Switching Strategy for Connected Vehicles Under Variant Harsh Weather Conditions

Jian Liu, *Graduate Student Member, IEEE,* Amirhossein Nazeri, *Graduate Student Member, IEEE,* Chunheng Zhao, Esmail Abuhdima, *Member, IEEE,* Gurcan Comert, Chin-Tser Huang, *Senior Member, IEEE*, Pierluigi Pisu, *Member, IEEE*

Abstract—With the development of 5G networks and advanced communication technologies, connected vehicles (CV) are becoming an increasingly important aspect of the future of transportation. The connected vehicles will usually generate a large amount of data that require fast and reliable communication channels with low latency. 5G millimeter-wave (mmWave) is crucial for the next generation of vehicle-to-vehicle (V2V) communications in CV scenarios. However, harsh weather conditions such as rain, snow, dust, and sand can significantly impact the performance of 5G mmWave channels for V2V communications. Maintaining seamless connections for connected vehicles during harsh weather conditions is a significant challenge that researchers must address. In this paper, we propose a two-stage strategy enabling connected vehicles to operate effectively under moderate and severe weather conditions. Our proposed approach involves a prediction step, which uses machine learning techniques to forecast weather patterns and determine the optimal communication strategy, followed by a switching step, which seamlessly chooses between frequency or channel switch based on the prediction. By incorporating these two steps, we aim to provide a robust and efficient communication system that can adapt to different weather conditions. The NS3 simulation results show that our switching strategy is effective and can benefit the field of connected vehicle technology.

Index Terms—Connected vehicles, 5G, harsh weather, switching strategy, and NS3.

I. Introduction

THIS paper expands the previous paper published in the 2022 IEEE International Conference on Wireless for Space and Extreme Environments (WiSEE) [1]. Compared to our previous conference paper, the primary contribution of this paper is introducing an additional frequency switch mode for moderate weather changes, which allows for maximum communication throughput. Rather than solely relying on channel switching between 5G mmWave and 4G LTE channels, our extended work proposes a four scenarios frequency change mode for moderate weather. By providing a comprehensive switching strategy for connected vehicles, we aim to enhance communication reliability and performance in adverse weather scenarios.

This paper was funded by U.S. DOT Tier 1 University Transportation Center, the Center for Connected Multimodal Mobility (C^2M^2). Jian Liu and Chin-Tser Huang are with University of South Carolina, Columbia, SC 29208 USA. Amirhossein Nazeri, Chunheng Zhao and Pierluigi Pisu are with the International Center for Automotive, Clemson University, Greenville, SC 29601 USA. Esmail Abuhdima and Gurcan Comert are with Benedict College, Columbia, SC 29204 USA.

Manuscript received February 19, 2023; revised May 5, 2023.

The development of wireless communication technology has led to the integration of different technologies, such as IoT and Intelligent Transport Systems (ITS), both into various applications, such as smart cities and connected vehicles [2] [3]. ITS aims to improve traffic flow, driving safety, and comfort through vehicle-to-vehicle communication [4]. 5G millimeterwave (mmWave) communication is a vital component for connected vehicles due to its higher transmission speed and lower latency compared to 4G Long Term Evolution (LTE) [2] channel. While 5G mmWave is generally the preferred communication channel for connected vehicles due to its high throughput. However, weather conditions such as severe rain, snow, and sand can significantly impact its performance [1]. In these cases, 4G LTE may provide a more reliable connection for connected vehicles, as it is less susceptible to harsh weather conditions. It is crucial to consider the impact of severe weather on the communication networks of connected cars to ensure seamless and secure communication.

The CVs are vehicle networks that transfer data with the cloud, network devices, and servers [5]. A reliable communication channel between vehicles is the most crucial aspect of a successful CV network. One of the main challenges of connected vehicles under severe weather conditions is the potential for degraded or disrupted communication between the cars. Harsh weather conditions, such as rain, snow, dust, and sand can significantly impact the performance of wireless communication channels, making it difficult for vehicles to maintain reliable and seamless connectivity. This flaw can lead to safety concerns and reduced efficiency in transportation, particularly in situations where real-time communication and coordination between vehicles are essential, such as in autonomous driving scenarios. Another challenge is that the communication degradation problem will occur in harsh weather. Severe weather can result in a significant drop in the quality of communication between vehicles, which might be dangerous as it may lead to collisions.

For a reliable connected vehicle network, the researchers in [6] have investigated the impact of different weather conditions on the safety of the CV network. Studies by [7] and [8] have used two unique attenuation models to examine the effect of weather conditions on 5G mmWave high-frequency communications and found that harsh weather conditions like rain, snow, dust, and sand have a significant impact on mmWave communications.

To provide reliable and uninterrupted communication in connected vehicle networks, a two-stage strategy is proposed in this paper to address weather-related impacts. The first stage involves predicting the future received signal strength indicator (RSSI) based on current weather and current RSSI information by using a long short-term memory (LSTM) network, as described in our earlier work [1]. This paper focuses on the second stage, where the decision to switch frequencies or channels is made based on the predicted RSSI and throughput. Our system has different strategies for moderate and severe weather conditions, with frequency switching activated for mild weather changes and channel switching for extreme weather changes. To validate the switch strategy, the NS3 Millicar model [9] has been extended by incorporating weather parameters and redesigning the automatic simulation generation system for easier testing. Our contribution to this paper can be summarized as follows:

- We propose using long short-term memory (LSTM) to predict the future signal strength of 5G mmWave and 4G LTE communication channels in harsh weather conditions based on the previous signal strength and different weather impacts: humidity, visibility, and particle size of the environment.
- Our proposed switching strategy for connected vehicles in harsh weather conditions involves two scenarios switch a frequency switch for moderate weather changes and a channel switch for severe weather changes. The simulation results support that our strategy works well in both cases. This two-stage approach provides a more targeted response to specific weather conditions, which can help maintain reliable vehicle connectivity.
- We expand upon the NS3 Millicar model [9] by integrating weather effects into the path loss functions. Our newly designed model can automatically generate NS3 simulation results based on various weather parameters, including particle size, visibility, and humidity. Our new N3 weather model is the first NS3 V2V model to consider weather conditions.

The paper is structured into six sections. Section II provides an overview of related work on handover, throughput, and received signal strength indicator (RSSI). Section III presents several main topics addressed in this article, while Section IV discusses the generation of weather data. Section V presents the numerical simulation and results. Finally, in the concluding Section, we summarize our findings and outline future work plans.

II. Related Work

Previous studies have explored various handover methods for 5G mmWave and 4G LTE networks. For instance, one study proposed using dynamic Q-learning and fuzzy convolution neural networks to make handover decisions for both networks [10]. Another study utilized the moving average slope of received signal strength (MAS-RSS) and signal to noise ratio (SNR) threshold in the handover decision process [11]. The MAS-RSS technique observes the trend of RSS fluctuation and allows for adaptive handover decisions based on changes in network conditions. Handover refers to moving from one cell to another and typically involves either 5G mmWave or 4G LTE base stations. In contrast to most other works on handover, our channel-switching approach does not involve base stations. We focus only on the direct communication channel between vehicles, in accordance with the 3GPP standard for next-generation vehicular systems.

Earlier research [12] used throughput to examine the uplink performance of the 5G mmWave network, emphasizing the impact of a wide range of factors on the network's performance, such as the number of users, beam-forming, and the usage of adaptive coding and modulation (ACM) methods. A different article also employed throughput [13] to look at how device thermal performance affected 5G mmWave networks communicated. It investigates how overheating affects signal quality, strength, and network performance. For assessing the performance of 5G mmWave, throughput is a valuable metric. RSSI is another metric for measuring 5G communication performance. One study [14] utilized RSSI feedback from individual users to design a new hybrid beamforming approach. In another study, [15], a strategy was presented for optimizing the user-BS connection based on RSSI to improve the overall signal quality of 5G wireless networks. The authors in [16] proposed an innovative algorithm for identifying indoor locations in 5G mmWave systems using beamforming and RSSI. Our paper utilized RSSI as a means of prediction in the initial prediction step and throughput in the switching step. We conducted several simulations to examine the correlation between them.

III. Switching Model

A. Design Overview

To address the V2V communications degradation problems under harsh weather conditions, we propose a framework that features a two-tier machine learning-based vehicle switching strategy. As shown in Fig.1, our system consists of two components: (1) prediction of the received signal strength indicator (RSSI) and (2) a frequency switch or channel switch procedure. Our previous results using LSTM, as cited in [1], demonstrate the ability to predict accurate future RSSI values based on current RSSI values and weather data information. This paper focuses on the second switching strategy process. The strategy incorporates a dual-scenario switching that involves frequency changes for moderate harsh weather and channel switches for severe weather. In the case of mild weather, our system implements a frequency change to ensure seamless communication, and it will pick one of the four available frequencies: 28 GHz, 39 GHz, 60 GHz, and 73 GHz. During severe weather conditions, a channel switch is employed, which involves a transition from the 5G mmWave to the 4G LTE channel.

B. Attenuation Model of Dust and Sand

Dust and sand can have a significant effect on millimeter wave propagation. Millimeter waves have a shorter wavelength than radio waves, which makes them more susceptible to being scattered or absorbed by small particles such as dust and sand. When millimeter waves encounter dust or sand particles, they can be scattered in many directions, which can cause them to

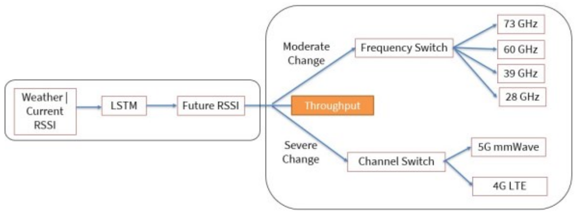


Fig. 1: System Overview

lose their strength and weaken. This scattering effect can also cause interference between different signals, making it difficult to distinguish between them. In addition to scattering, dust, and sand can absorb millimeter waves. This absorption effect can cause the signal to lose strength as it travels through dust or sand, weakening it when it reaches its destination.

Overall, the effect of dust and sand on millimeter wave propagation can be significant and can limit the range and effectiveness of millimeter wave communication and sensing systems. To mitigate these effects, techniques such as signal processing, beamforming, and antenna design can be used to improve the robustness and reliability of millimeter wave systems in dusty or sandy regions.

This paper uses the Mie scattering method to develop a mathematical model that calculates the reduction in strength of mmWave propagation. The model considers the ratio of particle diameter (sand/dust) to the wavelength of the signal for accurate results and is particularly applicable at higher frequencies. The key parameters affecting the attenuation value are particle radius, frequency, humidity, and complex permittivity. The attenuation of dust and sand is defined as α in dB according to Sharif and Musa et al. [17], [18] as shown in equation (1).

$$\alpha_{(dB)} = \frac{a_e f d}{v}[C_1 + C_2 a_e^2 f^2 + C_3 a_e^3 f^3] \quad (1)$$

Where C_1, C_2, and C_3 are unknown coefficients that depend on the real part and imaginary part of the complex permittivity of the dusty/sandy medium, a_e is the radius of the sand in meters, v is the visibility in km, f is the frequency in GHz, and d is the attenuation length. Humidity (H) can significantly affect the complex permittivity of materials, particularly those sensitive to moisture. Complex permittivity measures how a material responds to an electric field. It consists of two components: the real part (dielectric constant) and the imaginary part (loss factor). Overall, the effect of humidity on complex permittivity can vary depending on the specific material and the humidity level. It is essential to consider the impact of humidity on a material's dielectric properties when designing and testing electronic devices or other applications that involve the use of electric fields. The effect of the moisture humidity on the dielectric constant and loss factor is represented by

$$\varepsilon_1 = \varepsilon' + 0.04H - 7.78 \times 10^{-4} H^2 + 5.56 \times 10^{-6} H^3 \quad (2)$$

$$\varepsilon_2 = \varepsilon'' + 0.02H - 3.71 \times 10^{-4} H^2 + 2.76 \times 10^{-6} H^3 \quad (3)$$

Visibility is another important parameter affecting the transmitting medium's attenuation factor. Visibility refers to the degree to which an object, person, or location can be seen or perceived. In general, it describes the clarity and sharpness of what can be seen and is often used to describe the conditions under which something is visible. For example, regarding weather, visibility may refer to the distance at which objects can be seen due to factors such as fog, haze, dust, and sand.

C. RSSI Prediction using LSTM networks

RSSI is a crucial parameter measuring the quality of a communication link at the receiver end. It is widely used as the main parameter for vertical and horizontal handovers [19], [20]. However, a high-performance and accurate RSSI prediction model is required to achieve seamless connectivity through channel switching. In our previous paper [1], we implemented an accurate LSTM-based RSSI predictor to help decide whether switching is needed between 5G and 4G technologies on different occasions. LSTM network is the state-of-the-art artificial neural network suited for time-series forecasting and speech recognition that outperforms other machine learning models. Each LSTM unit consists of three fundamental gates: Input, Output, and Forget gates. The Forget gate decides whether to keep or remove an old record. The Input gate learns from the new coming data, while the Output gate updates the processed data.

Our LSTM prediction stage involves designing a single LSTM layer with 100 LSTM units and a Dropout layer with a value of 0.3. As suggested by its name, the Dropout is in charge of arbitrarily discarding neurons and units throughout the neural network training process to prevent over-fitting. An ultimately linked dense layer serves as the top layer and is intended to produce the estimated values. The deep LSTM model was implemented using Python 3.9.12 and TensorFlow 2.9.0 and trained over 40 epochs with a batch size of 1024.

D. Switching Under Different Weather

In the event of harsh weather, we have prepared two scenarios: moderate and severe weather conditions. Before presenting our strategy, we must highlight two basic facts according to the Third Generation Partnership Project (3GPP). 5G mmWave offers faster transfer speeds, greater traffic capacity, and reduced latency compared to 4G LTE networks. 5G mmWave operates in the frequency range between 24 GHz and 100 GHz, with higher frequency channels providing better communication capabilities. When the weather is normal, 5G mmWave is the preferred channel over 4G. When the weather worsens, it is better to use 5G mmWave but with a lower frequency band in the case of moderate weather deterioration - frequency change scenario. Suppose weather conditions worsen again so that the 28GHz channel can no longer provide reliable communication. In that case, our system will initiate a channel switch from 5G mmWave to 4G LTE - channel switch scenario.

In the frequency switch scenario, we have selected four frequency levels: 28 GHz, 39 GHz, 60 GHz, and 73 GHz. These frequencies have received significant attention from researchers, and 28 GHz and 39 GHz are already being utilized commercially in T-Mobile and Verizon cell phone networks.

IV. Weather Data Generation

In this section, we will discuss the generation of harsh weather we are focusing on. As previously mentioned in Section II, the three main weather parameters that our model considers are visibility, humidity, and particle radius.

A. Local Climatological Data (LCD) Dataset

Following a thorough search of available public weather data online, we found that the LCD weather dataset [21] was suitable for our simulation purpose. This dataset provides humidity and visibility data for various locations in the United States. For our simulation, we used the weather data of BLANDING MUNICIPAL AIRPORT, UT, US, from 01/01/2021 to 12/31/2021. We chose this area because it is closer to the desert, and its weather data are collected every twenty minutes.

B. Three Particle Size Levels

The LCD dataset provides visibility and humidity information but not the particle size of sand or dust in sandy areas. As demonstrated in the study [8], most sand particle sizes fall between 90 μm and 600 μm. To make our simulation results more realistic to the real world, we divided particle sizes into three levels, as illustrated in Table I, and randomly generated values for each group during the simulation.

TABLE I: Three Particle Size Levels

Parameters	Value Range
Low Level (μm)	90-200
Medium Level (μm)	200-400
High Level (μm)	400-600

V. Simulation Results and Discussion

We perform a series of simulations to examine the impact of moderate and severe weather on 5G mmWave frequency channel and 4G LTE channel. Our simulation analysis denotes different weather parameter impacts on both channels. Furthermore, we will examine existing equipment that can be refined and adapted to fit our proposed design.

A. Simulation Setup

A comprehensive simulation setup has been described in [1]. Our prior research shows that the multivariate LSTM model can predict future RSSI values under various weather conditions. However, the main limitation of using RSSI values is that they cannot be used to compare the transmission performance from two different technologies, like 4G LTE and 5G mmWave. For example, under similar harsh weather conditions, 4G LTE may drop from -45 dBm to -48 dBm with a 6% decrease, while 5G mmWave may drop from -75 dBm to -85 dBm with an 11% decrease. A 6% decrease in LTE channel does not necessarily indicate better communication than an 11 % decrease in 5G mmWave. Therefore, we need a different metric to compare the communication performance. To address this issue, we propose to include throughput into our system. Throughput refers to the amount of data successfully transferred from one location to another within a specific time frame. We have expanded our NS3 model [1] by incorporating throughput as the primary metric for comparing transmission performance.

TABLE II: Simulation Parameters

Parameters	Value Range
Particle Size (μm)	90-600
Visibility (km)	2-10
Humidity (%)	0-100
Frequency (GHz)	2.1, 28, 39, 60, 73
Speed (m/s)	20
V2V Scenario	Highway
Vehicle States	Line-of-Sight

In our updated simulation scenario, two vehicles drive in the same direction at the same speed and aim to maintain communication via sidelink through various 5G mm-Wave frequencies or a 4G LTE channel, as shown in Fig. 2. The communications will be impacted as they traverse harsh weather environments with dust and sand. To evaluate this impact, we utilize our modified NS3 module to simulate communication throughput across different channels. Our system will then choose the optimal channel in harsh weather. The simulation parameters are shown in Table II.

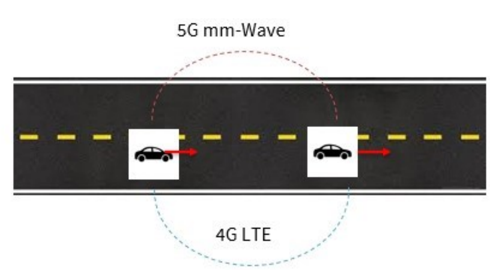


Fig. 2: Simulation Design

B. Moderate Weather Change Scenario

We simulated our updated NS3 model using the LCD weather dataset to show its performance under moderate weather conditions. For clearly displaying reasons, we will use one day to discuss the simulation result. The front vehicle sets up different communication channels to the back vehicle simultaneously, and the throughput is shown in Fig. 3, 4, and 5 for three particle size levels. The results in Figure 3 suggest that communication is reliable when particle size is large at 28 GHz, while 39 GHz shows fluctuating throughput. On the other hand, 60 GHz and 73 GHz have poor performance. In Figure 4, we observed that under medium particle conditions, 28 GHz and 39 GHz demonstrate stable communication, but 60 GHz and 73 GHz experience a significant drop in throughput. Finally, in Figure 5, most channels are reliable for small particle size, with only 60 GHz and 73 GHz experiencing a few communication issues. Notably, the 28 GHz and 39 GHz frequencies consistently exhibit stable and reliable throughput, suggesting that our system can switch to these frequencies to maintain communication reliability during moderate weather conditions.

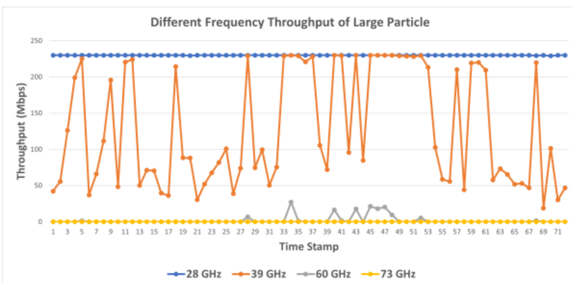


Fig. 3: Different Frequency Throughput of Large Particle.

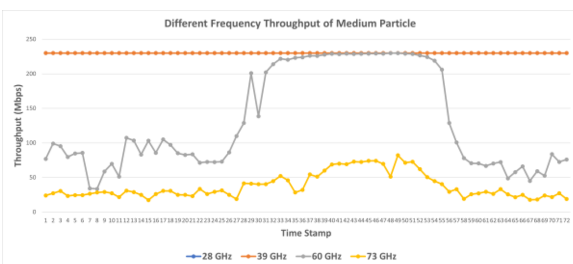


Fig. 4: Different Frequency Throughput of Medium Particle.

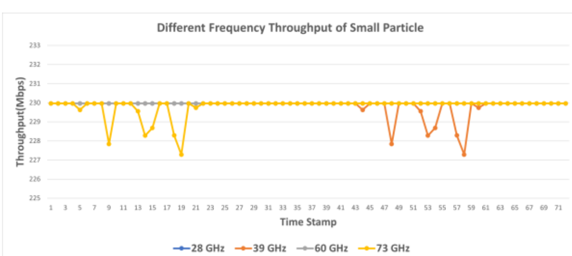


Fig. 5: Different Frequency Throughput of Small Particle.

C. Severe Weather Change Scenario

To simulate severe weather conditions, we altered the visibility of the LCD dataset and ran simulations for twovehicle scenarios. We conducted different simulations for three particle size groups to ensure consistency with moderate weather. Results, shown in Fig. 6, 7, and 8, indicate that in environments with large particle size, 5G mmWave is heavily impacted and communication fails completely. In these cases, vehicle communication should switch to 4G LTE channels. In medium particle size environments, 4G LTE typically performs better, with 5G mmWave only outperforming it in a few instances. In Fig 7, at timestamps 32, 37, and 70, the 5G mmWave throughput exceeded the 4G LTE channel; in these cases, we need to switch to the 5G mmWave channel. At these points, the corresponding humidity drops to 67 and 57, which matches our previous results that when humidity decreases, the attenuation effect is also decreasing. In Fig. 8, 25% of time stamps need to switch to a 4G LTE channel in case of severe weather, and about 75% choose a 5G mmWave channel.
According to these three figures, as the particle size of the dust or sand environment increase, severe weather tends to affect communication performances more largely.

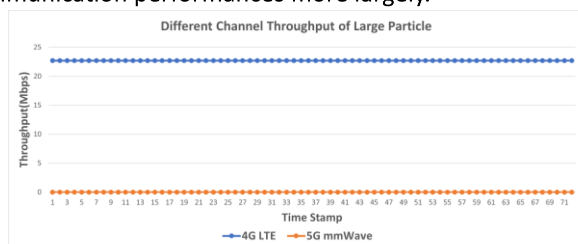


Fig. 6: Different Channel Throughput of Large Particle.

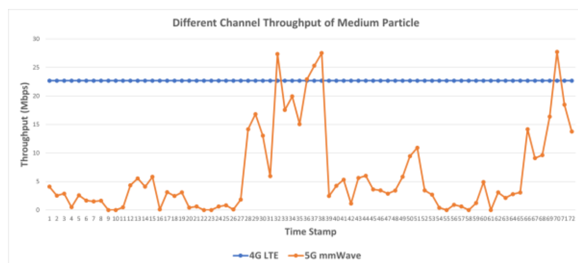


Fig. 7: Different Channel Throughput of Medium Particle.

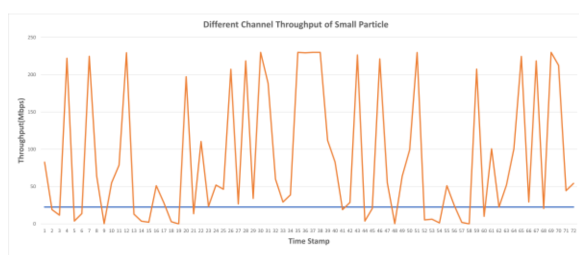


Fig. 8: Different Channel Throughput of Small Particle.

D. Relationship between Throughput and Predicted RSSI

Our proposed switching strategy relies on throughput as the primary criterion for determining whether a switch should occur. However, one major limitation of this approach is that the throughput simulation time in NS3 can be too long. A 2second throughput running time in the NS3 simulator might cause ten minutes in the real world. To address this issue, we aim to investigate the correlation between throughput and the predicted RSSI. The correlation between throughput and predicted RSSI for moderate and severe weather is shown in Fig. 9 and 10. The blue line represents throughput, while the orange line represents predicted RSSI. As observed, a strong correlation exists between the two metrics, implying that we can employ the expected Received Signal Strength Indication (RSSI) as an indicator to predict the throughput performance to save simulation time.

E. An Existing Promising Equipment

We want to draw attention to a piece of equipment already available in the market, namely, the CubeSA 60Pro [22]. This device shares some similarities with our proposed model. The CubeSA 60Pro operates on 5G 60 GHz mmWave continuously, and when the signal faces challenges during harsh weather conditions, it automatically switches to a 5 GHz channel. The existence and effectiveness of such equipment validate our proposed switching strategy's feasibility and provide further evidence that our strategy can be implemented in future equipment designs.

VI. Conclusion

In this paper, we extend our previous prediction stage into a two-stage switching strategy for connected vehicles under different harsh weather conditions. We introduce a new meaningful and comparable metric, throughput, as the determinant for frequency or channel switch in case of severe weather. The simulation results demonstrate the effectiveness of our proposed strategy. For future work, we will validate this proposed model by conducting experiments on the dielectric constant, particle size range, and dust concentration in the desert region of the United States. Additionally, we aim to implement reinforcement learning in the switching strategy and evaluate its performance.

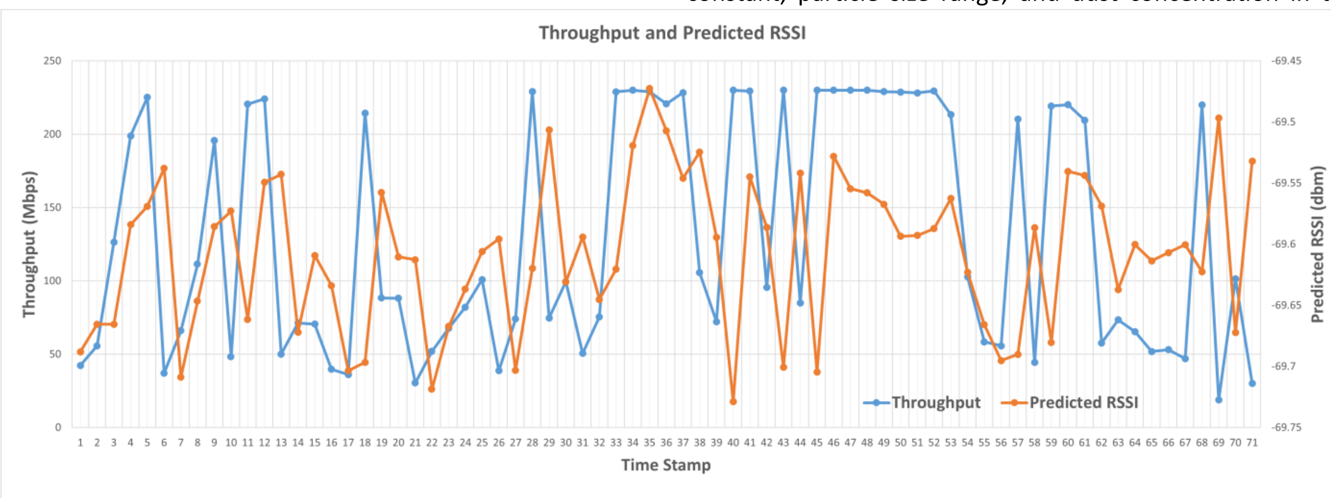


Fig. 9: Relationship between Throughput and Predicted RSSI under Moderate Weather.

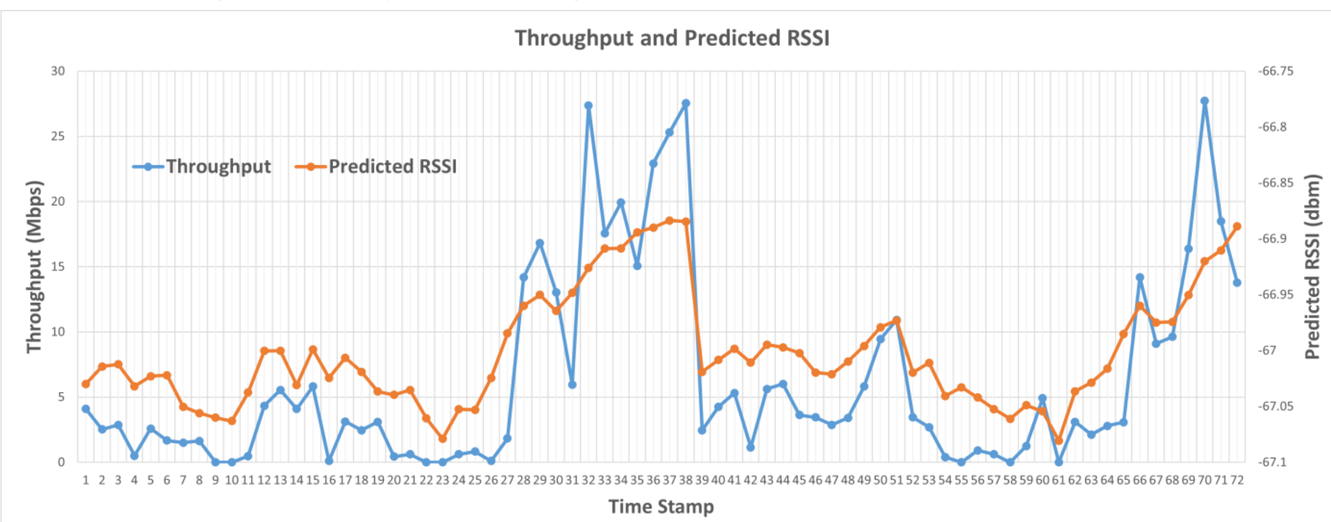


Fig. 10: Relationship between Throughput and Predicted RSSI under Severe Weather.

Acknowledgments

This study is partially supported by the Center for Connected Multimodal Mobility (C^2M^2) (USDOT Tier 1 University Transportation Center) headquartered at Clemson University, Clemson, SC. Any opinions, findings, and conclusions or recommendations expressed in this paper are those of the authors and do not necessarily reflect the views of C^2M^2 and the official policy or position of the USDOT/OST-R, or any State or other entity, and the U.S. Government assumes no liability for the contents or use thereof. It is also partially supported by the U.S. Department of Energy-National Nuclear Security Administration (NNSA) PuMP, MSIPP IAM-EMPOWEREd, MSIPP, Department of Education MSEIP programs, NASA ULI (University of South Carolina-Lead), and NSF Grant Nos. 1719501, 1954532, 2131080, and 2131080.

References

[1] J. Liu, A. Nazeri, C. Zhao, E. Abuhdima, G. Comert, C.-T. Huang, and P. Pisu, "Investigation of 5g and 4g v2v communication channel performance under severe weather," in *2022 IEEE International Conference on Wireless for Space and Extreme Environments (WiSEE)*, 2022, pp. 12–17.

[2] S. K. Khan, U. Naseem, H. Siraj, I. Razzak, and M. Imran, "The role of unmanned aerial vehicles and mmWave in 5G: Recent advances and challenges," *Transactions on Emerging Telecommunications Technologies*, vol. 32, no. 7, Jul. 2021. [Online]. Available: https://onlinelibrary.wiley.com/doi/10.1002/ett.4241

[3] M. N. Tahir, P. Leviakangas, and M. Katz, "Connected Vehicles: V2V¨ and V2I Road Weather and Traffic Communication Using Cellular Technologies," *Sensors*, vol. 22, no. 3, p. 1142, Jan. 2022. [Online]. Available: https://www.mdpi.com/1424-8220/22/3/1142

[4] C. Sommer and F. Dressler, *Vehicular Networking*. Cambridge: Cambridge University Press, 2014. [Online]. Available: https://www.cambridge.org/core/books/vehicular-networking/ 52B9E6242861C7B43FE6386CBB68FCE4

[5] H. Wang, T. Liu, B. Kim, C.-W. Lin, S. Shiraishi, J. Xie, and Z. Han, "Architectural Design Alternatives Based on Cloud/Edge/Fog Computing for Connected Vehicles," *IEEE Communications Surveys & Tutorials*, vol. 22, no. 4, pp. 2349–2377, 2020.

[6] E. Adomah, A. Khoda Bakhshi, and M. M. Ahmed, "Safety Impact of Connected Vehicles on Driver Behavior in Rural Work Zones under Foggy Weather Conditions," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2676, no. 3, pp. 88–107, Mar. 2022. [Online]. Available: http://journals.sagepub.com/ doi/10.1177/03611981211049147

[7] S. Dimce, M. S. Amjad, and F. Dressler, "mmWave on the Road: Investigating the Weather Impact on 60 GHz V2X Communication Channels," in *2021 16th Annual Conference on Wireless On-demand Network Systems and Services Conference (WONS)*, Mar. 2021, pp. 1–8.

[8] E. Abuhdima, J. Liu, C. Zhao, A. Elqaouaq, G. Comert, C.-T. Huang, P. Pisu, and A. H. Nazeri, "Impact of Dust and Sand on 5G Communications for Connected Vehicles Applications," *IEEE Journal of Radio Frequency Identification*, vol. 6, pp. 229–239, 2022.

[9] M. Drago, T. Zugno, M. Polese, M. Giordani, and M. Zorzi, "Millicar: An ns-3 module for mmwave nr v2x networks," in *Proceedings of the 2020 Workshop on ns-3*, 2020, pp. 9–16.

[10] Department of Communications Engineering & Advanced Telecommunication Technology (ATT), School of Electrical Engineering, Faculty of Engineering, Universiti Teknologi Malaysia, S. M. Hussain, and K. M. Yusof, "Dynamic Q-learning and Fuzzy CNN Based Vertical Handover Decision for Integration of DSRC, mmWave 5G and LTE in Internet of Vehicles (IoV)," *Journal of Communications*, pp. 155–166, 2021. [Online]. Available: http://www.jocm.us/show-255-1651-1.html

[11] Department of Electrical Engineering and Information Technology, Universitas Gadjah Mada, Yogyakarta 55281, Indonesia, S. Alam, S. Sulistyo, I. W. Mustika, and R. Adrian, "Handover Decision forV2V Communication in VANET Based on Moving Average Slope of RSS," *Journal of Communications*, pp. 284–293, 2021. [Online]. Available: http://www.jocm.us/show-257-1670-1.html

[12] M. Ghoshal, Z. J. Kong, Q. Xu, Z. Lu, S. Aggarwal, I. Khan, Y. Li, Y. C. Hu, and D. Koutsonikolas, "An in-depth study of uplink performance of 5G mmWave networks," in *Proceedings of the ACM SIGCOMM Workshop on 5G and Beyond Network Measurements, Modeling, and Use Cases*. Amsterdam Netherlands: ACM, Aug. 2022, pp. 29–35. [Online]. Available: https://dl.acm.org/doi/10.1145/3538394.3546042

[13] M. I. Rochman, D. Fernandez, N. Nunez, V. Sathya, A. S. Ibrahim, M. Ghosh, and W. Payne, "Impact of Device Thermal Performance on 5G mmWave Communication Systems," in *2022 IEEE International Workshop Technical Committee on Communications Quality and Reliability (CQR)*. Arlington, VA, USA: IEEE, Sep. 2022, pp. 1–6. [Online]. Available: https://ieeexplore.ieee.org/document/9918612/

[14] H. Hojatian, V. N. Ha, J. Nadal, J.-F. Frigon, and F. Leduc-Primeau, "RSSI-Based Hybrid Beamforming Design with Deep Learning," in *ICC 2020 - 2020 IEEE International Conference on Communications (ICC)*, Jun. 2020, pp. 1–6, iSSN: 1938-1883.

[15] J. Shen, Y. Hao, Y. Yang, and C. Zhao, "User-BS Selection Strategy Optimization with RSSI-Based Reliability in 5G Wireless Networks," *Applied Sciences*, vol. 12, no. 12, p. 6082, Jan. 2022. [Online]. Available: https://www.mdpi.com/2076-3417/12/12/6082

[16] O. AlHory, O. Shoushara, H. Al Suri, M. Al Shunnaq, and F. Awad, "5G mmWave Indoor Location Identification Using Beamforming and RSSI," in *2020 11th International Conference on Information and Communication Systems (ICICS)*, Apr. 2020, pp. 091–095, iSSN: 25733346.

[17] S. M. Sharif, "Attenuation properties of dusty media using mie scattering solution," *Progress In Electromagnetics Research M*, vol. 43, pp. 9–18, 2015.

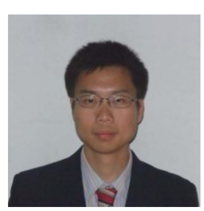
[18] A. Musa and B. S. Paul, "Prediction of electromagnetic wave attenuation in dust storms using mie scattering," in *2017 IEEE AFRICON*. IEEE, 2017, pp. 603–608.

[19] S. Alam, S. Sulistyo, I. W. Mustika, and R. Adrian, "Handover decision for v2v communication in vanet based on moving average slope of rss." *J. Commun.*, vol. 16, no. 7, pp. 284–293, 2021.

[20] H. T. Yew, A. Chekima, A. Kiring, A. I. Mbulwa, J. A. Dargham, and S. K. Chung, "Rss based vertical handover schemes in heterogeneous wireless networks: Past, present future," in *2020 IEEE 2nd International Conference on Artificial Intelligence in Engineering and Technology (IICAIET)*, 2020, pp. 1–5.

[21] "Datasets | Climate Data Online (CDO) | National Climatic Data Center (NCDC)." [Online]. Available: https://www.ncdc.noaa.gov/ cdo-web/datasets

[22] "MikroTik." [Online]. Available: https://mikrotik.com/



Jian Liu received his B.S. degree in Applied Chemistry from Tianjin University, China. He received one M.S. degree in Statistics and one M.S. degree in Computer Science from West Virginia University, USA in 2018. Jian is now a Ph.D. student in the Department of Computer Science and Engineering, University of South Carolina. His research focuses on 5G network transmission and security. He is also interested in cloud and edge computing and blockchain.

Amirhossein Nazeri received his BSc and MSc degrees in the Electrical and Computer Engineering from the Iran University of Science and Technology, and Texas Tech University, respectively. He is currently working towards his PhD in Automotive Engineering department at Clemson University. His research interests lies in Machine Learning and Deep Learning applications in telecommunication, autonomous vehicles, cybersecurity, and computer vision.

Chunheng Zhao received the B.E. degree in Automotive Engineering from Harbin Institute of Technology, China, in 2016, and the M.S. degree in Automotive Engineering from Clemson University, in 2019. He is currently pursuing a Ph.D. degree in Automotive Engineering at Clemson University International Center for Automotive Research. His research interests include functional safety and security issues in connected and automated vehicles. He is also interested in deep learning-based perception and control in autonomous driving.

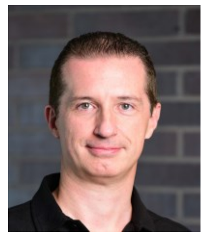
Esmail Abuhdima received the B.Sc. and M.Sc. degree in Electrical and Electronic Engineering from Tripoli University, Tripoli, Libya and the Ph.D. degree in Electrical Engineering from University of Dayton, Dayton, Ohio, in 1998, 2009, and 2017 respectively. He is currently with Computer Science, Physics and Engineering Department, Benedict College, Columbia, SC. His research interests include Wave Propagation, Simulation of Radar Signals, Antenna and Electromagnetic Field Theory, RF design and systems.He serves as an Editorial Board Mem-

bers in American Journal of Electromagnetics and Applications(AJEA). Also, he is a reviewer in Advances in Science, Technology and Engineering Systems Journal (ASTESJ) and the Institution of Engineering and Technology(IET).

Gurcan Comert received the B.Sc. and M.Sc. degree in Industrial Engineering from Fatih University, Istanbul, Turkey and the Ph.D. degree in Civil Engineering from University of South Carolina, Columbia, SC, in 2003, 2005, and 2008 respectively. He is currently with Physics and Engineering Department, Benedict College, Columbia, SC. His research interests include applications of statistical models to transportation problems, traffic parameter prediction, and stochastic models.

Chin-Tser Huang received the B.S. degree in Computer Science and Information Engineering from National Taiwan University, Taipei, Taiwan, in 1993, and the M.S. and Ph.D. degrees in Computer Sciences from The University of Texas at Austin in 1998 and 2003, respectively. He is a Professor in the Department of Computer Science and Engineering at University of South Carolina at Columbia. His research interests include network security, network protocol design and verification, and distributed systems. He is the director of the Secure Protocol Implementation and Development (SPID) Laboratory at the University of South Carolina. He is the author (along with Mohamed Gouda) of the book “Hop Integrity in the Internet,” published by Springer in 2005. His research has been funded by DARPA, AFOSR, AFRL, NSF, NEH, and USDOT. He is an NRC Research Associate in 2020, and a recipient of the

USAF Summer Faculty Fellowship Award and of the AFRL Visiting Faculty Research Program Award in 2008-2021. He is a Senior Member of IEEE and ACM.



Pierluigi Pisu is a Professor of Automotive Engineering in the Carroll A. Campbell Jr. Graduate Engineering Center at the Clemson University International Center for Automotive Research with a joint appointment in the Holcombe Department of Electrical and Computer Engineering at Clemson University. He has a Ph.D. in Electrical Engineering from The Ohio State University (2002) and a M.S. in Computer Engineering from the University of Genoa, Italy. His research interests lie in functional safety, security, control and optimization of CyberPhysical Systems for next generation of high performance and resilient connected and automated systems with emphasis in both theoretical formulation and virtual/hardware-in-the-loop validation. He published 50 journal and 100 conference papers; he holds 3 patents and published a book on “Fault Detection and Isolation with Applications to Vehicle Systems”.