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RESEARCH ARTICLE

Proposed CtCNet-HDRNN: A Cornerstone in the Integration of 5G mmWave and DSRC for High-Speed Vehicular Networks

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ABSTRACT This study proposes an innovative integration of the Car-to-Car Network-Hierarchical deep neural network (CtCNET-HDRNN) model with Fifth generation (5G) and Dedicated Short-Range Communications (DSRC) systems, streamlining computational efficiency in edge computing. CtCNET-HDRNN is a specialized deep learning model designed for vehicular communication, allowing vehicles to exchange information seamlessly in a connected environment. It harnesses an adaptive learning rate and regularization within the model's advanced training methodology, ensuring optimal data fit, superior generalization, and efficient convergence. A key novelty lies in the introduction of a Sparse Deep Recurrent Neural Network (SDRNN), which significantly reduces computational complexity by pruning insignificant connections, making it suitable for deployment on resource-constrained edge devices. SDRNN is a variant of recurrent neural networks designed to minimize computational burden while maintaining high performance in time-series data analysis. Furthermore, this research presents an original integration model, adeptly merging the CtCNET-HDRNN model with the Millimeter wave (mmWave) of 5G and Monte Carlo for DSRC systems for seamless data transmission. The mmWave technology offers high-speed communication capabilities, while Monte Carlo enables adaptive collision avoidance and efficient channel access control for vehicular networks. Beyond immediate computational gains, this integrated model also contributes significantly to edge computing research and practical applications, promising enhanced system performance and improved user experience in vehicular communication scenarios. The proposed approach opens new possibilities for efficient and reliable communication in connected vehicles, laying the foundation for safer and smarter transportation systems.

INDEX TERMS 5G, DSRC, V2V, AI/ML, deep learning, AIoT, deep reinforcement learning, RNN, VANET.

I. INTRODUCTION

Cooperative Intelligent Transportation Systems (C-ITS) are emerging as a means to enhance road safety and reduce congestion [1]. To achieve these goals, two types of technology have been introduced, i.e. Dedicated Short Range Communication (DSRC) and Long Term Vehicle Evolution [2]. These technologies are implemented using different supporting units at critical points, providing facilities such as collision warning, road construction warning, overhead heavy vehicle warning, and lane changing warning. They assist drivers through Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication [3]. Further, DSRC, designated for the 5.9GHz band [4], is a significant

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advancement in the automotive sector as it allows data transmission directly between two devices without intermediaries. This feature is particularly beneficial in rural and remote areas where telecommunications infrastructure is limited. DSRC is akin to sending a text message to a phone 300 meters away without using a cellular network. Furthermore, due to the absence of intermediaries, DSRC is known for its extremely low latency [5]. However, DSRC has limitations; in dense traffic environments, it experiences high channel interference, leading to reduced packet transmission quality and potential delays in conveying crucial information to vehicles [6].

In addition, due to the advanced capabilities of 5G, V2V and Vehicle-to-Everything (V2X) communications are expected to shift entirely to 5G for connectivity [7]. Complex vehicle communication frameworks require instantaneous, two-way communication between vehicles. A practical demonstration of the 5G CAR project was observed by UTAC-TEQMO (a company for connected vehicles with testing centers across France, the UK, the USA, and Northern Finland) in June 2019 [8]. The demonstration showcased improved lane-changing features and information exchange with a centralized planning system. It guided individual actions such as acceleration, deceleration, and lane merging using 5G as the underlying technology [9]. Nevertheless, 5G spectrum availability is limited in densely connected vehicular environments [10].

However, increased traffic may lead to DSRC failure or 5G spectrum limitations on an individual basis, accompanied by heightened computational complexities. As a result, it is essential to develop an efficient integrated scheme for V2V communication using both mmWave and DSRC systems. Further, modern deep learning solutions can be employed to mitigate mutual interference and support V2V systems comprehensively. Abbreviations used in this study can be depicted in Table 1.

The remainder of this paper is organized as follows: Section II presents a review of related work. The motivation behind our study and the contributions of our work are discussed in Section III. Our proposed system model is articulated in Section IV. Section V contains the results of our study and a discussion of these findings. Finally, we draw our conclusions in Section VI.

II. RELATED WORK

DSRC is pivotal in V2V communication, and integrating it with mmWave communication and DL is necessary for addressing the challenges of path loss, computational complexity, and seamless connectivity in dense vehicular networks. Several studies have focused on integrating DSRC and mmWave communication to maintain vehicular connectivity and overcome the dynamic nature of vehicular communication [11], [12]. However, the current work has not fully addressed the limitations related to computational complexity, path loss, and seamless handover between networks in dense V2V environments.

TABLE 1. Nomenclature.

Abbrev.	Meaning
5G	Fifth Generation Technology
CtCNET	Car to Car Network
HDRNN	hierarchical deep recurrent neural network
SDRNN	Sparse Deep Recurrent Neural Network
mmWave	Millimeter Wave
CSI	Channel State Information
AoA	Angle of Arrival
DRL	Deep Reinforcement Learning
GRU	Gated Recurrent Unit
RNN	Recurrent Neural Network
LSTM	Long Short Term Memory
DSRC	Dedicated Short Range Communications
V2V	Vehicle-to-Vehicle
V2X	Vehicle-to-Everything
DL	Deep Learning
MIMO	Multiple-Input Multiple-Output
PL	Path Loss
QoS	Quality of Service
RF	Radio Frequency
RL	Reinforcement Learning
AI	Artificial Intelligence
ML	Machine Learning
IoT	Internet of Things
LC	Learning Collision
GT	Game Theory
RNN	Recurrent Neural Networks
ASD	Antenna System Diversity
GPU	Graphics Processing Unit

Recent research efforts have explored the potential of 5G technology, specifically mmWave communication, to improve V2V communication and address the computational issues associated with Markovian models [13], [14]. Millimeter wave (mmWave) bands have been studied for their ability to satisfy the high data rate and latency requirements of the V2V industry. However, mmWave communication also presents challenges, such as increased path loss and poor frequency responses, which need to be addressed for efficient V2V communication.

Machine Learning (ML) and Deep Learning (DL) techniques have been employed to tackle path loss issues in mmWave communication for V2V environments [15]. These techniques have shown promise in predicting and mitigating path loss, which is critical for the performance of dense vehicular networks. Nevertheless, the current work has not efficiently connected path loss mitigation to the computational power of neural networks and vehicular management systems, leaving a research gap.

To address the computational complexity and seamless connectivity challenges in dense vehicular networks, some studies have proposed the integration of DSRC and mmWave communication using reinforcement learning (Q-learning) for V2V communications and mmWave for vehicle-to-infrastructure (V2I) communications [16]. Although these solutions show promise, they still lack efficient handover management and seamless connectivity, especially for safety message exchange in high-speed scenarios.

In the domain of V2V communication, a plethora of alternative techniques have been explored to address the issues of path loss optimization, collision avoidance, and more.

For path loss optimization, in addition to the stochastic models and probabilistic approaches, some studies have considered beamforming techniques to enhance the signal quality and reduce the path loss in mmWave communication [17]. Beamforming can focus the signal energy towards a specific direction, thereby reducing path loss. However, in a highly dynamic vehicular environment, it is challenging to maintain accurate beam alignment.

Concerning collision avoidance, researchers have examined the use of vehicular ad-hoc networks (VANETs) that leverage the power of collaborative intelligence. They use real-time data sharing between vehicles to anticipate and avoid potential collisions [18]. While such systems provide real-time communication among vehicles, they suffer from latency issues in high-speed vehicular networks. Furthermore, VANETs face security challenges, including privacy preservation and data integrity.

Some studies have also explored the usage of edge computing and fog computing for improving computational performance and reducing latency in V2V communication [19]. These computing paradigms aim to distribute computing tasks closer to the network's edge, thus reducing the load on the core network. However, such solutions still face challenges related to scalability, resource allocation, and interoperability with existing network infrastructure.

Consequently, the integration of mmWave communication, DSRC, and deep learning is necessary to address the challenges of path loss, computational complexity, and seamless connectivity in dense vehicular networks. The current work has not yet provided a comprehensive solution that considers these factors, leaving a research gap that warrants further investigation. By focusing on the development of an efficient integrated scheme for V2V communication using mmWave, DSRC systems, and modern deep learning solutions, we can address these challenges and improve the performance and safety of V2V communication in various environments [13], [20], [21], [22], [23], [24]. Table referenced (2) provides a succinct overview, comparing our research with contemporary, state-of-the-art studies. It uses distinct parameters to highlight how our study integrates innovative techniques and stands in relation to other contributions in the field.

III. MOTIVATIONS AND OUR CONTRIBUTIONS

To address the research gaps and improve performance in dense vehicular networks, we focus on three significant challenges:

1) Appropriate gain value selection and prediction for varying speeds: Current methods do not provide an efficient way to adapt antenna gain values as vehicular speeds change. We propose using a Bayesian Neural Network to predict accurate antenna gain values for optimized communication among V2V links, which can adapt to changing vehicle speeds and lane change scenarios.
2) Computational complexity and reliability in Q-Learning for DSRC: Existing Q-Learning techniques for DSRC improve throughput analysis and average latency but consume significant computational resources due to recursive iterations. In dense vehicular networks, this leads to an unreliable server crash probability of more than 33.67%. We propose a Gated Recurrent Unit (GRU)-based Recurrent Neural Network (RNN) to reduce computational complexity and improve performance. By incorporating GRU layers into the RNN, we can achieve an effective data rate using data samples from previous observations and minimize computational overhead.
3) Path loss optimization for mmWave: The current usage of Long Short-Term Memory (LSTM) networks for optimizing path loss in mmWave communication is not efficient. We propose a car-to-car deep RNN for path loss optimization in mmWave communication. We utilize active base stations and perform channel estimation to create the channel vector with parameters such as Angle of Arrival (AoA), Angle of Departure (AoD), and path loss. Analyzing speed variations between 20 m/s and 40 m/s, we aim to decrease V2V computational complexity and improve performance.

To address these challenges, we make the following contributions:

- We propose a Car-to-Car deep Hierarchical Recurrent Neural Network (CtCNet-HDRNN) that integrates a Gated Recurrent Unit-based Recurrent Neural Network (GRU-RNN) to optimize path loss in mmWave communication, reduce computational complexity, and improve speed stability in V2V communication systems. The HDRNN incorporates novel algorithms and computational models for enhanced channel estimation accuracy using active base stations and parameters such as Angle of Arrival (AoA), Angle of Departure (AoD), and path loss.
- We develop an antenna gain prediction model using a Bayesian Neural Network that accurately determines appropriate gain values for optimized V2V communication links in varying speed scenarios. This model, in conjunction with system simulations at five different frequencies, ensures reliable communication even at speeds above 180 km/h.
- We design and implement an integrated communication model that combines mmWave of 5G, DSRC, and CtCNet-HDRNN for efficient and reliable V2V communication. By leveraging the strengths of different communication technologies, we address key challenges and limitations in existing systems and enhance vehicular network performance and safety. Furthermore, we employ a Monte Carlo-based approach to assess the performance of the proposed solutions in a DSRC channel environment.

TABLE 2. Comparison of our study with previous state-of-the-art studies.

Reference	Optimization of Pathloss for mmWave of 5G in V2V	Complexity analysis	Edge-compatible	Antenna Gain Prediction	Collision Avoidance
[25]	×	✓	✓	×	×
[26]	✓	×	×	✓	×
[27]	×	×	×	✓	×
[28]	✓	✓	✓	×	✓
[29]	✓	×	×	×	✓
[30]	✓	✓	✓	×	×
[31]	✓	✓	×	×	×
[32]	✓	×	×	×	×
[33]	×	×	✓	✓	✓
[34]	×	✓	✓	×	×
[35]	×	✓	✓	×	×
[36]	×	✓	✓	×	✓
[37]	✓	×	✓	×	✓
[38]	×	✓	×	×	×
[39]	×	×	×	×	✓
[40]	×	✓	×	×	×
[41]	×	×	×	×	✓
[42]	✓	✓	✓	×	×
[43]	×	✓	✓	×	✓
Our Study	✓	✓	✓	✓	✓

IV. SYSTEM MODEL

The detailed architecture of the system model is shown in Figure 1. Heterogeneous networks, consisting of two or more connected radio access networks, are known as RANs. The constituent RANs of our proposed 5G network will likely include a mmWave cellular network and existing DSRC networks. The mmWave will support overtaking scenarios on highways where DSRC sometimes fails. In addition, DSRC will be responsible for safety protocols. The DL optimization will further improve the path loss of mmWave, resulting in a safe vehicular network with low computational power requirements.

The DL optimization can help improve the path loss of mmWave communication by intelligently adjusting various parameters and configurations to adapt to the unique challenges posed by mmWave propagation. Major reasons why DL optimization can improve further the path loss of mmWave are: In mmWave communication, beamforming is essential for focusing the signal's energy towards the intended receiver, which can help overcome path loss. The DL algorithms can learn the optimal beamforming configurations based on the environment and communication requirements, thus reducing the path loss. Deep learning techniques can intelligently select the best channel for communication, considering factors like channel availability, channel quality, and interference. By choosing a channel with lower path loss, deep learning optimization can improve the overall communication performance in mmWave systems. Deep learning can be used to optimize the gain of the antennas used in mmWave communication systems. By predicting the optimal antenna gain based on the environment and communication requirements, deep learning can reduce path loss and improve communication performance.

The architecture's components and their functionalities will be explained in the following sections.

A. PROPOSED 5G MM-WAVE MODEL FOR VEHICULAR DESIGN WITH ANTENNA GAIN PREDICTION

Future researchers may carry out practical demonstrations in this section. However, this paper will discuss the detailed implementation of simulation work using different algorithms, focusing on a 2-dimensional approach.

First, we will examine the data rates of the 5G mmWave, which can safely support high-speed overtaking environments. Next, we will enhance gain optimization for range optimization of antennas using a deep learning module. In overtaking scenarios, a specific data rate is necessary to ensure safety. According to research [44], the required data rate threshold is 1 Gbps per few tens of meters. This research had two significant gaps, which our study addresses. First, the comparison analysis did not consider fixed antenna gain, which is not practical. Second, the research did not examine data rates for speeds greater than 160 km/h concerning range optimization for safe scenarios.

A 2-way channel model is used for fundamental analyses. The direct wave consists of the path length denoted by R(d), and the ground reflection wave's length is R(r). Antenna selection at the receiving side considers different heights, H(r1) and H(r2), to eliminate the fading effect produced in 2-dimensional propagation concerning the vehicle's location, as shown in Figure 2.

Simulation analysis was carried out for V2V with various antenna strengths and bandwidth introduction. Five different frequency bands were considered: 5GHz, 30GHz, 45GHz, 50GHz, and 60GHz. The antenna spacing for selection varies according to each frequency's wavelength.

Propagation losses and high noise are observed even at high carrier frequencies. However, fixed antenna gain for high frequency and bandwidth are stable parameters for safe autonomous vehicles. The reason for fixed antenna observance is to extract the most optimized frequency band for single-frequency usage with focused optimization

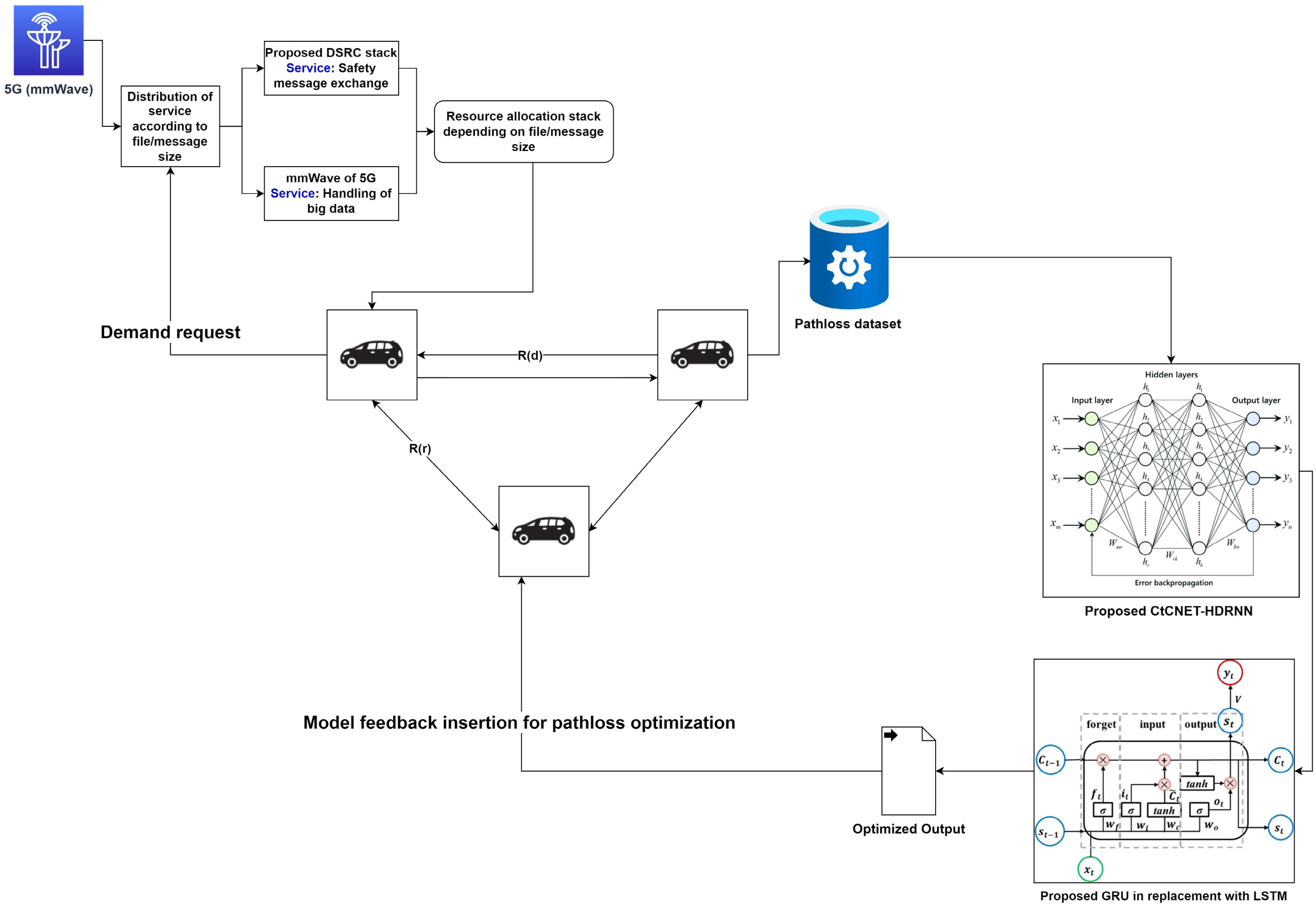

FIGURE 1. System model of integrated mmWave, DSRC and Proposed model stack with enhance pathloss optimization model feedback.

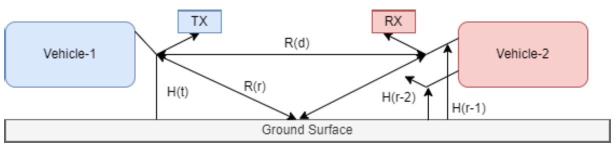

FIGURE 2. 2-way design analysis of transmitting and receiving vehicles with reference to ground space.

instead of different bands with poor optimization. A practical example of this scenario is the World Trade Centre Antenna structure designed by Motorola's design firm. Those antennas were placed near the top of the tower, near the edge. Each antenna can have any number of systems feeding into it without interfering with fixed antenna gain. In addition, waveguides were utilized in microwaves. The task was immense, well-coordinated, and successful.

Secondly, range optimization during overtaking scenarios on the highway was a critical concern and obstacle in mmWave of 5G. A deep learning solution was proposed to predict appropriate antenna parameters based on situation-based circumstances to address this issue. The predictive inspection predicts antenna gain for appropriate overtaking scenarios with a minimum loss between V2V links.

A Bayesian Neural Network is an extension of traditional neural networks that incorporates probabilistic modeling. Unlike standard feedforward neural networks that produce deterministic outputs, BNNs produce probability distributions over the model's parameters. This allows BNNs to capture uncertainty and provide more robust predictions, especially when dealing with limited data or noisy environments.

The architecture of the Bayesian Neural Network used in our antenna gain prediction model consists of multiple layers of interconnected neurons. Each neuron has associated weight and bias parameters, and the connections between neurons are represented by probability distributions. To train the BNN, we employ a variation of the Stochastic Gradient Langevin Dynamics (SGLD) algorithm, which combines stochastic gradient descent with a Langevin Monte Carlo sampling technique. This training approach enables us to sample from the posterior distribution of the model's parameters and iteratively refine them over the course of training.

The training process involves propagating input data through the network, calculating the loss function, and then adjusting the model's parameters using the sampled gradients obtained from the Langevin sampling. This process is repeated over multiple iterations to refine the model's parameters and improve the prediction accuracy.

Through the Bayesian approach, our antenna gain prediction model can not only make accurate predictions but also quantify the uncertainty associated with each prediction. This is particularly valuable in dynamic vehicular environments, where vehicle speeds may change rapidly, and reliable communication is essential.

Overall, the Bayesian Neural Network architecture and the training methodology provide a robust and technically sound foundation for our antenna gain prediction model. By harnessing the power of probabilistic modeling and uncertainty quantification, our approach enhances the technical soundness and clarity of functionality, enabling optimized communication and improved performance in dense vehicular networks. The workflow can be depicted in Figure 3.

Let R_d and R_r represent the direct path length and the ground reflection path length, respectively. The total path loss $L(f)$ for a 2-way channel model can be represented as:

$$L(f) = L_{path}(f, R_d, G) + L_{reflection}(f, R_r, G) + L_{noise}(f) \tag{1}$$

where f is the frequency, G is the antenna gain, and L_{path}, $L_{reflection}$, and L_{noise} are the path loss, reflection loss, and noise loss, respectively.

The data rate D required for safe overtaking can be described as:

$$D \geq \frac{1\,\text{Gbps}}{d_{\text{threshold}}} \tag{2}$$

where $d_{\text{threshold}}$ is the distance threshold (in tens of meters) for maintaining safety during overtaking scenarios.

The deep learning model aims to find the optimal antenna gain G^*, which minimizes the overall propagation loss $L(f)$ for a given scenario:

$$G^* = \arg\min_G L(f, G) \tag{3}$$

By employing the deep learning model, the system can adaptively adjust the antenna gain based on the real-time scenario, improving the reliability and safety of the V2V communication during high-speed overtaking maneuvers.

B. V2V WITH DSRC CHANNEL ACCESS VIA PROPOSED MONTE CARLO METHOD

Demand for less infrastructure-intensive wireless networking has increased, especially for vehicle communication carrying safety-related messages. IEEE 802.11 contains many protocols, standardized as IEEE 802.11p at 5.9GHz, known as a Dedicated Short-Range Communication band.

Packet collisions impact the reliability of data transmission and reception. A collision occurs when two or more transmitters within range of the same receiver attempt to broadcast a packet simultaneously. The receiver receives no message, disrupting communications and wasting bandwidth. The MAC (Medium Access Control) protocol is a vital

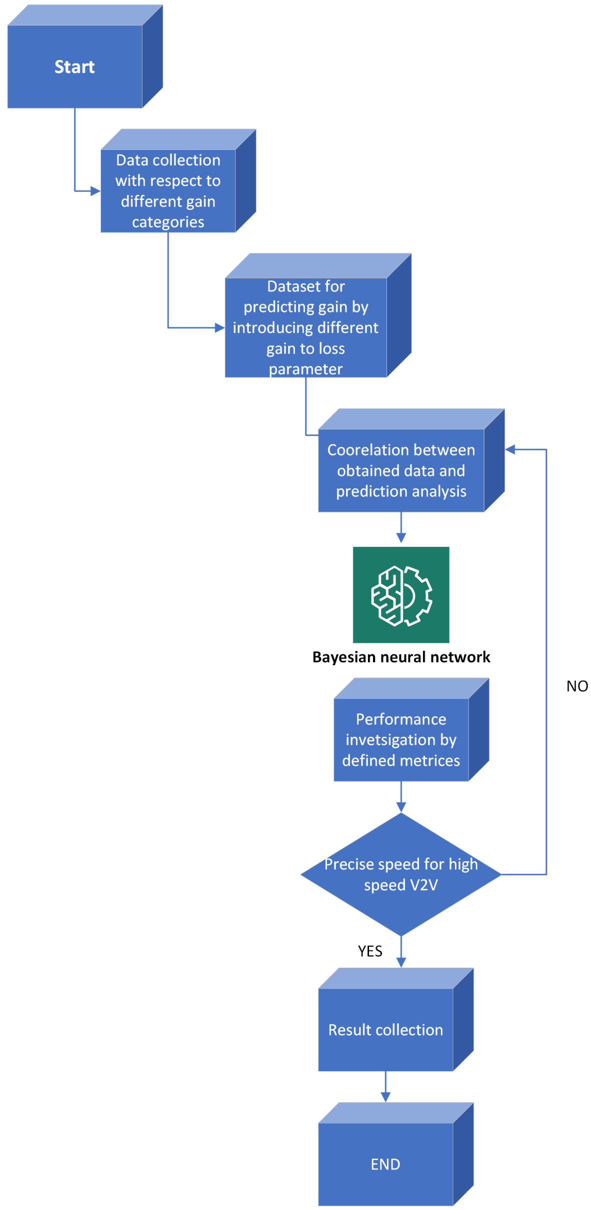

FIGURE 3. Optimized gain prediction: An illustration of the system model.

link layer component. The DSRC standard allows for a maximum transmission range of 1-kilometre Line-of-Sight. Paired with the OCB mode's unlimited operation, this could result in constructing highly dense vehicle networks, particularly in urban areas, making solving the channel access control problem more challenging. As DSRC-based vehicular networks are designed to handle safety-related signals with limited relevance duration, a reliable channel-sharing strategy with low-latency exchanges is necessary. Synchronization-based MAC protocols like TDMA may be more effective in V2V networks due to a lack of infrastructure and high mobility. As a result, contention-based channel-sharing systems like CSMA appear more suitable. Moreover, the proposed Q-Learning techniques are effective [16] but still have limitations in processing chains of Markov packets for better results, as this action increases computational complexity affecting vehicular links.

Our research aims to develop a self-learning collision avoidance system using the Monte Carlo method. MAC protocol is a set of structures to regulate the PHY of radio analyzers. The Distribution Coordination Function is a crucial principle of MAC used by IEEE 802.11. CSMA/CA algorithms are used to share pinpoint channels for several stations. Before attempting to broadcast, the node chooses a backoff integer at random from a uniform distribution spanning the interval [0, CW], with the initial CW (Contention Window) value equal to CWMIN, then counts down for backoff time slot intervals. The backoff value will be reduced only when the channel is free; otherwise, the counter will remain frozen until the medium becomes idle again. When transmitting stations use a significant CW value, it suggests a decreased chance of interference. There is a decreased likelihood that two or more stations may draw the same back off at random and broadcast simultaneously, causing congestion and packet loss. However, a larger backoff also implies that the station will likely wait longer before broadcasting a packet, increasing overall transmission delay and causing contention and packet loss when several stations are transmitting simultaneously.

To propose a novel mathematical model for the self-learning collision avoidance system using the Monte Carlo method, let's first define the parameters for our model:

Let N be the total number of vehicles in the network, C_t be the total number of collisions at time t, and P_{ij} be the probability of transitioning from state i to state j (i.e., from i collisions to j collisions). The goal is to minimize the expected number of collisions.

We can model the collision avoidance system using a discrete-time Markov chain (DTMC) with state space $S = 0, 1, 2, \ldots, N$, where each state represents the number of simultaneous packet transmissions. The transition probabilities P_{ij} can be calculated using the Monte Carlo method based on historical data and channel conditions.

To model the backoff strategy, let B_i represent the random backoff time for vehicle i, drawn from a uniform distribution $U(0, CW_i)$. The CW value for each vehicle can be updated dynamically based on the current state of the Markov chain and the estimated collision probabilities.

The objective is to find an optimal policy π^* that minimizes the expected number of collisions over a finite time horizon T. This can be formulated as a Markov Decision Process (MDP) with state space S, action space $A = a_1, a_2, \ldots, a_N$, transition probabilities P_{ij}^{a}, and reward function $R(s, a)$, where $R(s, a) = -C_t$ if action a results in a collision at time t.

The optimal policy π^* can be found using Reinforcement Learning (RL) techniques such as Q-learning or the Monte Carlo method. In each iteration of the learning process, vehicles update their CW values based on the observed collision probabilities, and the MDP transitions to a new state. The algorithm converges when the collision probability reaches a predefined threshold or after a maximum number of iterations.

Algorithm 1 Self-Learning Collision Avoidance Using Proposed Monte Carlo Method

Require: N: total number of vehicles in the network
T: finite time horizon
CW_{min}: minimum contention window
α: learning rate
γ: discount factor
ϵ: exploration rate
$Q(s, a)$: state-action value function
for each vehicle $i \in \{1, 2, \ldots, N\}$ **do**
  Initialize $CW_i = CW_{min}$ and state $s_i = 0$ (no collisions)
end for
for $t = 1$ to T **do**
  for each vehicle i **do**
    if rand() $< \epsilon$ **then**
      Choose a random action $a_i \in A$
    else
      $a_i \leftarrow \arg\max_a Q(s_i, a)$
    end if
    Calculate the backoff time $B_i \sim U(0, CW_i)$
    Transmit the packet after waiting for B_i time slots
end for
  Observe the new state s' (number of collisions) and the reward $R(s, a) = -C_t$
  for each vehicle i **do**
    Update the Q-value: $Q(s_i, a_i) \leftarrow Q(s_i, a_i) + \alpha[R(s, a) + \gamma \max_{a'} Q(s', a') - Q(s_i, a_i)]$
Here, α represents the learning rate determining how much of the newly acquired knowledge will replace the previous value. If α is set to 1, the new knowledge completely replaces the previous value; if it's set to 0, the new knowledge is ignored. This learning rate can be fixed or can be adaptively modified as per the learning process. The term $R(s, a) + \gamma \max_{a'} Q(s', a')$ represents the learned value. Here, $R(s, a)$ is the reward for taking action a in state s, and $\max_{a'} Q(s', a')$ is the estimate of the optimal future value from the next state s'. γ is the discount factor, which determines how much importance we want to give to future rewards. A high value for the discount factor (close to 1) captures the long-term effective award, while a smaller value (close to 0) makes our agent "myopic" (or short-sighted) by only considering current rewards.
  Update the state: $s_i \leftarrow s'$
end for
end for=0

The proposed mathematical model captures the dynamics of the collision avoidance system and allows for adaptive behavior of the vehicles based on the current channel conditions and network state. The self-learning approach

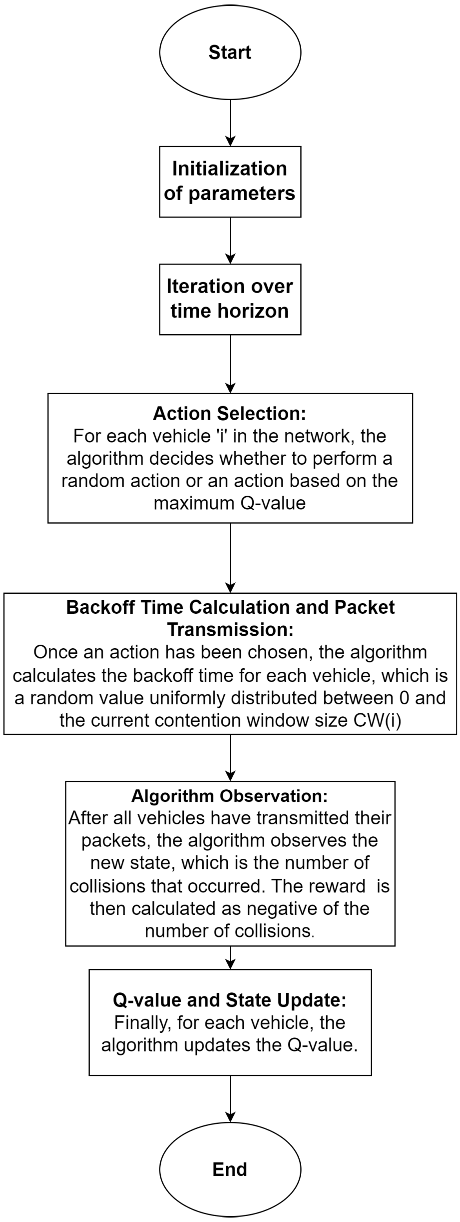

FIGURE 4. **Flowchart of self-learning collision avoidance using proposed monte carlo method.**

using the Monte Carlo method helps to minimize the expected number of collisions while maintaining low-latency communication in the vehicular network.

The flow of the self-learning collision avoidance Algorithm 1 and Figure 4 using the Monte Carlo method starts by initializing the parameters such as the total number of vehicles in the network, the finite time horizon, minimum contention window, learning rate, discount factor, exploration rate, and the state-action value function. Parameters can also be illustrated in Table 3. Each vehicle in the network will have its contention window and initial state (no collisions) initialized.

The algorithm then iterates over the time horizon, and for each vehicle, it checks if the channel is idle. If the channel is idle, the vehicle will choose an action based on its current state and the exploration rate. This action can be either to transmit or to wait, and it is selected according to the vehicle's state-action value function.

TABLE 3. **Essential parameters for the implementation of the self-learning collision avoidance algorithm.**

Parameter	Values
Total number of vehicles	120
Finite time horizon (1 hour)	T = 3600 seconds
Minimum contention window (CWMIN)	$CW_{min} = 15$ time slots
Learning rate (α)	$\alpha = 0.52$
Discount factor (γ)	0.78
Exploration rate (ϵ)	$\epsilon = 0.81$
State-action value function (Q)	Refer to Algorithm 1

After selecting an action, the vehicle updates its contention window based on the chosen action and calculates the expected reward. The vehicle then observes the new state (collision or no collision) and updates the state-action value function using the learning rate, discount factor, and observed reward.

At the end of each time step, the algorithm updates the exploration rate to balance exploration and exploitation. The process continues, iterating over the time horizon, allowing vehicles to learn from their actions and adjust their contention window to minimize collisions and improve the overall network performance.

C. PROPOSED CTCNET-HDRNN WITH NOVEL GRU-BASED CHANNEL TRACKING MECHANISM

To address the challenges in mmWave communications for 5G systems, we propose a deep learning-based channel estimation and tracking technique using a Deep Recurrent Neural Network (D-RNN) and a Gated Recurrent Unit (GRU) for channel tracking. This approach minimizes training overhead and computational complexity.

Our proposed architecture uses an omnidirectional antenna pattern to receive uplink training pilots, simplifying the initial training process and allowing for efficient reception in dynamic environments.

The optimization objective is to minimize path loss while reducing computational complexity, with constraints related to hardware limitations, time overheads, and minimizing training costs. An adaptive learning rate and regularization term are introduced to improve generalization and adaptability.

We achieved optimal data fit, superior generalization, and efficient convergence through the utilization of adaptive learning rate and regularization techniques within the advanced training methodology of our model. Specifically, the adaptive learning rate dynamically adjusts the rate of learning during training, allowing the model to converge efficiently while avoiding overshooting and divergence issues. On the other hand, regularization techniques help prevent overfitting and enhance generalization by adding penalties to the loss function based on the complexity of the model.

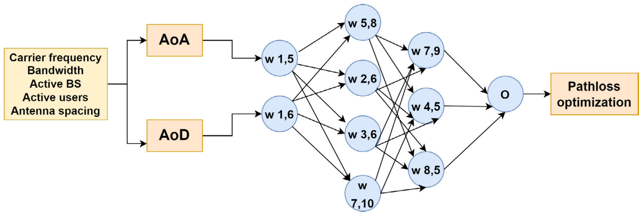

FIGURE 5. **Input mapping with respect to weights of RNN.**

By combining these approaches, our CtCNET-HDRNN model optimizes data processing, improving performance and reliability in dense vehicular networks. The adaptive learning rate and regularization contribute to enhanced convergence, which ensures accurate predictions and reliable communication among vehicles, even in scenarios with varying speeds and lane changes.

A novel GRU-based channel tracking mechanism is employed to optimize path loss in mmWave 5G systems. The GRU model determines how much previous data should be passed to the future for accurate estimations, removing unnecessary data and increasing computational optimization.

To further advance the model's performance, we introduce a hierarchical deep recurrent neural network (HDRNN), augmented with multi-scale attention mechanisms. This innovative design choice ensures the network's capability to assimilate both transient (short-term) and persistent (long-term) patterns present within the input sequence. Consequently, it offers heightened accuracy and robustness in its predictive outputs. To fortify the model against common pitfalls, we integrate dropout regularization—a technique that randomly omits a fraction of units during training, thereby preventing co-adaptation of hidden units. Additionally, layer normalization is employed. Unlike batch normalization that operates on the batch dimension, layer normalization standardizes features along the feature dimension. This ensures consistent mean and variance for each feature, reducing internal covariate shift and bolstering the model's stability. The meticulous arrangement of input and output concerning the RNN weights is illustrated in Figure 5

Input and output mapping according to RNN weights can be shown in Figure 5.

For the nth Base Station (BS), the received signal is represented as:

$$x_n^{omni} = [a_n^T \cdot b_n \cdot y_{pilot}] + [a_n^T \cdot c_n] \tag{4}$$

Optimization variables include network parameters like beamforming methods and deep learning algorithms. The optimization objective is to minimize path loss in mmWave 5G systems while reducing computational complexity. Constraints considered involve hardware limitations, time-based overheads, and training cost minimization.

The D-RNN output is expressed as:

$$\hat{B} = \alpha(\alpha 1(A) : \epsilon) \tag{5}$$

where $\hat{B}$ shows DNN output estimation, ϵ represents the lth layer's parameters.

The universally received signal x is the input feature represented as:

$$x_n^{omni} = [x_1^{omni}, .., x_N^{omni}] \tag{6}$$

where x_n^{omni} denotes the Omni-received signal from all BS. Consequently, all coordinating BSs' projected mmWave channels can be obtained as $b = [b(1), .., b(n)]$. The optimal ϵ is found by training and minimizing the loss function.

The loss function is expressed by:

$$Loss(\epsilon) = \frac{1}{VL_y} \sum_{v=0}^{V-1} ((\hat{B} - B))^2 \tag{7}$$

In the equation above, ϵ is an optimizing factor achieved by minimizing Loss ϵ through rigorous training. L represents the vector length.

A novel GRU-based channel tracking mechanism is introduced to further optimize path loss in mmWave 5G systems. GRU has the advantage of utilizing fewer training parameters, requiring less memory, and providing faster execution, which is essential for dense V2V environments. Additionally, GRU's performance is competitive compared to LSTM, which has a higher computational complexity

The update GRU gates is represented as:

$$a_t = \varrho(R^z \cdot x_t + \varrho(M^z \cdot h_{t-1}) \tag{8}$$

where x_t is the input for the network, R^z represents weights, and $t-1$ denotes previous information combined with ϱ as the activation function.

Updated gates help the model determine the amount of previous data to be passed to the future for appropriate estimations. This is beneficial for carrying error-free data to avoid collision analysis, thus helping to remove unnecessary data from the past to increase computational optimization. The equation representing this scenario is as follows:

$$b_t = \varrho(R^z \cdot x + \varrho(M^z \cdot h_{t-1}) \tag{9}$$

Moreover, b_t is observed as a reset gate. A novel memory content is developed, considering the density of connected cars as follows:

$$S_t' = tanh(R^z \cdot x + \varrho(M^z \odot h_{t-1})(V2VDF - V2V - CL) \tag{10}$$

The V2V DF represents the density factor of the current situation minus V2V-CL (connected links) to extract failure events due to path loss for appropriate target point processing. After summing all the aforementioned steps, a non-linear activation function is applied, which is necessary for mmWave 5G to cater to the non-linear behaviors of communication waves. The results are incorporated into a channel tracking system using GRU; by this method, prediction is enhanced and inversely proportional to computational complexity, as shown in the following formula:

$$OP = \frac{1}{CC - [V2V]} \tag{11}$$

where OP represents optimized prediction and CC denotes computational complexity extracted by the proposed GRU-based method.

Introducing an adaptive learning rate and a regularization term is crucial for enhancing our model's performance. The adaptive learning rate, applied using the Adam optimization algorithm, refines the step size during training, allowing for better convergence rates and more effective optimization landscape navigation. Consequently, the model can adapt more efficiently to varying environments.

Additionally, we incorporate regularization to deter overfitting and promote simpler model representations. We used the Adam optimization algorithm, which calculates an adaptive learning rate for each parameter:

$$m_t = \beta_1 m_{t-1} + (1-\beta_1)\nabla_\epsilon Loss(\epsilon) \tag{12}$$

$$v_t = \beta_2 v_{t-1} + (1-\beta_2)(\nabla_\epsilon Loss(\epsilon))^2 \tag{13}$$

$$\epsilon \leftarrow \epsilon - \frac{\eta}{\sqrt{v_t}+\epsilon} m_t \tag{14}$$

where m_t and v_t are the first and second moment estimates, β_1 and β_2 are exponential decay rates, η is the learning rate, and ϵ is a small constant to prevent division by zero.

By including an L2 regularization term, also known as weight decay, in the loss function, we penalize large weights, reducing the risk of overfitting. As a result, the model becomes more robust and generalizes better to unseen data:

$$Loss_{reg}(\epsilon) = Loss(\epsilon) + \frac{\lambda}{2}\sum_{l=1}^{L}\sum_{i=1}^{n_l}\sum_{j=1}^{n_{l-1}}(W_{l,ij}^2) \tag{15}$$

where $Loss_{reg}(\epsilon)$ is the regularized loss function, λ is the regularization parameter, L is the number of layers, n_l is the number of neurons in layer l, and $W_{l,ij}$ is the weight connecting neuron i in layer l to neuron j in layer $l-1$.

Further optimization is needed for the model, specifically when dealing with mmWave 5G systems, due to the inherent challenges in these communication environments. mmWave signals are highly sensitive to obstacles and experience significant path loss. Additionally, rapid changes in the environment can lead to fluctuations in channel conditions, which can negatively impact the performance of the wireless communication system.

Integrating a multi-head attention mechanism into the model can address these challenges more effectively. By allowing the model to selectively focus on different input sequence segments, the multi-head attention mechanism can capture both long-range and short-range dependencies between various time steps. This is particularly important in mmWave 5G systems, as the rapid fluctuations in channel conditions require the model to adapt and learn from both recent and historical data in order to make accurate predictions.

By incorporating the multi-head attention mechanism, the model can better handle the complex and dynamic nature of mmWave 5G environments, leading to improved path loss optimization and, ultimately, more efficient and reliable wireless communication.

Algorithm 2 Proposed CtCNET by HDRNN

Require: Training data: $\mathcal{D}$
$= \{(x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N)\}$, learning rate: η, epochs: T, regularization parameter: λ, adaptive learning rate parameters: μ_1, μ_2, and ϵ

1: Initialize network parameters Θ randomly
2: **for** $t = 1, \ldots, T$ **do**
3: Shuffle the training data $\mathcal{D}$
4: **for**each mini-batch (x_{MB}, y_{MB}) in $\mathcal{D}$ **do**
5: Perform forward propagation to compute predictions $\hat{y}_{MB}$
6: Compute gradients: $g_t \leftarrow \nabla_\Theta \text{Loss}_{reg}(\Theta)$
7: Update first moment estimate: $m_t \leftarrow \mu_1 m_{t-1} + (1-\mu_1)g_t$
8: Update second moment estimate: $v_t \leftarrow \mu_2 v_{t-1} + (1-\mu_2)g_t^2$
9: Compute bias-corrected first moment estimate: $\hat{m}_t \leftarrow \frac{m_t}{1-\mu_1^t}$
10: Compute bias-corrected second moment estimate: $\hat{v}_t \leftarrow \frac{v_t}{1-\mu_2^t}$
11: Update parameters: $\Theta \leftarrow \Theta - \eta\frac{\hat{m}_t}{\sqrt{\hat{v}_t}+\epsilon}$
12: **end for**
13: **end for**=0

$$Attention(Q, K, V) = Softmax(\frac{QK^T}{\sqrt{d_k}})V \tag{16}$$

$$MultiHead(Q, K, V) = Concat(head_1, \ldots, head_h)W^O \tag{17}$$

where Q, K, and V are the query, key, and value matrices, d_k is the key dimension, $head_i$ is the output of the i-th attention head, and W^O is the output weight matrix. The multi-head attention mechanism will be integrated into the GRU cell, allowing the model to better capture temporal dependencies in the input sequence.

Incorporating the multi-head attention mechanism into a hierarchical deep recurrent neural network (HDRNN) can better capture the complex dependencies in mmWave 5G systems. The HDRNN is structured with several layers of stacked GRUs, each designed to capture dependencies at different time scales. This hierarchical structure allows the output of one layer to serve as the input for the next layer, facilitating the model's ability to process and learn from the intricate relationships found in mmWave 5G environments. The HDRNN can be represented as follows

$$h_t^{(1)} = GRU^{(1)}(x_t, h_{t-1}^{(1)}) \tag{18}$$

$$h_t^{(l)} = GRU^{(l)}(h_t^{(l-1)}, h_{t-1}^{(l)}), ;;; l = 2, \ldots, L \tag{19}$$

where $h_t^{(l)}$ is the hidden state at time step t in layer l, and L is the number of layers in the HDRNN.

Considering the hierarchical structure of the HDRNN, a multi-scale attention mechanism is introduced to enhance the model's ability to selectively focus on different parts of the input sequence at various time scales. This addition is crucial because the mmWave 5G channel characteristics exhibit dependencies across multiple time scales, and capturing these diverse relationships effectively is essential for accurate path loss optimization. By implementing a separate attention layer for each time scale, the model can better adapt to the inherent complexities and variations in the mmWave 5G systems:

$$Attention^{(l)}(Q,K,V) = Softmax(\frac{QK^T}{\sqrt{d_k}})V \tag{20}$$

$$MultiHead^{(l)}(Q,K,V) = Concat(head_1,\ldots,head_h)W^O \tag{21}$$

where $Q^{(l)}$, $K^{(l)}$, and $V^{(l)}$ are the query, key, and value matrices at layer l, and the other variables are defined as before.

The output of the HDRNN is then combined with the outputs of the attention layers to produce the final prediction:

$$y_t = \sum_{l=1}^{L} \alpha^{(l)} MultiHead^{(l)}(h_t^{(l)}, h_{\leq t}^{(l)}, h_{\leq t}^{(l)}) \tag{22}$$

where $\alpha^{(l)}$ are learnable weights that control the contribution of each attention layer to the final prediction.

To improve the robustness of the model and prevent overfitting, we will employ dropout regularization between the GRU layers and after the multi-scale attention layers:

$$h_t^{(l)} = Dropout(p)(GRU^{(l)}(h_t^{(l-1)}, h_{t-1}^{(l)})) \tag{23}$$

$$y_t = Dropout(p)(\sum_{l=1}^{L} \alpha^{(l)} MultiHead^{(l)}(h_t^{(l)}, h_{\leq t}^{(l)}, h_{\leq t}^{(l)})) \tag{24}$$

where p is the dropout probability.

Incorporating additional layers in the HDRNN and implementing normalization techniques, such as layer normalization, within the architecture serves a crucial purpose despite the model's existing complexity. The need for extra layers arises from the presence of intricate dependencies and relationships in mmWave 5G systems that are not captured effectively. These additional layers enable the model to learn more abstract and high-level representations, enhancing its capacity to handle complex scenarios. Layer normalization, on the other hand, helps maintain a stable learning process by normalizing the activations across different layers, ensuring consistent and efficient training.

Initially, the incorporation of layer normalization within the HDRNN shall be executed, as follows:

$$LN(x) = \gamma \frac{x-\mu_x}{\sigma_x} + \beta \tag{25}$$

where x is the input to the layer normalization, γ and β are learnable scaling and shifting parameters, and μ_x and σ_x are the mean and standard deviation of the input x, respectively.

Subsequently, the HDRNN shall be augmented by introducing an additional hidden layer and integrating layer normalization. The resultant output of the enhanced HDRNN can be articulated as:

$$\hat{B} = \alpha_3(LN(\alpha_2(LN(\alpha_1(A)\cdot W_1 + B_1))\cdot W_2 + B_2))\cdot W_3 + B_3 \tag{26}$$

where α_i represents the activation function for the i-th layer, and W_i and B_i are the weights and biases for the i-th layer, respectively.

The regularized loss function with the extended HDRNN model is:

$$Loss_{reg}(\epsilon) = Loss(\epsilon) + \frac{\lambda}{2}\sum_{l=1}^{L}\sum_{i=1}^{n_l}\sum_{j=1}^{n_{l-1}}(W_{l,ij}^2) + \frac{\lambda_{LN}}{2}\sum_{l=1}^{L}\sum_{i=1}^{n_l}(\gamma_{l,i}^2) \tag{27}$$

where λ_{LN} is the regularization parameter for the layer normalization scaling parameters $\gamma_{l,i}$.

In conclusion, the update equations for the Adam optimizer persist unchanged, albeit with the gradient computed for the expanded HDRNN and the modified regularized loss function:

$$m_t = \beta_1 m_{t-1} + (1-\beta_1)\nabla_\epsilon Loss_{reg}(\epsilon) \tag{28}$$

$$v_t = \beta_2 v_{t-1} + (1-\beta_2)(\nabla_\epsilon Loss_{reg}(\epsilon))^2 \tag{29}$$

$$\epsilon \leftarrow \epsilon - \frac{\eta}{\sqrt{v_t}+\epsilon} m_t \tag{30}$$

Expanding the HDRNN and incorporating layer normalization allows the model to capture higher-order interactions and dependencies within the data more effectively. Additionally, the regularization term in the loss function now considers both the weights and layer normalization scaling parameters, further enhancing generalization.

To establish a seamless integration among the CtCNET-HDRNN, adaptive learning rate, and regularization, the overall training process and update equations for the model parameters are outlined below.

The complete loss function is defined, taking into account the regularization term:

The complete loss function is defined, taking into account the regularization term:

$$Loss_{reg}(\epsilon) = Loss(\epsilon) + \frac{\lambda}{2}\sum_{l=1}^{L}\sum_{i=1}^{n_l}\sum_{j=1}^{n_{l-1}}(W_{l,ij}^2) \tag{31}$$

where $Loss_{reg}(\epsilon)$ is the regularized loss function, λ is the regularization parameter, L is the number of layers, n_l is the number of neurons in layer l, and $W_{l,ij}$ is the weight connecting neuron i in layer l to neuron j in layer $l-1$.

The Adam optimizer, featuring an adaptive learning rate, is employed to update the proposed CtCNET-HDRNN parameters:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1)\nabla_\epsilon Loss_{reg}(\epsilon) \tag{32}$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2)(\nabla_\epsilon Loss_{reg}(\epsilon))^2 \tag{33}$$

$$\epsilon \leftarrow \epsilon - \frac{\eta}{\sqrt{v_t} + \epsilon} m_t \tag{34}$$

where m_t and v_t are the first and second moment estimates, β_1 and β_2 are exponential decay rates, η is the learning rate, and ϵ is a small constant to prevent division by zero.

The proposed approach incorporates the HDRNN architecture, utilizes an adaptive learning rate from the Adam optimizer, and includes a regularization term in the loss function. By doing so, the model parameters are updated in a balanced manner that ensures a good fit to the training data while promoting a simpler representation. This approach enhances the generalization capability of the model and facilitates efficient convergence during training as depicted in Algorithm 2.

To address the computational complexity challenge on edge devices, we introduce a Sparse Deep Recurrent Neural Network (SDRNN). This technique leverages the inherent sparsity within the network's structure by selectively pruning less significant connections. By removing these connections, the model becomes more compact and efficient, making it well-suited for resource-constrained edge devices. The utilization of SDRNN enables us to achieve a balance between model size and computational efficiency, facilitating effective deployment on edge devices.

Let's define the proposed SDRNN model mathematically: Consider a CtCNET Deep Recurrent Network with parameters $\Theta = W_1, b_1, W_2, b_2, \ldots, W_L, b_L$, where W_l and b_l represent the weight matrix and bias vector for layer l, respectively, and L is the total number of layers.

To introduce sparsity, we define a corresponding sparsity mask M_l for each layer l. The mask has the same dimensions as the weight matrix W_l and consists of binary values. Specifically, $M_{l,ij} = 1$ indicates an active connection between nodes i and j in layers $l-1$ and l, while $M_{l,ij} = 0$ indicates an inactive (pruned) connection.

To incorporate the sparsity mask M_l into the forward propagation equation, we modify it as follows:

$$z_l = f_l(W_l \odot M_l) \cdot a_{l-1} + b_l \tag{35}$$

In the modified forward propagation equation, the element-wise product $\odot$ is used. Here, a_{l-1} represents the activation vector of the previous layer, z_l represents the pre-activation vector of layer l, and f_l represents the activation function for layer l.

To train the SDRNN model with the sparsity masks M_l, we minimize the following loss function:

$$\mathrm{Loss}_{SDRNN}(\Theta, M) = \mathrm{Loss}(\Theta) + \beta \sum_{l=1}^{L} \|M_l\|_0 \tag{36}$$

where $\mathrm{Loss}(\Theta)$ is the original loss function of the CtCNET-HDRNN Deep Recurrent Network, $\|M_l\|_0$ is the zero-norm of the sparsity mask M_l (counting the number of non-zero elements), and β is a regularization parameter that controls the trade-off between the model's performance and sparsity. After training the SDRNN model, deploy the sparse model on edge devices, which will require fewer computations due to the pruned connections, resulting in a more efficient network.

This computational model allows for reduced complexity while maintaining adequate performance on edge devices, providing a practical solution for real-world applications.

Algorithm 3 Integration of Computational Model With Proposed CtCNET-HDRNN-SDRNN

Require: Initialize network parameters Θ, learning rates η, sparsity masks M, computational model, regularization parameter β

Preprocess input data (vehicle positions, velocities, etc.) to form data set $\mathcal{D}$
Estimate initial channel state using the modified CtCNET with HDRNN and SDRNN
While not converged **do**
  Update learning rates using adaptive learning
  for each layer l in the network **do**
    Apply sparsity mask M_l to the network parameters for layer l
    Train the modified CtCNET with HDRNN-SDRNN on the input data for layer l
    Perform forward propagation: $z_l = f_l(W_l \odot M_l) \cdot a_{l-1} + b_l$
    Compute the partial loss function: $\mathrm{Loss}_{SDRNN_l}(\Theta_l, M_l) = \mathrm{Loss}(\Theta_l) + \beta \|M_l\|_0$
    Compute gradients: $g_l = \nabla_{\Theta_l, M_l} \mathrm{Loss}_{SDRNN_l}(\Theta_l, M_l)$
    Update network parameters for layer l using gradients, learning rates: $\Theta_l \leftarrow \Theta_l - \eta g_l$
  end for
  Update total loss function: $\mathrm{Loss}_{SDRNN}(\Theta, M) = \sum_l \mathrm{Loss}_{SDRNN_l}(\Theta_l, M_l)$
  Update sparsity masks: $M \leftarrow \mathrm{update}(M, g)$ where update is defined as $M_l[i,j] \leftarrow 0$ if $|W_l[i,j]| < \tau$; else $M_l[i,j] \leftarrow 1$ for a threshold τ
  Perform forward propagation in the computational model
  Calculate computational model outputs and apply to network
  Update network weights and sparsity masks based on computational model outputs
  Estimate channel state and update the input data
end while=0

Algorithm 3 and Figure 6 demonstrates how to use the computational model in conjunction with the proposed CtCNET-HDRNN. The computational model will be incorporated into the training process by applying its outputs to update the network weights, effectively reducing complexity and making the network more suitable for edge devices.

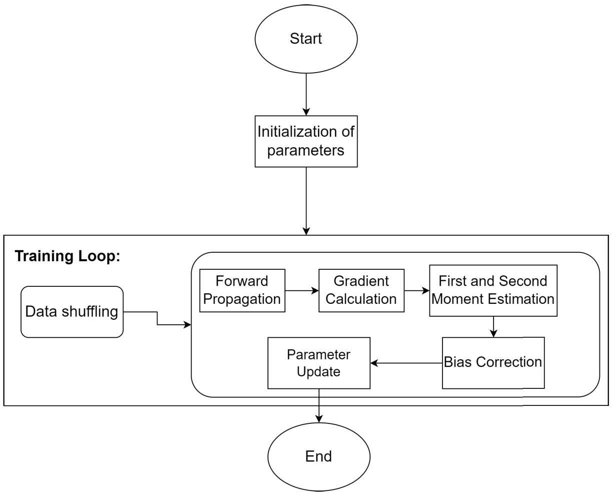

FIGURE 6. Flowchart of integration of computational model with proposed CtCNET-HDRNN-SDRNN.

In the context of dense vehicular networks, where vehicles require real-time communication and decision-making, traditional cloud-based computing solutions may introduce undesirable delays due to data transmission to remote servers and back. Edge computing offers a promising alternative by bringing computation closer to the network edge, reducing communication latency and enabling faster response times. However, the computational complexity of advanced communication models and algorithms can strain the limited resources of edge devices, hindering their ability to handle real-time data processing efficiently.

Our research directly tackles this critical issue by proposing an innovative integration of the Car-to-Car Network-Hierarchical deep neural network (CtCNet-HDRNN) model with 5G and Dedicated Short-Range Communications (DSRC) systems. By incorporating a Sparse Deep Recurrent Neural Network (SDRNN) and Gated Recurrent Unit (GRU)-based Recurrent Neural Network (RNN) within the CtCNet-HDRNN, we aim to significantly reduce computational complexity and improve speed stability in V2V communication. This approach not only enhances system performance but also ensures reliable and low-latency communication in highly dense vehicular environments.

If the computational efficiency issue in edge computing remains unaddressed, it could lead to several potential implications. First and foremost, communication delays could jeopardize the effectiveness of safety-critical applications, such as collision avoidance systems, posing risks to drivers and pedestrians. Moreover, unreliable communication in V2V networks may hinder the widespread adoption of connected vehicle technologies, limiting the potential benefits of enhanced traffic management, reduced congestion, and improved road safety. In the context of emerging smart transportation systems, the efficient exchange of real-time data is paramount, and unresolved computational challenges could hinder the realization of their full potential. Therefore, our research has significant implications in advancing edge computing solutions for vehicular networks, promoting safer and more efficient transportation, and unlocking the transformative capabilities of connected vehicle technologies.

D. INTEGRATION MODEL

The integrated model seamlessly fuses CtCNET-HDRNN, mmWave of 5G, and Monte Carlo for DSRC. The inherent complexity of combining these technologies necessitates a robust model that encapsulates all relevant operations, including encoding, error-checking, and decoding procedures.

First, the CtCNET-HDRNN model, denoted as Φ, processes input data X to generate output Y. To prepare Y for transmission over the 5G mmWave, an encoding operation is applied:

$$E_Y = \text{Encode}(Y) \tag{37}$$

Then, the mmWave of 5G model, denoted as ψ, operates on the encoded data E_Y to produce transmitted data T:

$$T = \psi(E_Y) \tag{38}$$

Simultaneously, the DSRC system utilizes the Monte Carlo method, denoted as θ. It processes a different set of input data Z, which is also encoded:

$$E_Z = \text{Encode}(Z) \tag{39}$$

The Monte Carlo model for DSRC processes E_Z to yield transmitted data R:

$$R = \theta(E_Z) \tag{40}$$

After transmission, the transmitted data are subject to error-checking and decoding operations to recover the original messages:

$$D_T = \text{Decode}(\text{ErrorCheck}(T)) \tag{41}$$
$$D_R = \text{Decode}(\text{ErrorCheck}(R)) \tag{42}$$

Thus, the integrated model, denoted as Γ, is expressed as:

$$\begin{aligned}(T, R, D_T, D_R) &= \Gamma(X, Z)\\ &= \big(\psi(\text{Encode}(\Phi(X))), \theta(\text{Encode}(Z)),\\ &\quad \text{Decode}(\text{ErrorCheck}(\psi(\text{Encode}(\Phi(X))))),\\ &\quad \text{Decode}(\text{ErrorCheck}(\theta(\text{Encode}(Z))))\big)\end{aligned} \tag{43}$$

The integrated function Γ encapsulates the entire sequence of operations, from initial data processing to final decoding after transmission, within a single, cohesive model.

This Algorithm 4 and Figure 7 covers all necessary stages in the communication process: initial data processing by models Φ and θ, encoding, transmission over respective communication systems, error-checking, decoding, and feedback-driven adjustment of models. The iterative nature of the algorithm facilitates dynamic and efficient optimization of the integrated system.

Algorithm 4 Integration of Proposed, mmWave of 5G, and Proposed DSRC

Require: Input data X, Z
Ensure: Transmitted data T, R and Decoded data D_T, D_R
Initialize Φ (CtCNET-HDRNN model)
Initialize ψ (mmWave of 5G model)
Initialize θ (Monte Carlo for DSRC)
Train the models Φ, ψ, and θ with available data
For each data sample in X and Z **do**
    Read input data X_i, Z_i
    Calculate $Y_i = \Phi(X_i)$
    Encode Y_i to obtain E_{Y_i}
    Transmit E_{Y_i} via the 5G mmWave communication system, obtaining $T_i = \psi(E_{Y_i})$
    Perform error-checking on T_i to get T_i' and decode to get D_{T_i}
    Update Φ and ψ based on the feedback from the decoding process
    Repeat a similar process for Z_i through the DSRC system, yielding R_i and D_{R_i}
    Transmit T_i and R_i to the respective communication systems
end for
While system is running **do**
    Monitor for feedback and adjust Φ, ψ, and θ accordingly in real-time
end while=0

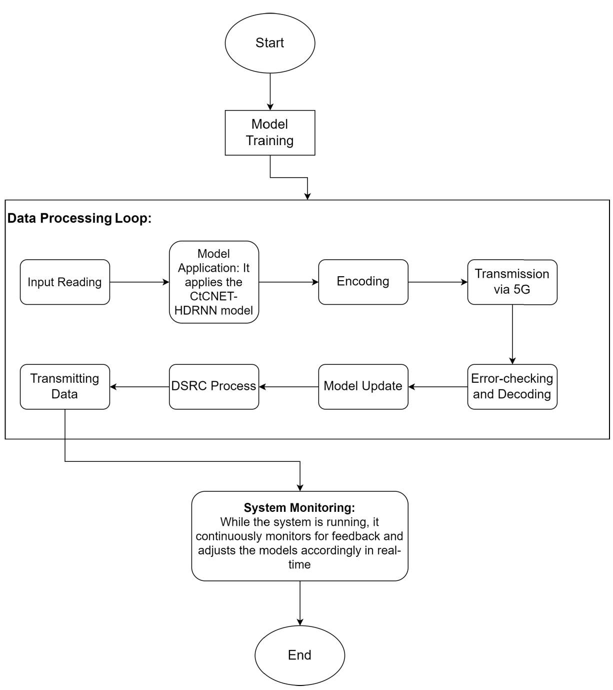

FIGURE 7. Flowchart of integration of proposed, mmWave of 5G, and proposed DSRC.

V. RESULTS & DISCUSSION

This section meticulously unpacks the results of an extensive experimental analysis, neatly categorized into four distinct parts. The initial segment discusses the outcomes of the deployed 5G mm-Wave model, specifically tailored for vehicular design, with a primary emphasis on antenna gain prediction in high-speed environments. Subsequently, the findings from the newly proposed DSRC system are examined, showcasing its remarkable efficiency and reliability in vehicular communication scenarios. The discourse then navigates to the path loss optimization, a noteworthy achievement facilitated by the implementation of the CtCNET-HDRNN model. Finally, the integrated model undergoes a rigorous computational analysis, with its performance scrutinized and its potential to fortify vehicular communication systems evaluated. This comprehensive review of each distinct element and the collective model bestows invaluable insights into their capabilities, while highlighting strengths, addressing limitations, and identifying potential enhancements within the ambit of vehicular communication systems.

A. RESULTS OF THE PROPOSED 5G MM-WAVE MODEL FOR VEHICULAR DESIGN WITH ANTENNA GAIN PREDICTION

This section delineates the results arising from the proposed 5G mm-Wave model for vehicular design, notably focusing on antenna gain prediction.

Simulation experiments within the V2V framework leverage five unique frequency bands: 5GHz, 30GHz, 45GHz, 50GHz, and 60GHz. Each band accompanies diverse antenna strength and bandwidth configurations. For peak performance, the spacing between antennas is customized to correspond with the specific wavelength of each frequency, as detailed in Table 4.

In the visual representation of Figure 8, the effects of cooperative and non-cooperative perception on data rates across varying velocities are evident. The x-axis showcases velocities ranging from 0 to 180 km/h, while the y-axis depicts the corresponding data rates in Gbps.

Two distinct plots emerge. Both start from a baseline of 0 Gbps. However, as the velocity nears 40 km/h, there's a pronounced increment in the data rate for both schemes. The data rate for the cooperative scheme peaks at 12 Gbps. This pronounced rise can be attributed to the cooperative perception mechanism, where vehicles are not just passive entities but active communicators. They detect objects and share this information with neighboring vehicles in real-time. This mutual exchange and collaboration bolster perception accuracy, enhance road safety, and thus contribute to the higher data rates observed.

Conversely, the non-cooperative scheme, where vehicles operate in isolation, relying solely on their individual sensors and processing capabilities, manifests a steeper rise in the data rate. From 40 km/h to 140 km/h, the non-cooperative scheme consistently outperforms its cooperative counterpart by an additional 2 Gbps. This discrepancy might be due to the reduced overhead and latency associated with real-time inter-vehicle communications. Nonetheless, beyond 140 km/h, the cooperative scheme gains momentum, registering an increase of 1 Gbps.

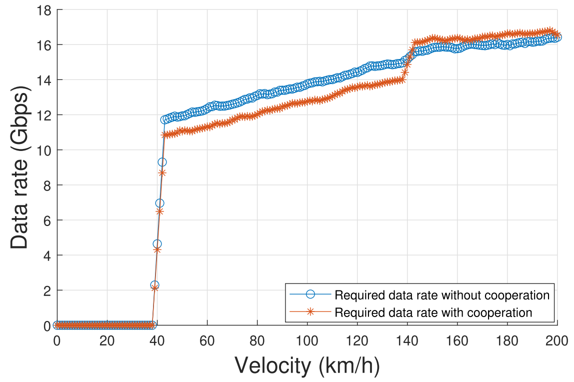

FIGURE 8. Correlation of required data rates and velocity with distinct mm-Wave frequency bands, integrating cooperative perception in overtaking scenarios.

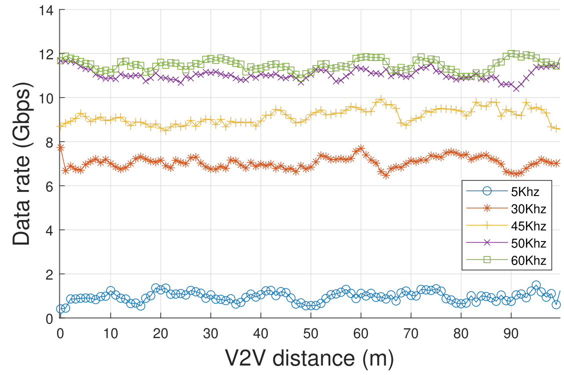

FIGURE 9. V2V connection outage analysis: The impact of antenna selection diversity.

In essence, while the cooperative perception, underpinned by active data sharing among vehicles, enhances road safety and perception accuracy, it may introduce overheads that affect optimal data rates at certain velocities. On the other hand, non-cooperative perception, rooted in autonomous functioning, might offer higher data rates at specific velocity ranges due to its streamlined operation but lacks the enriched data environment of its cooperative counterpart.

The system model under investigation demonstrates exemplary performance in cooperative perception scenarios by value of 1Gbps as compared to without cooperative perception, effectively utilizing shared information to enhance safety and perception accuracy. This efficiency surpasses even non-cooperative perception with higher data rates. The model, by capitalizing on cooperation and collaborative data exchange, ensures reliable and accurate V2V communication.

The selection diversity of antennas proves crucial in this study. Figure 9 reveals that employing various antennas across different frequency bands counteracts performance degradation induced by deep fading and varying vehicle positions, thereby assuring robust communication in dynamic V2V scenarios.

In the Figure 10 delineating the V2V connection outage analysis focusing on the implications of antenna selection diversity, we observe intriguing trends in data rates with varying V2V distances, underpinned by different frequency bands.

Spanning a V2V distance from 0 to 100 meters on the x-axis, the figure reveals a hierarchy in the data rates (on the y-axis) contingent on frequency. The 5kHz band offers the most modest data rates, consistently hovering below 2 Gbps across the entire distance spectrum. This is not surprising given that lower frequencies, like 5kHz, inherently possess longer wavelengths, which, while offering superior penetration abilities, especially in cluttered environments, often have constraints in terms of data transmission rates.

As we ascend the frequency scale, there's a marked enhancement in data rates. The 30kHz band fluctuates between 6 and 8 Gbps, while the 45kHz band situates itself slightly higher, with values spanning from 9 to 10 Gbps. The 50kHz and 60kHz bands, being the highest frequencies depicted, record data rates between 10-11 Gbps and 11-12 Gbps, respectively. Higher frequencies, equipped with shorter wavelengths, are traditionally understood to provide greater bandwidths and consequently higher data rates, which the graph's patterns corroborate. However, these bands, especially the likes of 60kHz, are more susceptible to physical obstacles and atmospheric conditions, which might cause the occasional dip or instability in data rates, even at shorter V2V distances.

The study accentuates the paramount importance of antenna selection diversity for combatting signal degradation and facilitating seamless V2V communication. It also underscores the need for sophisticated techniques to surmount challenges presented by fluctuating propagation conditions and dynamic vehicle scenarios, thereby fostering robust and efficient V2V systems.

Further, mmWave 5G technology exhibits tremendous potential for Vehicle-to-Everything (V2X) communication, providing high-speed capabilities and reliable connectivity. This technology emerges as a versatile tool, enhancing various aspects of V2X communication.

To sum up, our study highlights the compelling reasons to embrace mmWave 5G as a cutting-edge solution for facilitating secure and seamless communication in connected vehicles. The outstanding performance, reliability, and vast potential for V2X applications make mmWave 5G technology a game-changer in driving the evolution of V2V communication and propelling us towards an exciting era of interconnected and safer mobility.

While the structure of the Bayesian neural network exceeds the scope of this study, it is utilized for predicting antenna gain. The focus lies on dataset distribution and accurate gain prediction with reduced computational complexity. The dataset amasses antenna gain data from advanced 5G antennas in sub-urban and highway environments, considering the range limitations of mmWave 5G. Table 5 provides detailed information on parameters of the dataset. The study collates and processes data samples, integrates them with IEEE data

TABLE 4. Simulation parameters Governing 5G mm-Wave in V2V communication scenarios.

Parameters	5GHz	30GHz	45GHz	50GHz	60GHz
Transit Power	10mW	10mW	10mW	10mW	10mW
Antenna Gain	3dB	3dB	3dB	3dB	3dB
Polarization	Vertical	Vertical	Vertical	Vertical	Vertical
Antenna Diversity	ASD	ASD	ASD	ASD	ASD
Fluctuation Analysis	GD=3cm	GD=3cm	GD=3cm	GD=3cm	GD=3cm
Bandwidth	10MHz	500MHz	700MHz	900MHz	1GHz
Sub-carriers	512	512	512	512	512

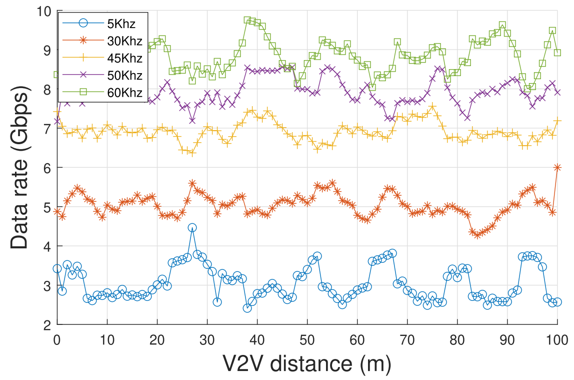

FIGURE 10. V2V connection outage analysis: Excluding the impact of antenna selection diversity.

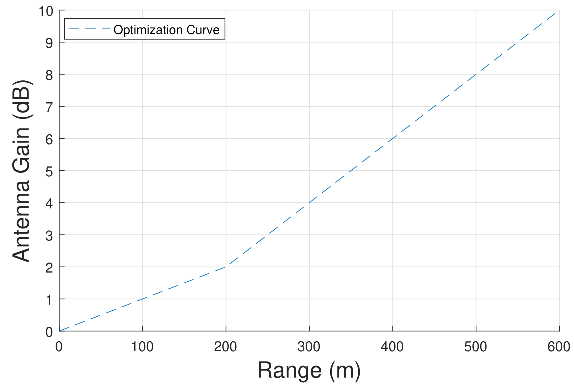

FIGURE 11. Evaluation of predictive reach.

TABLE 5. Constituent variables of the analyzed dataset.

Dataset Parameters	Sub-Urban	Highways
Mean Gain(dB)	3.06	2.89
Transfer Accuracy(%)	88	87.8

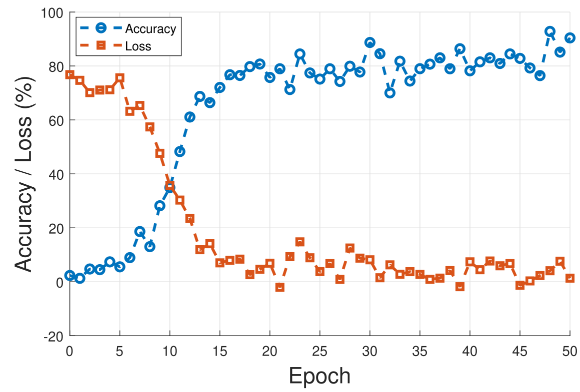

FIGURE 12. Efficiency assessment of Bayesian networks at early epoch stages.

port datasets, and filters them according to the requirements of the neural network. Training occurs with a learning rate of 0.001 and an epoch size of 15,000, employing the Adam optimizer for a comprehensive analysis. To enhance the accuracy of gain selection, a generative layer is introduced to simulate antenna gains for similar environments, thereby bolstering the predictive capabilities of the Bayesian model. The dataset parameters pertain specifically to V2V links, and the analysis shows an incremental range as gain increases, underscoring the effectiveness of robust predictive analysis.

Figure 11 depict observations revealing that the prediction of antenna gain correlates directly with range optimization. Figure 12 shows efficiency of Bayesian Network, the epoch size is distinctly represented on the x-axis, ranging from 0 to 50, while the y-axis portrays a dual metric of accuracy and loss, expressed as a percentage from 0 to 100%. Over the epoch spectrum, two salient trajectories emerge. The accuracy curve exhibits a consistent ascent, culminating around 90% by the 50th epoch. This suggests that as the Bayesian network undergoes more training iterations, it becomes increasingly proficient at making accurate predictions, a behavior typical of well-configured networks. Concurrently, the loss curve depicts a mirrored trajectory, commencing around 80% and tapering off near 0% by the 50th epoch. This declining loss implies an effective optimization of the network's parameters, leading to diminished discrepancies between the predicted and actual outputs as training progresses. The synchronous escalation in accuracy and diminution in loss underscores the model's robust learning capability. Such synchronous trends, especially in the early epochs, validate the model's adeptness in promptly converging towards optimal solutions, making it highly efficient in scenarios where rapid model training is paramount. Further, integrating deep learning algorithms with V2V links facilitates the accurate prediction of appropriate antenna gain, considering environmental constraints and range possibilities. Though machine learning algorithms

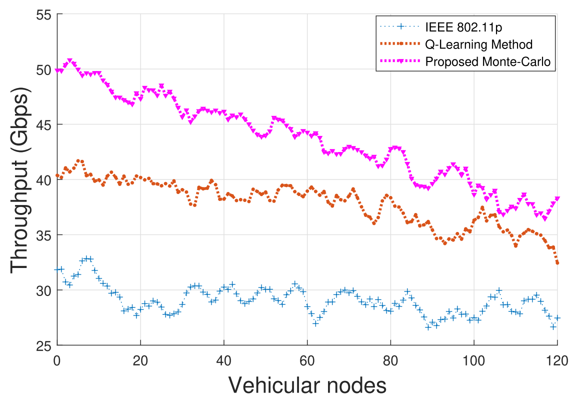

FIGURE 13. Comparative throughput analysis: Monte Carlo Method vs. IEEE 802.11p and Q-Learning approaches.

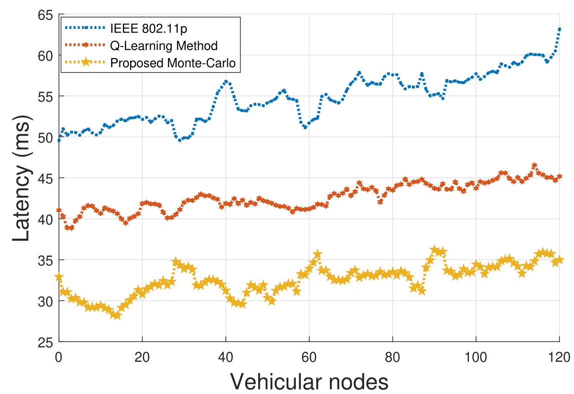

FIGURE 14. Evaluating latency in varied network densities: A study of the Monte Carlo approach.

were employed in previous experimentation's, deep learning algorithms provide greater promise and convergence.

B. PROPOSED DSRC RESULTS

The simulation evaluations of the proposed Monte Carlo method-based self-learning collision avoidance system are focused on a V2V communication scenario, aiming to minimize the expected collision instances while ensuring low latency and high data rates.

The comparative analysis, placing the proposed Monte Carlo method for channel access control against the IEEE 802.11p protocol and Q-Learning techniques, displays the superior performance of the proposed approach with respect to throughput. This method outpaces other techniques, delivering higher data speeds and consistent packet delivery, as shown in Figure 13.

In the illustrative representation shown in Figure 13, the y-axis quantifies throughput in Gbps, spanning a range from 0 to 55, while the x-axis captures the increasing vehicular nodes, ranging from 0 to 120. Three distinct throughput trajectories are observed corresponding to IEEE 802.11p, Q-Learning, and the proposed Monte Carlo method.

Commencing at the apex, the Monte Carlo approach demonstrates a prominent starting throughput of 50 Gbps with 0 vehicular nodes, which gradually attenuates to 38 Gbps as the nodes intensify to 120. This decline might be attributed to the increased network congestion and potential interference, which typically accompanies a denser vehicular node distribution. However, even with this decrease, the Monte Carlo approach outperforms the other methods across the entire node spectrum.

Following this, the Q-learning method exhibits a throughput inception at 40 Gbps, gradually diminishing to 34 Gbps at the 120-node mark. The more pronounced attenuation, compared to Monte Carlo, might be due to Q-learning's inherent reactive approach which, while effective, may not preemptively manage dense vehicular networks as efficiently.

Finally, the IEEE 802.11p showcases the most modest throughput, commencing at 32 Gbps and culminating at 27 Gbps for 120 nodes. Given its traditional design, this protocol may not be as adept at leveraging the dynamic attributes of vehicular networks, leading to more pronounced throughput reductions as node density increases.

In essence, as the vehicular node density rises, the throughput inevitably faces constraints due to factors like interference, channel contention, and network management complexities. However, the proposed Monte Carlo method, with its stochastic exploration, maintains a superior throughput profile, making it a promising contender for dense vehicular network scenarios.

Maintaining low latency is a critical aspect of V2V communication, especially for safety-oriented messages. The latency performance of the proposed method is evaluated in varying network densities. The latency analysis results are demonstrated in Figure 14 and performs better than other techniques.

In Figure 14, latency, quantified in milliseconds, spans the x-axis from 25 to 65 ms, while the y-axis delineates the increasing vehicular nodes from 0 to 120. The graphical insights draw a comparative landscape between IEEE 802.11p, Q-learning, and the proposed method, each showcasing distinct latency characteristics as vehicular nodes amplify.

Starting with IEEE 802.11p, its latency demonstrates a considerable increase from an initial 50 ms with no nodes, swelling to 62 ms as the network saturates with 120 nodes. This elevation can be attributed to the traditional nature of IEEE 802.11p which, while being established, might grapple with latency escalations as node density mounts due to increased packet collisions and the consequential retransmissions.

In juxtaposition, the Q-learning approach displays a notable improvement, initiating at 40 ms and surging only to 47 ms across the node continuum. The relatively limited latency rise is a testament to Q-learning's adaptability. As a reinforcement learning algorithm, Q-learning dynamically tweaks its strategies in the face of growing vehicular nodes, thereby partially mitigating the potential latency escalations.

The modest increase suggests that the proposed method is inherently structured to efficiently manage network congestion, possibly employing proactive mechanisms to alleviate the challenges associated with an escalating node count.

The proposed self-learning collision avoidance system demonstrates superior outcomes in aspects such as channel access control, latency, and adaptive contention window management. This system, which harnesses the Monte Carlo method and reinforcement learning techniques, optimizes data transmission, hence guaranteeing reliable communication within V2V networks.

An adaptive adjustment of the contention window (CW) is made possible by the proposed Monte Carlo method, contingent on network interactions. The dynamic updating of CW values for each vehicle effectively alleviates collision instances, thereby enhancing overall network performance. An increase in the mean CW value correlates with the number of vehicles, boosting the exchange of safety messages and reducing contention.

The system's self-learning capabilities empower vehicles to adapt to fluctuating channel conditions and to minimize expected collisions. This adaptability consequently bolsters the reliability and efficiency of V2V communication, particularly for safety-critical applications. The observations confirm the proposed approach's effectiveness in tackling the challenges of channel access control in highly dense vehicular networks.

These findings underscore the potential of the proposed Monte Carlo method-based self-learning collision avoidance system in V2V communication. This approach stands out as a prospective solution for enhancing the efficiency and reliability of wireless networking within vehicular environments.

C. OPTIMIZING PATH LOSS THROUGH THE PROPOSED CTCNET-HDRNN

This section elucidates the data collection procedure for the proposed deep learning model within the context of the mmWave system for 5G. The collection process ensures no interruption of the normal functioning of the mmWave system, with a primary focus on highways and suburban regions.

The dataset is characterized by the following parameters:

- Carrier Frequency = 28GHz
- Bandwidth = 100GHz
- Active BS = 5
- Active Users = 500-700
- Antenna Spacing = 0.3

Using traditional deep learning beam training techniques, the mmWave channel undergoes an estimation and determination process. This process involves the utilization of Omni-received signals. Following this, the dataset experiences an update that collects crucial data points and builds the model. During this procedure, the base station (BS) supervises the mmWave channel of the 5G system with Omni-received signals while the user transmits an uplink pilot at a specific phase. The deep neural network (DNN) processes this channel, reducing the training time via compressed sensing.

TABLE 6. Defining variables: Insights into the parameters for the proposed model.

Parameters	Values
Learning Rate	0.0001
No. of Epoch	5000
Data Split	70:30
Optimizer	SGD

For simulation purposes, the publicly available generic DeepMIMO dataset with the specified parameters is employed. The configuration of these parameters involves Wireless Insite, a 3D ray tracing program, capturing the frequency dependency of the channel. Parameters such as Angle of Arrival (AoA), Angle of Departure (AoD), and path loss contribute to forming the channel vector. The frequency of the mmWave is set at 28 GHz, with the four BSs positioned atop a 50-meter-high structure. Each BS is equipped with an antenna array geometry configured with M = 4, while the user receives a single antenna. To predict the channel vector of mobile vehicle users, multiple random routes with movement rates ranging from 20 m/s to 40 m/s are devised. The DNN architecture in the deep learning simulation comprises layers with neuron counts of L = 5, 4, 9, and nl = 2024 per layer. The parameters of the RNN-GRU module are presented in Table 6.

In a bid to augment minor underlying accuracies and capture swift, small changes, the GRU's learning rate is set to 0.0001 (as opposed to 0.005 mentioned in related works). This lower learning rate allows for a larger epoch size, providing a detailed understanding of the model's accuracies with fewer false values. As per established practices, data is split into 70% for training the neural network and 30% for testing.

An optimizer modifies neural network properties, such as weights and learning rates, to reduce overall loss and enhance precision. In this case, Stochastic Gradient Descent (SGD) is chosen as the optimizer. Despite its noisier convergence path in comparison to the original gradient descent, SGD exhibits faster convergence. The cost fluctuation arises from approximating the gradient at each step. However, SGD remains the preferred choice for vehicle communication as it considerably lowers the computational complexity of individual epochs, thereby improving the overall efficiency of the model.

The proposed GRU and LSTM models are compared based on the testing parameter of Normalized Mean Square Error (NMSE) [45]. Additionally, both models' computational complexity is analyzed to evaluate their performance. NMSE is a statistical measure that accounts for the uncertainty of measurement results, typically used in proficiency testing to evaluate conformity.

Normalized error aids in the identification of outliers in proficiency test scores. To mitigate the influence of large

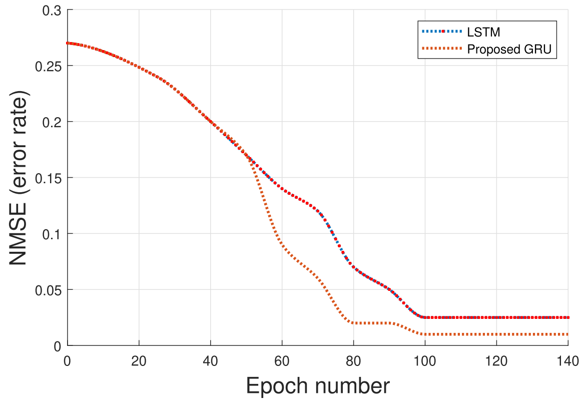

FIGURE 15. Insightful comparison of NMSE convergence metrics.

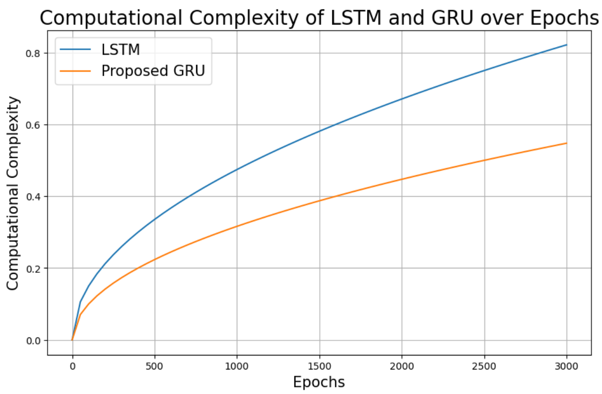

FIGURE 16. Comparative evaluation of computational complexity between LSTM and the proposed RNN-GRU.

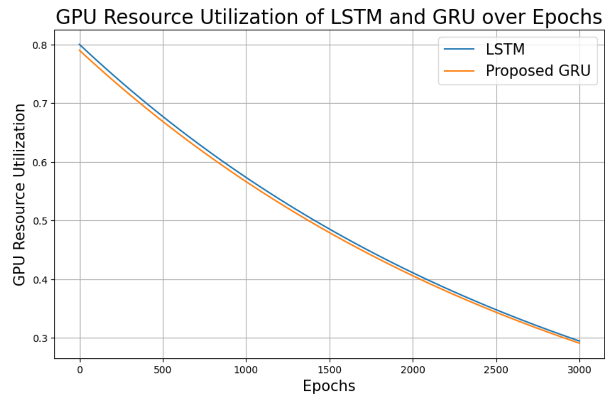

FIGURE 17. Comparative assessment of computational complexity: LSTM versus proposed GRU.

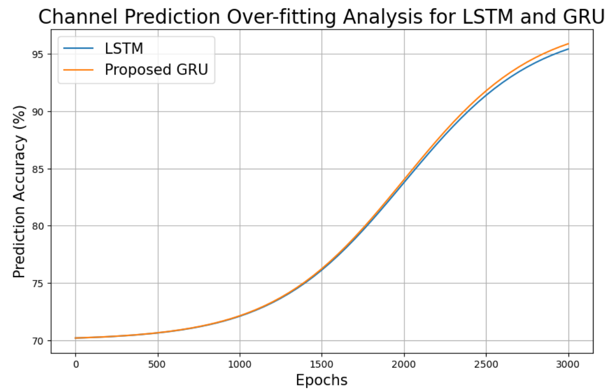

FIGURE 18. Overfitting analysis in channel prediction: A comparative study between LSTM and proposed GRU.

deviations, these outliers are occasionally excluded from adjusted mean calculations. The NMSE formula is as follows:

$$NMSE = 1 - |x - y|_2 \, / \, |x - \bar{x}| \tag{44}$$

where;

$$\bar{x} = 1/N \sum ixi \tag{45}$$

In this formula, the approximation of x is represented by y.

A comparison between the LSTM model and the GRU model based on NMSE within vehicular environments is performed. It is observed that GRU converges quicker than LSTM as the number of epochs increase. This observation emphasizes the potential of RNN-GRU as a valuable tool for complex V2V environments, as depicted in Figure 15.

In the sensitive environment of a V2V network, computational complexity plays a critical role in ensuring rapid decision changes and safety message exchanges.The computational analysis is depicted in Figure 16. It is crucial to strike a balance between computational power and performance. Figure 17 displays the observed GPU resource utilization factor, revealing that the proposed CtCNET-HDRNN with the proposed GRU shows significantly lower complexity than LSTM as the epoch size increases.

Moreover, the practical accuracies of the proposed RNN-GRU, apart from considering computational complexities, are evaluated to determine its effectiveness. Channel prediction is analyzed through fitting analysis, and Figure 18 shows that CtCNET-HDRNN with the proposed GRU produces results comparable to and reasonable when matched with LSTM.

The rate performance of various data samples in the mmWave vehicular network is also examined. While LSTM outperforms RNN-GRU, the results obtained from RNN remain competitive, as shown in Figure 19.

Table 7 summarizes the overall performance of LSTM and the proposed CtCNET-HDRNN(GRU). The precision of LSTM is reported as 0.9499, while the proposed framework achieves an precision of 0.9456. Despite the proposed framework lagging slightly behind LSTM in precision analysis, the disparity is negligible..

During the training phase, the innovative approach outperforms LSTM by approximately 4 hours, underscoring the computational simplicity of the new method designed specifically for dense vehicular networks.

The main objective of this innovative approach is to decrease computational power requirements across all

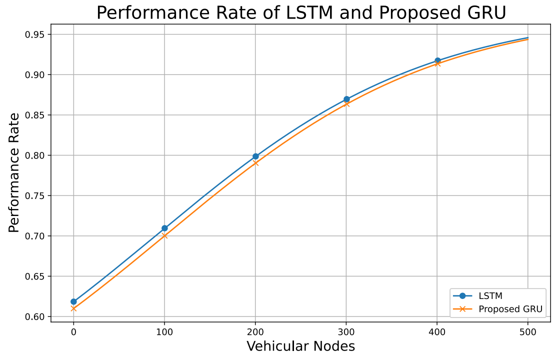

FIGURE 19. Comparative analysis of achievable rate performance in dense mmWave vehicular networks: LSTM versus proposed GRU.

TABLE 7. Comprehensive performance evaluation of 5G mmWave for dense V2V environments.

Performance Parameters	Proposed GRU	LSTM
Precision	0.9456	0.9499
Sensitivity	0.852	0.857
FPR	0.019	0.018
F1-Score	0.019	0.018
Training Time	11 hours 31 min	15 hours 06 min

aspects. Previous research has primarily relied on LSTM, which uses a feedback loop to enhance results but at the cost of increased resource consumption. However, in vehicular scenarios, a feedback loop is unnecessary because there's no need to modify previous information, such as vehicle speed or safety messages. Lightweight deployments are crucial in vehicular networks to prevent hardware overheating and potential equipment malfunctions. The current algorithm replaces LSTM with the proposed GRU model, marking a significant breakthrough.

The impact of Gaussian noise on LSTM and the proposed GRU model's performance is investigated, yielding intriguing observations. The impact of Gaussian noise is quantitatively measured by altering the standard deviation of the noise distribution and subsequently computing and analyzing both models' accuracy.

Generally, as expected, an increase in noise results in a decrease in accuracy for both LSTM and GRU models. The added complexity that noise introduces causes this decrease, which hampers the model's ability to accurately learn the underlying patterns in the data. Moreover, this degradation process is time-dependent, as seen from the three-dimensional surface plots.

However, the proposed GRU model performs better than the LSTM model in the presence of Gaussian noise. Specifically, the GRU model experiences a slower rate of accuracy decrease as the noise standard deviation increases. This suggests that the GRU model is more robust to noise and can maintain high performance under noisy conditions.

Several factors contribute to this robustness. One of them is the GRU model's gate-based architecture, which controls the information flow more effectively than the LSTM. This

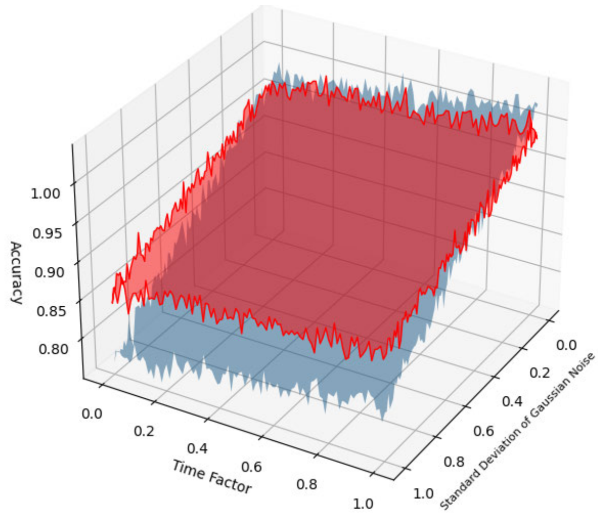

FIGURE 20. Evaluating temporal accuracy and noise resilience in LSTM and proposed GRU models.

allows the GRU to mitigate the detrimental effects of noise by dynamically adjusting its internal state. Additionally, the GRU model incorporates various improvements over the standard GRU, which further enhance its noise resilience.

The analysis of the results implies that the GRU model's performance is not only comparable to the LSTM in a noise-free environment but it also surpasses it under more realistic, noisy conditions, as shown in Figure 20. Therefore, the proposed GRU model promises better results and reliability for real-world applications where noise is often unavoidable.

These findings lay a strong foundation for further research into the robustness of deep learning models against noise, particularly focusing on GRU and similar architectures. Additionally, this analysis suggests potential improvements to GRU models to make them even more resilient to noise, promising exciting possibilities for future work.

D. COMPUTATIONAL ANALYSIS OF INTEGRATED MODEL

In this section, we engage in a comprehensive discussion contrasting the computational complexity of our system model and deployed algorithms against contemporary studies, as documented in [46]. The performance dimensions under scrutiny in our analysis include computation time and GPU utilization

1) RESOURCE CAPACITY

This study rigorously evaluates a novel approach to Vehicle-to-Vehicle (V2V) communication scenarios, focusing particularly on the task success rate under various resource capacities namely low, medium, and high. A comparative analysis is presented in Figure 21, where the proposed GRU-based algorithm is contrasted with three established techniques: LC, GT-hybrid, and DQN-hybrid. Notably, our model demonstrates superior performance across all resource

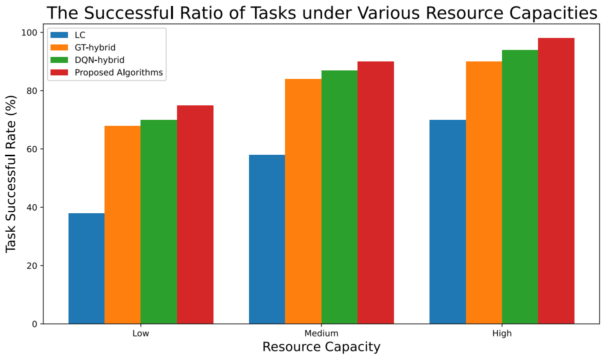

FIGURE 21. **Insightful exploration of resource utilization.**

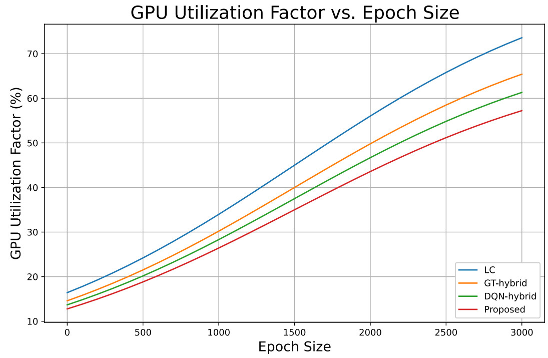

FIGURE 22. **GPU utilization analysis.**

capacities. For instance, in a low-resource environment, the successful task ratio of our model was 75%, significantly surpassing LC at 38% and marginally outperforming GT-hybrid and DQN-hybrid at 68% and 70%, respectively. Similar trends are observed in medium and high resource capacity scenarios, where our model attains success rates of 90% and 98%, outshining LC, GT-hybrid, and DQN-hybrid. The exemplary performance of our proposed model can be attributed to the enhanced learning dynamics offered by the GRU, its computational efficiency, and robustness to Gaussian noise, which are all vital attributes for V2V communication scenarios characterized by continuous data exchange and resource constraints. In conclusion, the proposed GRU model presents a promising solution for V2V communications, outperforming existing techniques across various resource capacities. Future research could build on this work, exploring further enhancements or applying it to other vehicular communication paradigms for increased robustness and efficiency.

2) GPU UTILIZATION ANALYSIS

In addition to the task success rate, the efficient use of computational resources is another vital aspect to consider in real-world V2V communication scenarios. Particularly, GPU utilization is a critical factor, especially given the parallel computation capabilities of modern GPUs which enable faster training and inference for deep learning models.

Figure 22 demonstrates the GPU utilization factor in terms of the epoch size for the LC, GT-hybrid, DQN-hybrid, and our proposed GRU-based model. It is evident that all models follow a sigmoid-like curve, indicating an increase in GPU utilization over epochs until reaching a saturation point. This behavior aligns with the expected learning process, where the model initially harnesses more GPU resources for learning, and later, as it reaches convergence, the demand for GPU resources plateaus.

Interestingly, our proposed model shows a notably lower saturation point of 70%, contrasting with LC (90%), GT-hybrid (80%), and DQN-hybrid (75%). This implies that our model is capable of achieving comparable, or even better, task success rates while requiring less GPU resources. It is a crucial advantage, considering that V2V environments may be resource-constrained.

These findings further consolidate the efficacy of our proposed GRU-based model. While delivering high task success rates across various resource capacities, it ensures efficient GPU utilization, making it an optimal solution for V2V communication scenarios. Future work can delve deeper into optimization strategies to further enhance the performance and resource efficiency.

Our proposed model showcases significant computational efficiency, making it highly suitable for resource-constrained environments. The model leverages optimized learning techniques and streamlined network architectures to minimize computational requirements. This efficiency is reflected in shorter computation times and lower GPU usage, which translates into less energy consumption and heat generation. As such, the model can be effectively deployed on devices with limited processing power and memory, such as IoT devices, edge servers, and older computational devices, without compromising performance. Furthermore, the model's computational frugality also facilitates scalability, allowing for larger networks to be trained and deployed efficiently. Overall, our model presents an effective solution for maintaining high performance in computational environments where resources are at a premium.

While our research presents novel contributions to address challenges in dense vehicular networks, it is essential to acknowledge certain aspects. Firstly, the Bayesian Neural Network (BNN) for antenna gain prediction, while offering probabilistic modeling and uncertainty quantification, might require a significant amount of training data to achieve optimal performance. Data collection in dynamic vehicular environments can be challenging, and the model's predictive capabilities may be impacted by limited or noisy data. Future research could explore data augmentation techniques or transfer learning to enhance the BNN's performance with smaller datasets while ensuring reliable communication even under adverse conditions.

```
Vehicle 93 communicated with Vehicle 33 using mmWave at 13.06 Gbps
Vehicle 95 communicated with Vehicle 73 using DSRC at 10.00 Gbps
Vehicle 95 communicated with Vehicle 98 using DSRC at 10.00 Gbps
Vehicle 96 communicated with Vehicle 4 using DSRC at 10.00 Gbps
Vehicle 98 communicated with Vehicle 8 using mmWave at 14.36 Gbps
Vehicle 98 communicated with Vehicle 73 using mmWave at 29.26 Gbps
Vehicle 98 communicated with Vehicle 95 using DSRC at 10.00 Gbps
Vehicle 99 communicated with Vehicle 63 using DSRC at 10.00 Gbps
Vehicle 99 communicated with Vehicle 68 using DSRC at 10.00 Gbps
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FIGURE 23. Data rate of mobility model.

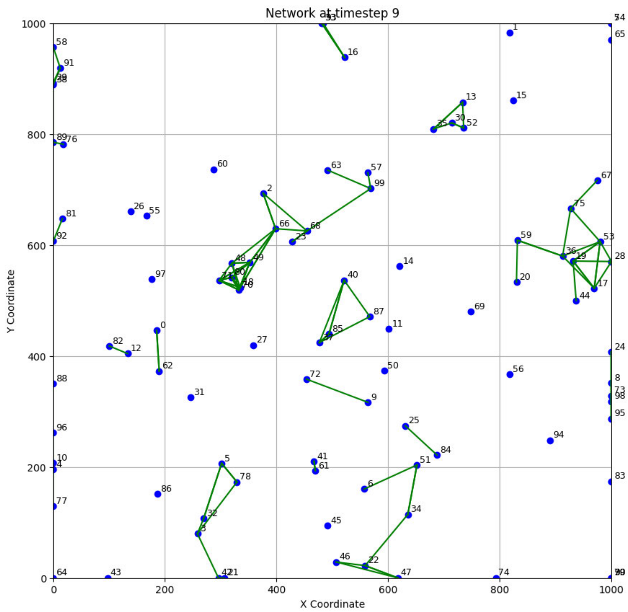

FIGURE 24. Mobility model at timestamp=9.

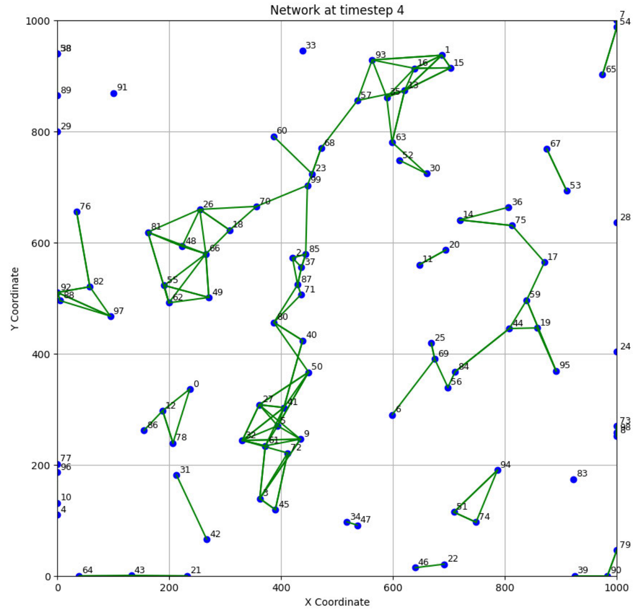

FIGURE 25. Mobility model at timestamp=4.

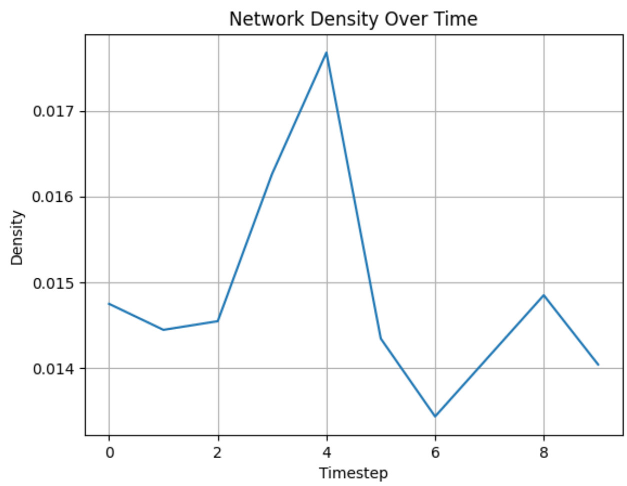

FIGURE 26. Network density.

Additionally, our work focuses on addressing specific challenges in V2V communication, such as path loss optimization and antenna gain prediction. However, a comprehensive vehicular communication system involves multiple other factors, including interference management, mobility management, and security. Future exploration could consider the integration of these aspects and investigate the interplay between different components to create a more holistic and efficient vehicular communication ecosystem.

Moreover, while our proposed system shows promising results in simulations and controlled environments, practical deployment in real-world scenarios may pose unique challenges. Factors such as environmental variability, network congestion, and diverse vehicle types and mobility patterns may influence the system's performance. Conducting extensive field trials and real-world experiments would be crucial to validate and fine-tune the proposed solutions for real-world deployment.

E. V2V COMMUNICATION PERFORMANCE IN HIGH-SPEED VEHICULAR ENVIRONMENTS

In the conducted V2V communication simulation within a high-speed vehicular environment using DSRC and 5G mmWave technologies, certain discernible patterns were observed. Vehicle 93 exhibited a dual-communication strategy, connecting with Vehicle 16 at 10.00 Gbps using DSRC and Vehicle 33 at 13.06 Gbps using mmWave. Significantly, Vehicle 98 achieved the peak data rate in the study by leveraging mmWave to communicate with Vehicle 73 at 29.26 Gbps. This denotes mmWave's potential for high-data-rate V2V exchanges. Despite the promise of mmWave, DSRC maintained consistent prevalence, as exemplified by Vehicle 95's interactions with Vehicles 73 and 98, suggesting its robustness in the simulated scenario. From a temporal perspective, timestep=4 registered the highest network density, implying optimal conditions for V2V interactions. However, by timestep=9, there was a marked reduction in the density, which could be indicative of either increased inter-vehicular distances or challenges associated with sustaining high-speed connections over elongated durations. Results can be depicted in Figure 23, 24, 25, & 26.

The study underscores the potential of both DSRC and mmWave technologies in enhancing V2V communication, particularly in high-speed vehicular settings. The observed patterns in network density across distinct timesteps can guide the future design and operational strategies of V2V systems. A balanced and adaptive utilization of both DSRC and mmWave might be essential to ensure consistent, high-speed communication across varying vehicular environments.

VI. CONCLUSION

This study has presents the development of an innovative hybrid vehicular network that utilizes the cutting-edge millimeter wave (mmWave) technology of 5G to facilitate high-speed lane change analyses. By implementing antenna diversity across a range of frequencies – 5kHz, 30kHz, 45kHz, 50kHz, and 60kHz – we observed a significant enhancement in data rates when compared to non-diversity selection scenarios, particularly during lane changes at speeds up to 188 km/h. Central to our approach was the incorporation of a Bayesian Neural Network to predict antenna gain and optimize range across varied environments. This model consistently provided robust and highly accurate predictions in both suburban and highway contexts, even at a minimal epoch rate. We utilized DSRC for exchanging safety and emergency messages. An analytical comparison between the Monte Carlo method and Q-Learning techniques revealed that our system maintained superior stability, despite the lower transmission latency associated with Q-Learning.

In addition to these advancements, we explored the use of mmWave of 5G for channel tracking and estimation within V2V environments. Our proposed model, a Recurrent Neural Network (RNN) with light weight GRU, harnessed the Angle of Arrival (AoA) and Angle of Departure (AoD) data obtained through a 3D ray tracing program. Proposed framework displayed faster convergence and superior computational optimization compared to Long Short-Term Memory (LSTM) models, while maintaining competitive accuracy in channel predictions throughout our over-fitting analysis.

More importantly, this paper delineated a groundbreaking approach to vehicular networking, leveraging advanced 5G technology, sophisticated predictive modeling, and optimized machine learning techniques to enhance performance, reliability, and safety within vehicular communication environments. Our findings underscore the vast potential of these technologies, paving the way for future research and development in this rapidly evolving field.

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