Adaptive Channel Switching for Connected Vehicles under Extreme Weather Conditions: A Reinforcement Learning Based Approach

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***Abstract*—Due to the enormous volume of data generated by connected vehicles (CVs), future vehicle-to-vehicle (V2V) communications will require a high-throughput communication channel. While 5G millimeter-wave (mmWave) technology generally meets these requirements, it suffers from the risk of performance degradation under harsh weather conditions such as heavy rain, snow or sand storms. This decline is primarily because of the high frequency of mmWave, which results in significant propagation attenuation loss. In contrast, 4G LTE is less susceptible to these environmental challenges. In an effort to improve communication performance reliability under severe weather conditions, we propose a Deep Reinforcement Learning (DRL)-driven approach. Our proposed framework utilizes the Received Signal Strength Indicator (RSSI), short-term throughput, and weather parameters as input variables. It employs cumulative throughput as the reward metric in the reinforcement learning process. As the framework interacts with the environment, it learns to dynamically switch between 5G mmWave and 4G LTE channels to maintain a robust and reliable communication link between CVs. Our approach has been validated through simulations using the ns-3 network simulator, enhanced with a customized weather model for 5G mmWave and 4G LTE channels. The simulation results confirm that our DRL framework substantially improves the reliability and performance of V2V communication within minutes, even in harsh environmental conditions.**

***Index Terms*—Connected Vehicles, V2V, mmWave, Reinforcement Learning**

I. Introduction

The concept of connected vehicles has brought a new direction for modern transportation, promising enhanced navigation and safety and also the realization of fully autonomous vehicles. Among various network options, V2V communication has emerged as a cornerstone for facilitating real-time data exchange between vehicles. The exchange of traffic and vehicular control information through V2V communication is critical for safe vehicle operations. To successfully implement a comprehensive autonomous driving ecosystem in the future, the communication channel must provide high reliability, low latency, and robust data throughput to facilitate the transfer of large volumes of data [1].

The 3rd Generation Partnership Project (3GPP) formalized Vehicle-to-Everything (V2X) communications through the 4G Long-Term Evolution (LTE) air interface in their Release-14 and in Release-16, 3GPP unveiled the 5G New Radio (NR), which incorporates the mmWave spectrum [2]. Despite the benefits of mmWave, such as increased bandwidth and lower latency, it faces challenges related to signal attenuation loss. Specifically, its high frequency band is prone to shorter transmission ranges and is easily obstructed by obstacles, as outlined in [3].

Several studies have examined the attenuation loss experienced under various weather conditions. For instance, the work by Dimce [4] employs metrics such as rain intensity, raindrop size distribution to assess attenuation loss due to rain and snow. Another study by [5] investigates the impact of dust and sand storms on 5G mmWave channels. Since attenuation loss is particularly significant under adverse weather conditions, the reliability of communication among CVs may be largely compromised when operating over 5G mmWave channels. This raises the primary question this paper aims to address: How can we ensure reliable communications for CVs under such challenging conditions?

In contrast to 5G mmWave, 4G LTE operates at lower frequencies, whose longer wavelengths are less susceptible to attenuation loss in adverse weather conditions. Our prior research [6] has outlined a dual-mode switching strategy for V2V communications among CVs. In general, CVs mostly utilize the 5G mmWave channel but switch to 4G LTE during inclement weather to maintain reliable communication. In our prior work, channel-switching decisions were mainly based on the Received Signal Strength Indicator (RSSI), which lacks network performance indicators. In this work, we develop an intelligent agent which evaluates multiple factors, including RSSI , short-term throughput, weather conditions, and the vehicle's current state. By factoring in cumulative throughput, we aim to ensure a high Quality of Service (QoS) for CVs, resulting in a more robust and informed channel-switching strategy.

Due to the high costs and challenges of accurately measuring environmental variables, we opted for simulation-based evaluation rather than real-world experiments. Utilizing the ns-

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3 simulator [7] allows us to assess 5G mmWave channel performance under varying weather conditions in a more feasible and controlled manner. In this simulation-based research, our primary contribution lies in assessing the performance of both 5G mmWave and 4G LTE channels for V2V communications under various adverse weather conditions, focusing on dust and sand environments. To mitigate communication degradation, we propose an automated channel-switching strategy that transitions from 5G mmWave to 4G LTE when CVs encounter sandstorms. To the best of our knowledge, this is the first study to employ a DRL-based framework to address V2V communication interruptions caused by extreme weather conditions. Our DRL-based solution offers notable improvements in maintaining reliable communication and optimizing channel-switching decisions based on environmental factors.

The rest of this paper is organized as follows. Section II gives an overview of some related work. Section III presents our DRL-based channel switching framework for V2V communications. We describe our simulation and data generation procedures in Section IV, and discuss evaluation results in Section V. Finally, in Section VI, we conclude the paper and suggest some future work.

II. Related Work

There have been several existing studies for V2V communication using mmWave, mainly for collision avoidance [8]. Most of their eventual goals were to enhance the V2V communication performance for improved traffic safety and driving convenience. The key enabler of V2V is the use of mmWave, which can achieve high speed and large capacity in V2V communication by providing a wide bandwidth in high frequency band. In addition to these directions, some researchers have investigated how mmWave could improve overall network efficiency and reliability [3].

Using a simulator to study 5G mmWave V2V communication offers several advantages regarding safety, cost-efficiency, and experimental control [9]. In a simulated environment, researchers can precisely manipulate variables such as weather conditions, traffic density, and vehicle speed to study their impact on communication performance without the risks and costs associated with real-world experiments.The primary focus of this paper is to explore vehicular communications under extreme weather conditions. Recent work by the authors cited in [4] has contributed to this area by incorporates the effects of rain and snow on V2V communication channels based on the ITU model. Additionally, another study [10] extends the ns-3 Millicar [9] model to evaluate the impact of dust and sand on 5G mmWave channel performance.

Recent studies have demonstrated the utility of reinforcement learning in making handover decisions between 5G mmWave and 4G LTE networks. The authors in [11] employed a deep Q-network to predict user associations for handovers and [12] employed a Proximal Policy Optimization (PPO) algorithm to manage handover frequency adeptly. However, these prior works primarily focus on scenarios involving base stations for handover between 5G and LTE. Our paper distinguishes from them in that we are the first to propose a V2V channel-switching mechanism that operates directly within vehicles. Our study introduces a DRL framework that autonomously switches between 5G and 4G networks when CVs encounter adverse weather conditions.

III. Deep Reinforcement Learning for Channel Switching

This section elaborates on our DRL based channel switching approach for V2V communications under adverse weather conditions. We first introduce some reinforcement learning concepts and then explain our proposed approach in detail.

A. Reinforcement Learning

Reinforcement Learning (RL) is a subfield of machine learning where an agent learns optimal behavior through trial and error interactions with its environment. Traditional RL algorithms perform well when the state-action space is relatively limited, allowing agent to explore all possible combinations and identify an optimal action policy. However, the effectiveness of RL algorithms diminishes as the size of the state-action space grows, mainly because the agent may not explore every state-action pair [11]. To mitigate this limitation, DRL employs Deep Neural Networks to model intricate relationships between complex state spaces and their corresponding actions. These networks undergo iterative adjustments based on reward signals, thereby fine-tuning the agent's decisions. A cornerstone in this field is the Deep Q-Network (DQN), introduced by Mnih et al. [13]. DQN combines the strengths of Q-learning with Artificial Neural Networks, providing an effective framework for RL training in complex scenarios where traditional RL algorithms struggle.

B. Proposed DQN-based Channel Switching

Our proposed framework aims to optimize vehicular communication performance under challenging weather conditions, specifically focusing on maintaining robust and high-throughput connections in V2V networks. The basic idea of our approach is to let CVs utilize 5G mmWave channels as much as possible, given their superior data rates and bandwidth. However, when vehicles traverse areas with severe weather conditions which significantly degrade the reliability of 5G mmWave communications, our system dynamically switches to the more robust 4G LTE channel. This adaptive scheme ensures a stable and high-performing communication network for CVs, regardless of the weather conditions they encounter.

The objective of our framework is to dynamically manage channel switching in a way that preserves both higher throughput and reliable communication for CVs, especially when they navigate through areas with severe weather. To achieve this, we employ a Deep Q-Learning Network where the agent's value and policy networks adapt based on specific state and reward evaluations. The agent is in charge of CV connection and the actions taken by the agent are based on these evaluations. Our design optimizes state, action, and reward functions to execute channel switching only when necessary. This strategy minimizes the number of switches and reduces the network's control signaling overhead. Our system's definitions for state, action, and reward are as follows:

1) State: In our previous research [6], we focused on only one main factor RSSI to measure the performance of connected cars. In this research, we add another metric: the throughput to measure communication of CVs over 5G mmWave or 4G LTE networks. In our model, these two metrics form the *state* that guides the decision-making process in our RL algorithm. We also consider environmental conditions like humidity, visibility, and the size of particles in the air to decide whether to switch channels.

2) Action: In our proposed scheme, the action space a is defined as a discrete set containing two primary actions: $A : \{\textit{Keep 5G mmWave channel}, \textit{Switch to 4G LTE channel}\}$. In the first action, the agent chooses to continue using (or switch back to) the 5G mmWave channel. This action is favorable under smooth weather and when high throughput is achievable. In the second action, the agent switches to or maintains a connection via the 4G LTE channel. This action is generally chosen when the agent predicts or detects severe weather conditions that could significantly affect the reliability of 5G mmWave communication.

3) Reward: In our study, we employ a unique reward design based on the concept of cumulative throughput during the driving journey. As CVs traverse weather conditions along the road, the short-term throughput for 5G and 4G channels varies dynamically. The 5G channel is the obvious choice under good weather conditions due to its higher data rate capabilities. However, in severe weather conditions, the performance of the 5G channel may deteriorate, causing the short-term throughput to plummet to zero. Under such situations, our algorithm intelligently switches to the more robust 4G channel. By using cumulative throughput as the reward metric, our system aims to balance the high-speed advantages of 5G and the reliability of 4G, optimizing the overall communication performance for CVs. While other communication factors like latency, reliability or control signals might be good measurement in a real experiment but they are out of range of this paper.

4) Algorithm Design: Our proposed Deep Q-Network (DQN) algorithm proceeds in two phases: the training phase and the execution phase. During the training phase, the algorithm doesn't directly interact with the environment; instead, it undergoes offline training. Initially, a comprehensive dataset is gathered, which includes variables like RSSI and short-term throughput for both 5G mmWave and 4G LTE channels. After pre-processing, this dataset serves as the training material for the DQN model. To ensure the model learns robustly and can adapt to a range of scenarios, an ϵ-greedy exploration strategy is employed. This enables the model to try out a variety of actions in different states, allowing it to fine-tune its understanding of the best channel-switching strategies under varying conditions. Algorithm 1 summarizes our DQN algorithm's training process during the training phase.

As shown in Algorithm 2, the execution stage leverages the trained Q-networks to determine channel-switching actions for CVs by selecting actions with the highest Q-values. Subsequent evaluation metrics are derived based on these actions.

Algorithm 1 Training DQN Procedure for Channel Switching

Input: Q-network, ns-3 weather simulator
Output: Q-network
Start:
Generate CVs' RSSI and short-term throughput.
Randomly initialize the policy π and model.
Loop:
Iteratively select one pair of CVs in the system.
For each CV pair, choose the action with the largest Q-value under corresponding weather condition.
Observe reward and new state based on agent actions.
Collect and save the data item state, reward, action, post-state into memory.
Sample a mini-batch of data from the memory.
Train the deep Q-network using the mini-batch data.
Update policy π based on action with maximum Q-value.
end loop
Return: Return the deep Q-network.

Algorithm 2 Execution Procedure for Channel Switching

Input: Trained Deep Q-network, ns-3 weather simulator
Output: Chosen channel, Evaluation results
Start:
Generate CVs' RSSI and short-term throughput.
Load trained Q-network model.
Loop:
For each CV pair, choose action with largest Q-value.
Observe state based on the actions selected.
Update the evaluation results: the cumulative throughput of CV pair.
end loop
Return: The chosen channel and evaluation results.

IV. Simulation and Evaluation

In this section, we outline the setup of our simulations and learning environment.

A. Simulation Design and Setup

We used the ns-3 network simulator [7] as the platform to generate our dataset to overcome the challenge of collecting real-world data on CV's communication. What is unique about our research is that we developed a custom weather module for ns-3, which is the first to incorporate the most up-to-date 3GPP channel models for V2V communication and is complete with variable weather impacts. Our enhanced ns-3 model can autonomously generate simulation outcomes based on weather parameters such as particle size, visibility, and humidity.

In this study, we concentrate on a use-case illustrated in Figure 1: two vehicles traveling along a highway at the same speed, experiencing different weather conditions along the road. The upper vehicle aims to establish a communication channel with the lower vehicle, either through a 5G mmWave or 4G LTE channel. The CV pair travel through n different sandstorm conditions and try to establish a smooth communication under different weathers. It is worth noting that although we started with a simplified two-vehicle scenario for illustrative purpose, our framework is designed to be easily extendable to more complex cooperative vehicle configurations and other V2V situations.

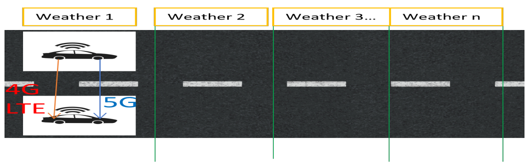

Fig. 1. Simulation Scenario Design.

B. V2V Communication Metric

In our simulation framework, vehicles traverse through various severe weather conditions that have a negative impact on both 5G mmWave and 4G LTE communications due to attenuation loss. We employ the Mie scattering model, as cited in [10] to quantify this loss. Specifically, we use the attenuation variable A_d (dB/km) which is given as Equation (1) :

$$A_d = \frac{a_e f d}{v}[C_1 + C_2 a_e^2 f^2 + C_3 a_e^3 f^3] \tag{1}$$

where a_e is the equivalent particle radius in meters, f is the frequency in GHz, d is the length of propagation wave, v is the visibility in km, C_1, C_2 and C_3 are constants defined by relative humidity.

To evaluate the effectiveness of our DRL-based channel-switching scheme under challenging weather conditions, we generated data for various factors that affect 5G mmWave performance, such as humidity, visibility, and particle size. We selected 28 GHz for the 5G mmWave frequency and 2.1 GHz for 4G LTE. Our ns-3 simulation code is publicly available on GitHub (https://github.com/ericliujian/ns3-mmwave-weather), and the simulation parameters can be found in Table I.

TABLE I
SIMULATION PARAMETERS

Particle Size (μm)	600-800	Visibility (km)	0.000-0.003
Humidity (%)	80-100	Frequency (GHz)	2.1, 28
Speed (Mph)	50	Distance (m)	100
V2V Scenario	Highway	Vehicle State	Line-of-Sight

C. Learning Environment

In this study, our DQN setup employs a fully-connected neural network as outlined in Table II. We used the Relu activation function for the hidden layers and opted for the Adam optimizer. The model starts with an initial learning rate of 0.001 and the discount factor was set to 0.99. Our replay buffer has a maximum storage capacity of 10,000 observation samples, and training is conducted in mini-batches of 128 samples each. We set the episodes as 100. After the training phase concludes, the model transitions into the execution phase and is deployed directly within our ns-3 simulation environment for performance assessment.

TABLE II
HYPER PARAMETERS

Hidden Layer: 3	Activation Function: Relu
Optimizer: Adam	Learning Rate: 0.001
Discount Factor: 0.99	Replay Size: 10000
Mini-batch Size: 128	Episodes: 100

V. NUMERICAL RESULTS AND ANALYSIS

To assess how real-world weather conditions affect mmWave and LTE transmission channels, we integrated weather data from the Climate Data Online (CDO) database into our simulations. Specifically, we utilized a year-long dataset from Blanding Municipal Airport in Utah, spanning from January 1 to December 31, 2022. This comprehensive dataset offers values of key climate variables - namely humidity and visibility. We incorporated these climate variables into our customized ns-3 weather model to generate training data, which includes the RSSI and short-term throughput metrics for CVs.

We trained the RL agent on this comprehensive, year-long dataset to let the agent learn how to make effective channel-switching choices. The purpose was to construct a highly adaptive Deep Q-Network (DQN) model that is fine-tuned to make optimal decisions under various weather conditions. In our framework, we used cumulative throughput as the reward metric. This choice of reward function allows the agent to prioritize decisions that would maximize the overall communication throughput, thereby ensuring Quality of Service (QoS) under varying environmental circumstances. Through this mechanism, the agent learns to switch channels to maximize this cumulative throughput, offering a more reliable and robust communication system for CVs.

To verify the viability of our approach, we conducted a simulation under a one-hour lasting sandstorm. In such circumstances, vision is poor and CVs need to communicate with each other continually to ensure safety. The decision-making process was guided by the DQN model previously trained on extensive weather data. As depicted in Fig.2, the experiment specifically underscores the fluctuations in short-term throughput for vehicles operating in the middle of a sandstorm. The 5G mmWave throughput is noticeably compromised to near zero at several time stamps due to the severe weather conditions, while the 4G LTE manages to keep the communication alive, although at a lower data rate.

When our DQN-trained agent comes into play, it proactively switches the communication channel to 4G LTE in response

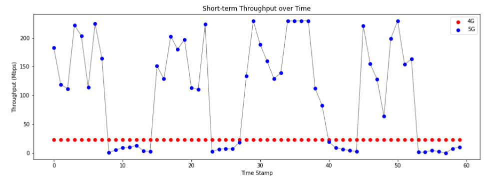

Fig. 2. Short-term throughput over time without switching.

to the deteriorating weather conditions. The outcomes of our adaptive channel-switching strategy are depicted in Fig. 3. The red dots represent the moments when the 4G LTE channel was selected, occurring 25 times out of 60. By employing dynamic channel switching, our system reaches a cumulative throughput of 109 Mbps during the sandstorm, roughly five times greater than relying solely on 4G LTE, which is only 22 Mbps.

To examine the responsiveness of our DQN agent during severe weather, we focus on the timing of channel switches. The one-hour sandstorm intensity oscillates between mild and severe, and during this period, CVs face approximately four extreme sandstorm episodes. Examining the timestamps closely, it is evident that our DQN agent successfully transitions from 5G channel to the 4G LTE channel within at most one minute when the sandstorm turns severe, and switches back to 5G channel within at most one minute when the sandstorm turns mild. This underscores our model's capability to promptly alternate between 5G mmWave and 4G LTE when faced with severe weather conditions.

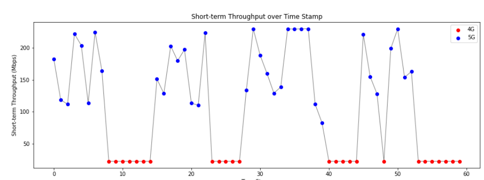

Fig. 3. Short-term throughput over time with channel switching.

Additionally, our dynamic channel-switching approach largely eliminates the possibility of total service blackouts that could last several minutes during sandstorms if the vehicles were only using 5G mmWave. This feature enhances the safety of V2V interactions by ensuring continuous although reduced communication through 4G LTE channel. Our approach can mitigate the risk of dangerous accidents resulting from complete communication failures.

VI. Conclusion

As the trend of global warming accelerates, the world is witnessing an increase in the frequency of severe weather events such as hurricanes and storms. Resilient and efficient V2V communication systems are needed to cope with harsh weather conditions and ensure the safety of drivers. In this paper, we first point out that the high-throughput, low-latency 5G mmWave technology is highly susceptible to performance degradation under extreme environmental conditions, while the slower 4G LTE technology is more resilient in such scenarios. Therefore, to reconcile these trade-offs, we propose a DRL-driven framework that smartly navigates the choice between 5G mmWave and 4G LTE channels. Our model learns to adaptively switch between channels to sustain a reliable, high-throughput communication link between CVs. The channel switch occurs within a minute of the onset of severe weather, highlighting our agent's ability to respond in a timely fashion. Simulation results show that our solution achieves higher cumulative throughput without experiencing total service dropouts, even under severe weather conditions like sandstorms. These outcomes confirm that our solution is practical and beneficial to real-world vehicular networks. One potential future work direction involves the integration of real-time weather prediction algorithms with multi-agent systems, through which we aim to enhance the reliability and reduce the latency of our approach.

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