Adaptive Millimeter Wave Channel Switching Based on Real-Time Weather Data Using Fuzzy Logic Control

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***Abstract*—Millimeter wave (mmWave) communication systems offer high data rates, but these systems are highly susceptible to environmental factors, particularly weather conditions such as rain, dust, and sand. This paper presents a novel approach to enhance the reliability of mmWave communication by implementing a Fuzzy Controller System (FCS) for dynamic channel switching. The proposed system integrates real-time measured weather data, such as rain rate, with the fuzzy logic controller to intelligently select the optimum frequency channel with the least attenuation under current atmospheric conditions. The fuzzy controller makes adaptive switching decisions by continuously analyzing environmental changes to maintain signal quality and system performance. Experimental results and simulations demonstrate that incorporating real measured data significantly improves the system's ability to respond to weather variability, ensuring stable and efficient mmWave communication. This work provides a practical framework for implementing intelligent, weather-aware channel-switching mechanisms in next-generation wireless communication networks.**

***Index Terms*—mmWave, weather conditions, fuzzy controller system, channel switching.**

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I. Introduction

THIS paper expands the previous paper published in IEEE 2024 RFID Technology and Applications [1]. Millimeter-wave (mmWave) communication systems are important to next-generation wireless technologies, such as 5G and future 6G networks, because of their data rates, bandwidth, and latency improvements [2]. Despite these advantages, the high frequencies of mmWave signals are particularly vulnerable to harsh environmental conditions, such as rain, dust, and sandstorms [3]. These weather conditions can significantly weaken signals and reduce the reliability of communication. Some previous studies have proposed machine learning [4] [5] and reinforcement learning [6] strategies to mitigate communication degradation caused by adverse weather conditions. However, these approaches are primarily based on historical weather data, and their performance is validated through simulation results. One significant limitation of simulations is that they do not incorporate real-time environmental data, so their proposed methods may have limited practical use in real-world scenarios. To address the absence of real-time weather data in previous research, our team introduces an innovative and practical solution by modifying a commercial mmWave device, the MikroTik Cube [7], and integrating it with real-time weather sensors into a novel testbed. Our newly developed testbed captures real-time environmental parameters, including temperature, humidity, visibility, and rain rate. At the same time, it evaluates mmWave communication performance under these actual weather conditions using the MikroTik Cube. Our proposed testbed can be mounted directly on vehicles, offering a new tool for investigating and resolving challenges in vehicular network communications under severe weather conditions. Maintaining reliable vehicle connectivity in harsh environments remains an important research area, and our testbed can be a solid foundation for future studies in vehicle-to-vehicle networks.

Traditional machine learning methods typically require large datasets and substantial computational resources for initial training, making them time-consuming [8]. Furthermore, trained ML models often lack transparency, resulting in decision-making processes that can be difficult to interpret [9], especially under rapidly changing conditions. In contrast, fuzzy logic control provides a more suitable approach, as it is inherently robust and computationally efficient. It can handle real-time sensor data without the need for extensive training [10]. Our proposed fuzzy logic controller is defined by expert rules about different weather conditions, making it particularly suitable for dynamic weather conditions. Then, our team integrates the fuzzy logic control system with a practical mmWave testbed, allowing dynamic frequency switching in response to real-time weather data. This approach maintains seamless connectivity under different environmental conditions.

Building upon our previous work [1], which introduced a fuzzy controller system capable of predicting communication degradation and proactively switching frequencies, this study integrates the fuzzy controller with a newly developed testbed that captures real-time weather data. Our paper provides three key contributions:

1) Design and implement a novel testbed capable of capturing various real-time environmental parameters.
2) Evaluation of our previously proposed fuzzy control system using real-time weather data, validating our system's effectiveness and practical applicability.
3) Establishment of a foundation for future research in robust vehicle network communications under severe weather conditions.

The remainder of this paper is structured as follows: Section II provides a literature review. Section III details the system architecture and methodology, while Section IV describes the experimental setup. Results and analysis are presented in Section V. Finally, Section VI concludes the paper and suggests directions for future research.

II. Literature Review

A. Millimeter Wave Communication and Weather Effects

Millimeter wave communication has gained significant attention for next-generation wireless networks due to its ability to provide multi-gigabit data rates. Rappaport et al. [11] conducted pioneering work, presenting propagation measurements and channel models for 28 gigahertz (GHz) and 38 GHz in urban environments. Their extensive measurements highlighted the potential and challenges of mmWave bands, particularly the susceptibility to environmental factors. The atmospheric effects on mmWave propagation have been extensively studied by the ITU-R, which provides standardized models for gaseous absorption, rain attenuation, and other atmospheric factors. Recommendation ITU-R P.838-3 [12] specifically addresses rain-induced attenuation, presenting a methodology to calculate rain attenuation based on rainfall rate and frequency, showing an exponential increase in attenuation with frequency in the mmWave bands. The impact of atmospheric phenomena on wireless communication links is a well-documented concern across various technologies. For instance, in the domain of free-space optical (FSO) communications, significant research has been dedicated to overcoming impairments caused by turbulent weather phenomena through methods like advanced coding techniques and diversity schemes to ensure link reliability [13]. Alkholidi and Altowij [14] investigated the effect of clear weather conditions on free-space optical and mmWave links, analyzing the impact of temperature, pressure, humidity, and dust. Their results demonstrated that even moderate changes in humidity can cause significant degradation in mmWave signal quality at frequencies above 60 GHz due to water vapor absorption. Similarly, De and Maitra [15] conducted a comprehensive analysis of rain-induced attenuation for Ka-band frequencies in India, examining the relationship between rain rate, drop size distribution, and specific attenuation. Their measurements revealed significant attenuation levels during heavy rain events, with distinct patterns observed between stratiform and convective rain types. Their findings demonstrate that medium drop diameters (up to 3 millimeters (mm)) are the primary contributors to various classes of rain attenuation, with temporal variations showing higher attenuation occurrences during afternoon hours.

B. Channel Switching Techniques in mmWave Systems

Channel-switching techniques are vital for maintaining reliable connectivity by dynamically adapting to these changing conditions. Adaptive channel allocation schemes dynamically adjust frequency resources based on channel conditions to maximize throughput during adverse weather. Deep Reinforcement Learning (DRL) has been used for intelligent channel switching between 5G mmWave and 4G LTE in vehicles under extreme weather, utilizing real-time Received Signal Strength Indicator (RSSI), throughput, and detailed weather parameters to optimize channel selection [6]. Prediction-based channel switching, employing machine learning to forecast weather, allows proactive switching to less affected frequencies [16]. Dynamic Soft Frequency Reuse, primarily for interference management, could also be leveraged for weather resilience by adapting frequency usage based on real-time weather impacts. Current 5G mmWave resource allocation often relies on static thresholds, highlighting the need for more dynamic and intelligent schemes. The concept of Dynamic Spectrum Sharing (DSS) in 5G, where spectrum is dynamically allocated based on traffic, offers a model for adapting frequency usage based on weather conditions [17], [18].

C. Fuzzy Logic in Wireless Communication

Fuzzy logic is effective for handling uncertainties in wireless communication systems. Its ability to reason with imprecise information and model complex relationships makes it suitable for dynamic wireless environments [19]. Fuzzy logic principles have been successfully applied in channel estimation, equalization, and decoding, offering faster convergence and reduced complexity in nonlinear and time-variant channels. The twenty core fuzzy logic concepts, like membership functions, fuzzy inference systems, and adaptive neuro-fuzzy inference systems, are versatile tools for wireless communication problems [20]. Fuzzy logic is also effective in intelligent resource allocation, handling unpredictable traffic, and imprecise channel conditions using linguistic terms for channel quality. Fuzzy resource allocators can prioritize traffic types based on requirements and channel conditions [21].

Fuzzy logic is valuable for making optimal handover decisions in heterogeneous wireless networks, considering

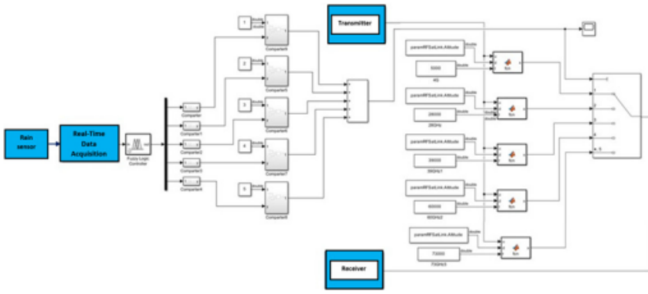

Fig. 1. System Block Diagram.

multiple criteria with varying uncertainties. Fuzzy logic-based systems integrate parameters like bandwidth, RSSI, and network type for robust handover decisions. Research highlights the effectiveness of fuzzy logic in vertical handover implementations [22].

D. Integration of Environmental Data in Communication Systems

Integrating environmental sensing enhances the adaptivity and resilience of wireless communication systems. This is particularly important for mitigating weather challenges in mmWave communication and optimizing network performance. Weather radar systems like NEXRAD [23] provide valuable data on atmospheric conditions, especially precipitation. Communication networks can potentially use this data to anticipate signal degradation and proactively adjust network parameters. Signal processing techniques used in radar systems can be adopted for communication networks to effectively utilize weather radar data. 5G technology provides a strong foundation for deploying extensive environmental sensing frameworks. Sensing-assisted communication frameworks are also being explored in non-terrestrial networks, using sensing to optimize resource allocation based on atmospheric attenuation [24].

III. System Architecture and Methodology

A. Overall System Overview

The proposed system is an intelligent, adaptive communication framework that ensures continuous connectivity under diverse and challenging environmental conditions, as shown in Fig. 1. At its core, the system utilizes real-time environmental measurements—such as visibility and rainfall intensity to dynamically select the most suitable transmission frequency from five available bands. Frequency selection is governed by a fuzzy logic controller, whose rule base is derived from extensive experimental data. This controller enables the system to respond quickly to environmental changes by choosing the frequency band that minimizes signal attenuation, thereby improving communication reliability and performance. In adverse weather conditions, such as heavy rain or low visibility, the system automatically switches to the lowest available frequency band-5 GHz. Although this band offers relatively lower data throughput, it provides superior propagation characteristics in harsh conditions, ensuring that communication links remain stable and uninterrupted. This adaptive switching strategy optimizes the system in various operational scenarios.

This study incorporates real-time environmental measurements to enable the system to respond promptly and minimize the risk of communication interruptions. A rain sensor is interfaced with the system using an Arduino microcontroller, which bridges the physical sensor and the Simulink-based simulation environment. The real-time data acquired from the sensor is processed within Simulink, allowing the control logic to make immediate decisions based on actual environmental conditions. This hardware-in-the-loop (HIL) configuration ensures that the physical controller can effectively manage frequency selection, adapt to changing conditions, and optimize overall system performance in real-time.

B. Fuzzy Logic Controller Design

The fuzzy logic controller (FLC) is central to the system's decision-making capability. It maps environmental conditions to appropriate frequency bands based on linguistic rules and expert-defined knowledge. The FLC processes two key inputs: rainfall intensity and visibility level, which significantly impact signal attenuation in millimeter-wave communication. Each input is fuzzified into linguistic variables using Gaussian and trapezoidal membership functions to reflect uncertainty and gradual transitions in environmental measurements. The controller then evaluates the inputs using a set of fuzzy inference rules, producing a frequency selection index as output. The output is then defuzzified using the centroid method to yield a crisp decision determining the optimal operating frequency. By embedding this controller in the Simulink environment and coupling it with real-time sensor data, the system achieves dynamic adaptation without requiring manual intervention or fixed thresholds.

C. Rule Base and Membership Functions

The fuzzy rule base is constructed using empirical data gathered from extensive testing under different weather scenarios. It consists of a series of IF-THEN rules that relate combinations of rainfall and visibility to the optimal frequency band. For instance:

1) IF Rainfall is High AND Visibility is Low, THEN Frequency is 5 GHz.
2) IF Rainfall is Low AND Visibility is High, THEN Frequency is 73 GHz.

Each linguistic variable is represented using overlapping membership functions, enabling smooth state transitions. The rules are designed to prioritize communication reliability over bandwidth when environmental conditions degrade. Soft boundaries and overlapping functions allow the system to gracefully handle uncertain or noisy input data, ensuring stable and consistent decision-making even during rapid environmental changes.

D. Channel Switching Decision Process

Once the fuzzy controller produces a frequency selection output, the system initiates the channel-switching procedure.

Fig. 2. Rain Sensor.

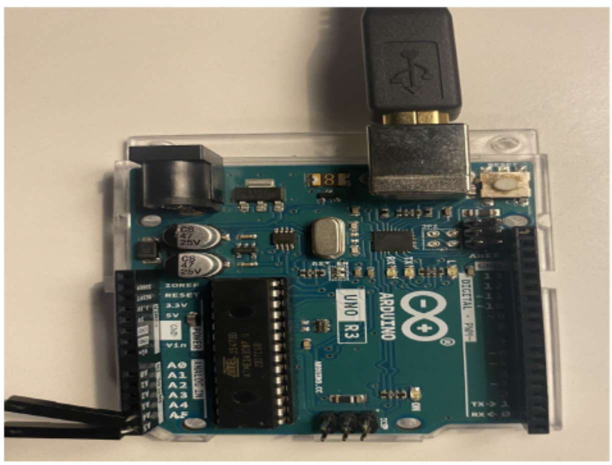

Fig. 3. Arduino-based Embedded System.

This process is implemented through a control logic module that monitors changes in the controller's output and triggers a frequency switch only when a significant deviation from the current frequency occurs, thus avoiding unnecessary switching. The channel-switching mechanism interfaces directly with the communication chain, reconfiguring the transmitter and receiver to operate at the newly selected frequency. To minimize transient disruptions, a short buffering interval is included to allow for synchronization and gain adjustment. The switching logic is optimized for real-time execution in Simulink and validated using both simulated and hardware-in-the-loop experiments, confirming its responsiveness and robustness in dynamic conditions.

IV. Implementation and Experimental Setup

A. Simulation Environment and Real-Time Testbed

The system architecture included three primary components: a rain sensor for environmental data acquisition, an Arduino microcontroller for real-time interfacing, and a Simulink-based simulation model for processing and control. These components are illustrated in Figs. 2, and 3, respectively.

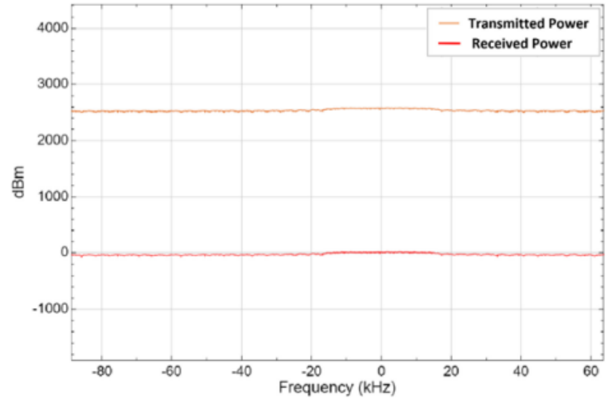

Fig. 4. Rx & Tx Power at No Rain.

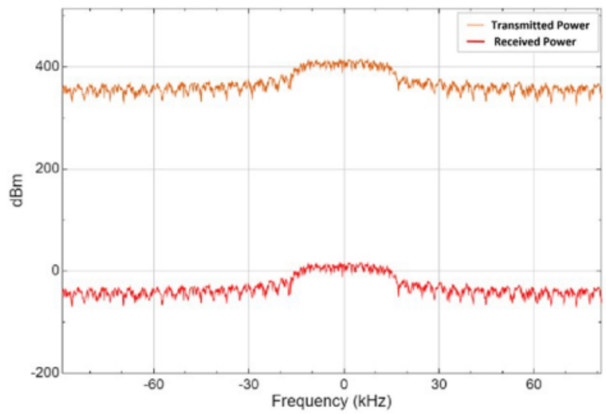

Fig. 5. Rx & Tx Power at Rain = 6 mm/hr.

The system was evaluated under various real-time rainfall measurements (in mm/hr) acquired via a rain sensor interfaced to an Arduino board. The Arduino transmitted the data directly to Simulink for processing. This real-time input enabled the fuzzy logic controller to dynamically select the appropriate operating frequency based on the detected rain intensity. This hybrid approach enabled flexible yet realistic evaluation of the system performance in multiple rain intensities.

To assess the performance of the fuzzy logic controller in frequency selection, five distinct test cases were implemented. In the first case, for no rain, the controller selected the highest frequency option, 73 GHz, as shown in Fig. 4 because the system is configured using the highest frequency band in clear weather. In the second one with light rain (6 mm/hr), the system selects 60 GHz, as shown in Fig. 5. When the rain rates get higher (10, 14, 16) mm /hr, the selection goes with a lower frequency (39, 28, 5) GHz respectively, as shown in Figs. 6 to 8.

The results demonstrate the controller's capability to intelligently adapt the communication frequency in response to changing environmental conditions. This adaptability ensures optimal link performance and reliability across a wide range of weather scenarios, validating the effectiveness of the proposed real-time frequency switching strategy.

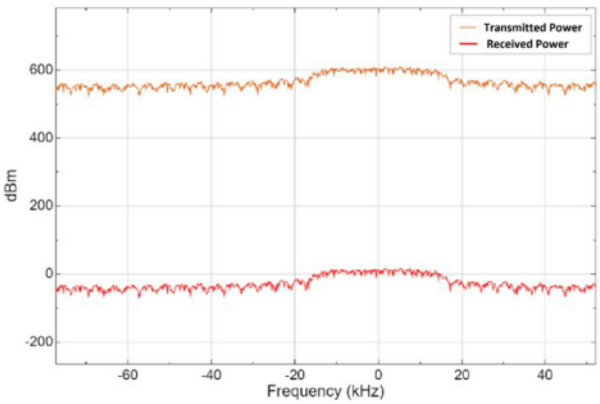

Fig. 6. Rx & Tx Power at Rain = 10 mm/hr.

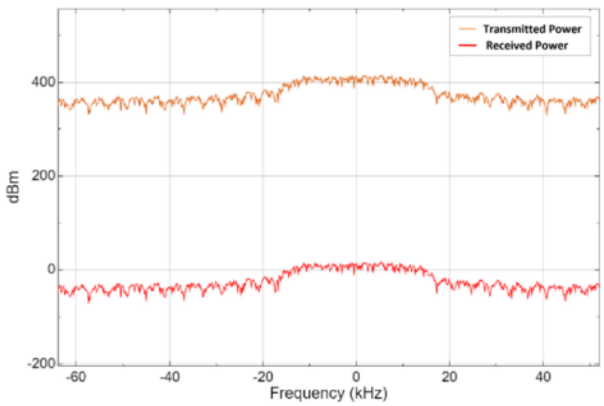

Fig. 7. Rx & Tx Power at Rain = 14 mm/hr.

B. Channel Frequency Bands Considered

The system supports five operational frequency bands, selected based on their relevance to modern communication systems, particularly in 5G and beyond. The 5 GHz is used as a fallback frequency for severe weather due to its favorable propagation characteristics. The 28 GHz is a primary 5G band suitable for moderate conditions. The frequency of 39 GHz offers higher bandwidth with moderate weather tolerance. The 60 GHz mmWave band has higher capacity but reduced reliability in poor weather. The 73 GHz is the highest frequency in the system, offering maximum data rates under optimal conditions. These bands were selected to balance performance, availability, and resilience to environmental degradation, enabling the system to make intelligent trade-offs between speed and reliability.

C. Communication System Parameters

The simulated communication link includes transmitter and receiver chains designed using standard digital modulation and filtering blocks. Key system parameters include Modulation Scheme: QPSK, Symbol Rate: 1 MSymbols/second, Sample Rate: 10 megahertz (MHz), Raised Cosine Filters: used at both the transmitter and receiver to minimize intersymbol interference, Doppler Compensation: included to simulate mobility and evaluate robustness, Noise Modeling: AWGN and phase noise components were incorporated for realism. The complete system was evaluated under varying signal-to-noise

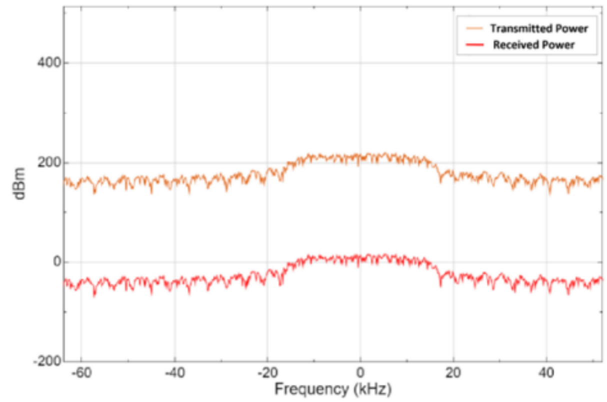

Fig. 8. Rx & Tx Power at Rain = 16 mm/hr.

ratio (SNR) conditions and environmental profiles to assess switching accuracy, latency, and link stability.

V. Results and Analysis

A. Performance Under Different Weather Conditions

In this experiment, the system is assumed to work in clear visibility and considers rainy conditions only. The system was tested across a range of simulated weather scenarios, including clear (no rain), light rain, moderate rain, heavy rain, and very heavy rain. In each scenario, rainfall intensity was varied in real time, and the fuzzy logic controller responded by selecting the most appropriate operating frequency with an average switching delay of approximately 0.7 seconds.

The fuzzy logic controller successfully adapted the communication frequency in each scenario. In light weather, higher frequency bands, such as 60 GHz and 73 GHz, were selected, allowing for higher throughput. As environmental conditions deteriorated, the controller gradually transitioned to lower frequencies, prioritizing link stability. In cases of severe rainfall and visibility below 1 meter, the system consistently switched to 5 GHz, maintaining uninterrupted communication with minimal attenuation. These results confirm that the system can maintain service continuity and optimize link performance in dynamic environmental conditions.

B. Fuzzy System Response to Real-Time Data

The responsiveness of the fuzzy logic controller to real-time inputs was evaluated by measuring the rainfall values and observing the fuzzy controller responses, which depend on the input value and the switch decision made. In each test case, the controller produced a smooth and immediate transition between frequency bands. The successful integration of the physical rain sensor and Simulink's real-time processing validated the hardware-in-the-loop setup as both accurate and reliable.

C. Signal Quality and Throughput Evaluation

To evaluate the benefits of the fuzzy-based approach, the system was compared to a threshold-based switching mechanism that used fixed limits for rain intensity and visibility. The traditional system often resulted in delayed switching and abrupt transitions, which led to short-term communication losses or unnecessary switching between bands. In contrast, the fuzzy system provided smoother transitions and better handling of uncertain or noisy data. This resulted in improved link reliability, reduced switching events, and better overall quality of service (QoS) across weather conditions.

D. System Strengths and Limitations

Signal quality was assessed using metrics such as signal-to-noise ratio (SNR), bit error rate (BER), and data throughput across different frequency bands. The results showed that when the 73 GHz is under clear conditions, the system achieved high throughput with acceptable BER. In the case of 39 GHz and 28 GHz, the system offered a balance between performance and reliability. In heavy rain, 5 GHz maintained communication with minimal signal degradation and lower throughput. The SNR degradation correlated strongly with rain intensity and visibility, validating the fuzzy system's frequency selections.

VI. Conclusion and Future Work

This paper presented an adaptive frequency selection system based on real-time environmental monitoring, combining fuzzy logic control with hardware-in-the-loop simulation. Experimental results demonstrated the effectiveness of the fuzzy logic controller in selecting the appropriate transmission frequency to minimize signal attenuation under various rain conditions.

Future work will enable a comprehensive, real-world evaluation of the system's performance and reliability under dynamic environmental conditions, further validating its applicability for intelligent communication systems in harsh weather environments.

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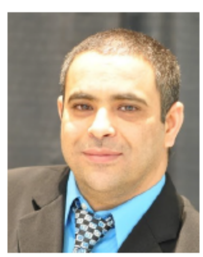

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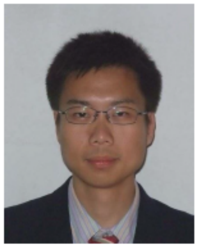

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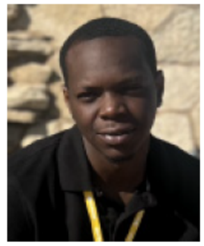

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