learning Based Approach For Channel Estimation And Equalization For Cognitive Radio Systems With Automated Handover Mechanism

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Abstract
The proposed work aims at developing an automated handover mechanism among the multiple access techniques based on a data driven CSI based on features such as channel gain, signal to noise ratio (SNR), Signal to Interference plus Noise Ratio (SINR), bit error rate (BER), throughput and user mobility. Additionally, the CSI is also leveraged to utilize the section of the bandwidth with optimal channel response rendering improved QoS. A Machine Learning based model (Deep Neural Network Model) trained with features such as pilot bits, received bits, path loss factor and signal to noise plus interference ratio (SINR) is used to estimate channel response and estimate the error rate, which is chosen as the primary QoS metric governing the handover. Various channel conditions are simulated for a frequency fading channel to estimate handover characteristics. A comparative analysis with existing work shows that the proposed work outperforms baseline approaches in terms of performance metrics. One of the technologies may perform better than the other under practical channel conditions and user attributes which points to the fact that co-existence and vertical handover among the technologies would increase the Quality of Service (QoS) if a choice among multiple techniques is provided. Moreover, estimating the wireless channel state information (CSI) would also facilitate the decision of picking a particular technology in real time scenarios
Keywords: *Handover, Deep Neural Networks, Bit Error Rate.*

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I. Problem Identificaiton & Formulation

Problem Identification

The problem with wireless communication is the random nature of wireless channel and the mobility of users. While the random nature of wireless channel creates distortions in the received signal, the mobility of user's results in fading effects and signal degradation. Typically these two effect act in conjugation and result in degradation in the Quality of Service (QoS) of the system, which can be evaluated in terms of the latency, interference and bit error rate of the system. Hanover in such systems are challenging due to the following challenges:

Heterogeneity of Networks: Different wireless networks have varying characteristics, including bandwidth, coverage areas, latency, and quality of service (QoS). Coordinating seamless handovers between networks with such disparities can be challenging.

Network Discovery and Selection: Mobile devices need to discover and select the appropriate network for handover based on factors like signal strength, network availability, and user preferences. Efficient algorithms are required for network selection.

Handover Decision Making: Determining when and where to initiate a vertical handover requires intelligent decision-making. Factors such as network conditions, application requirements, and user mobility patterns need to be considered

QoS and Service Continuity: Maintaining the quality of service (QoS) during a vertical handover is crucial. Ensuring that ongoing voice calls, video streams, or data transfers do not experience noticeable disruptions is challenging, especially when transitioning between networks with different QoS capabilities.

Authentication and Security: Vertical handovers may involve authentication and security challenges as devices switch between networks. Ensuring a secure handover process and protecting against potential security threats is essential

IP Address Management: When switching between different network types, a mobile device may need to acquire a new IP address. Managing IP addresses and maintaining connectivity during address changes can be complex.

Interoperability: Ensuring that different types of networks (e.g., cellular, Wi-Fi, satellite) can seamlessly interoperate during handovers can be challenging, particularly when they use different protocols and technologies.

Seamless Handover Protocols: Developing and implementing protocols that support seamless handovers across different network technologies is an ongoing challenge. These protocols need to handle data synchronization, state transfer, and signaling between the old and new networks.

Handover Triggers and Thresholds: Setting appropriate handover triggers and thresholds is essential. Too aggressive handover decisions can lead to unnecessary handovers, while too conservative decisions can result in poor QoS .

Power Consumption: Vertical handovers can consume additional power, especially when the mobile device needs to search for available networks and perform authentication procedures. Efficient power management strategies are needed .

User Preferences: Taking into account user preferences and policies regarding network selection and handover decisions can be challenging. Different users may have different preferences for network types and QoS parameters.

Network Congestion: Vertical handovers may be initiated to balance network load. Managing network congestion and ensuring that handovers contribute to network optimization are important considerations.

Real-time Adaptation: Network conditions and user requirements can change rapidly. Ensuring that handover decisions can adapt in real-time to these changes is a significant challenge .

The first step in understanding a fading affected wireless network which is subject to signal distorting needs the understanding for distortion less communication, which is governed by channel characteristics explained subsequently.

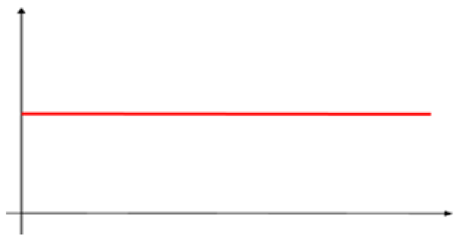
Practical channels do not follow the conditions for distortion less transmission given by:

$$mo(H(f) = k \quad \textbf{(3.1)}$$

Here,

H(f) is the channel frequency response K is constant

Channel Gain H(f)



Frequency

Fig.1 Channel Response of ideal channel

The other condition is the phase response being a linear function of time:

$$an(H(f) = -kf \quad \textbf{(3.2)}$$

Here,

$an(H(f)$ represents the phase K is a constant
F stands for frequency
H stands for channel response

II. Data Driven Models Analyzing Network Parameters

Stochastic computing can be a valuable tool for analyzing and optimizing Quality of Service (QoS) in wireless networks. QoS is crucial for ensuring that wireless communication systems meet the requirements of various applications and services. Machine learning models can predict QoS metrics such as latency, packet loss, and throughput based on historical network performance data, network conditions, and user behavior. These predictions can help in proactive QoS management. Also, such algorithms can optimize resource allocation in real-time by considering network congestion, user demands, and application priorities. This helps ensure that critical services receive the necessary bandwidth and latency guarantees. The deployed model can classify network traffic into different categories (e.g., voice, video, data) and prioritize them accordingly. This ensures that mission-critical applications receive higher priority .Thus, handover optimization using machine learning is a technique that leverages artificial intelligence and data-driven models to enhance the efficiency and effectiveness of the handover process in wireless communication networks, particularly in cellular networks. The goal is to make intelligent handover decisions that improve network performance, minimize latency, and enhance the overall user experience. Continuously update and fine-tune the machine learning models based on real-time network data and performance feedback. This allows the models to adapt to changing network conditions and user behaviors. Implement a decision-making process where the machine learning model evaluates the current network state and user context to determine if a handover is necessary and, if so, which cell or access point is the best candidate. Hence, Machine learning-based handover optimization has the potential to significantly improve network efficiency, reduce dropped calls, and enhance the user experience in wireless communication networks. However, it requires careful design, continuous monitoring, and ongoing optimization to maintain its effectiveness as network conditions evolve. This would be valid for Wide-Sense Stationary Uncorrelated Scattering Homogeneous (WSSUSH) and Wide-Sense Stationary Uncorrelated Scattering (WSSUS) channel models.

The proposed machine learning algorithm proposed in this approach is the neural networks, which greatly mimic the human thought process of parallel processing and self-adaptation, which is depicted in figure 4.5.

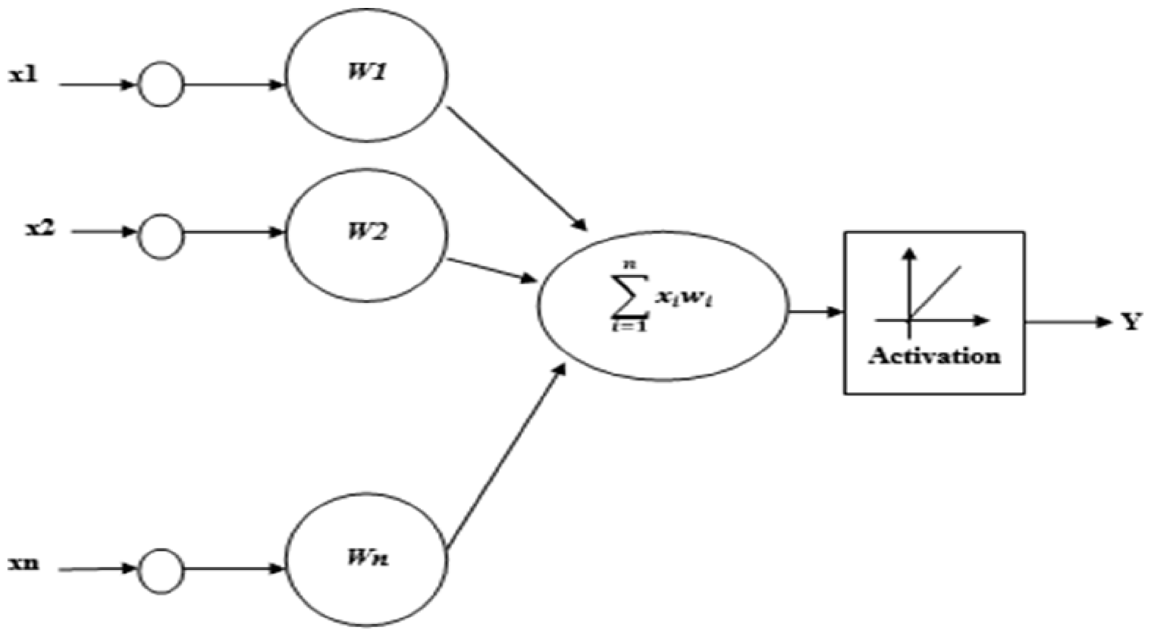


Fig.2 The Neural Network Model

III. Proposed Approach

The proposed methodology of the paper aims at designing an automated handover based approach for switching from on transmission mode to the other based on the sensed channel state information. The sensing mechanism can be mathematically described as:

$$E_{sensed} = (f) \qquad \textbf{(4.10)}$$

Here,

E_{sensed} is the sensed energy

x(f) is the frequency dependent energy variation of the signal

However, the situation becomes challenging if there is addition of noise in the channel resulting in higher energy in the spectrum holes thereby leading to false detection of holes or even non-detection of holes.

IV. Final Results & Tabular Discussions

Table 1: Variation of throughput with SNR

S.No	SNR	Throughput (MB/s)
1	5	5.2
2	10	8.0
3	15	10.0
4	20	11.2
5	25	12.0

The bit error rate as a function of SNR is also compared in table 5.3

Table 2: SNR-BER variation for system

SNR (dB)	BER	Condition
5	$>10^{-1}$	No Jamming
10	$<10^{-1}$	
15	10^{-3}	
20	10^{-4}	
25	10^{-5} - 10^{-6}	
5	$>10^{-1}$	Low and Moderate Jamming
10	$>10^{-1}$	
15	10^{-1}	
20	10^{-2}	
25	$<10^{-3}$	
5	$>10^{-1}$	High Jamming
10	$>10^{-1}$	
	$>10^{-1}$	
20	10^{-1}	
25	10^{-1} - 10^{-2}	

The BER analysis of the proposed system renders the following information:

1) The BER of the high jamming activity is the highest and reduces extremely slowly. This implies that the bandwidth chunk experiencing high jamming activity should be avoided for data transmission, else the reliability of the system in terms of accuracy, error and throughput performance of would be poor.

On the contrary, the low jamming activity spectrum can be utilized with caution and iterative channel sensing as the error rate reduces significantly.

The moderate jamming condition can be avoided or in case, the receiver is extremely sensitive can be utilized if the other sections of the bandwidth are occupied. The no jamming condition is an ideal condition which assumes no jamming. It is more of a theoretical yardstick to evaluate the performance of the system under different jamming conditions.

Handover Results

The handover results are presented next.

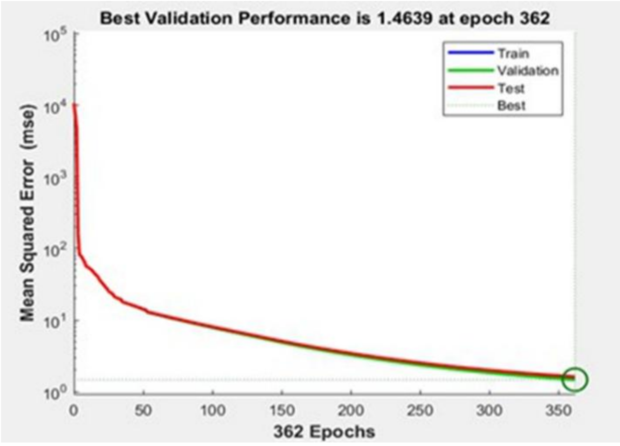


Fig 3 Neural Network Training Convergence

Fig.4 Handover under low fading conditions

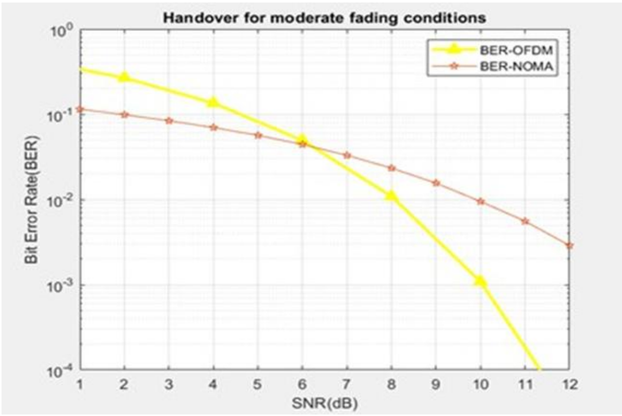


Fig.5 Handover under moderate fading conditions

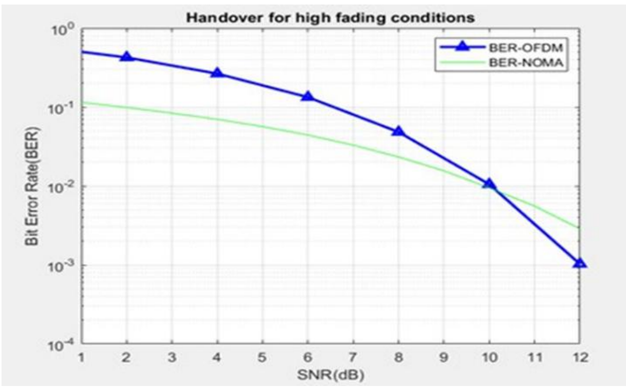


Fig.6 Handover under high fading conditions

Table 3 Fading-BER characteristics

S.No.	Fading Condition	σ	BER Range
1	Low	2.5	$10^{-4} - 10^{-6}$
2	Moderate	3.5	$10^{-3} - 10^{-4}$
3	High	5.5	$10^{-2} - 10^{-3}$

Table.4 Fading Handover Characteristics

S.No.	Fading Condition	σ	Switching SNR
1	Low	2.5	$6dB$
2	Moderate	3.5	$6dB$
3	High	5.5	$10dB$

The path BER for the OFDM-NOMA simulations under different path loss factors is presented in this table 5.4. It can be observed that as the path loss factor increases, the BER also starts increasing. Table 5.5 presents the switching SNR from NOMA to OFDM under different fading conditions.

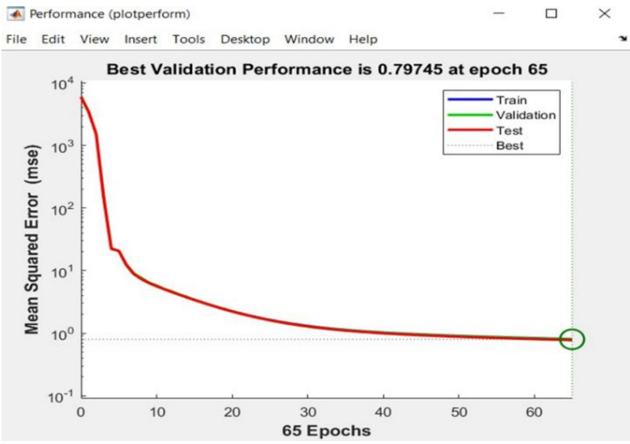


Fig.7 Model Cost Function

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