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Improving V2V Communication Reliability in Dynamic Vehicular Networks: A Software-Defined Radio-Based Approach

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ABSTRACT

Smart Transportation Systems (STS) leverage Vehicle-to-Vehicle (V2V) communication to enhance road safety, traffic efficiency, and urban mobility. However, ensuring reliable V2V communication remains challenging due to signal power instability, environmental interference, and scalability limitations. This study explores the optimization of V2V communication using Software Defined Radio (SDR) technology, which offers a cost-effective and adaptable approach for real-time signal processing. An SDR-based V2V communication system was developed using GNU Radio and HackRF One, with signal power calibration conducted through comparative measurements involving a Spectrum Analyzer across varying distances (3-15 meters) and environmental conditions. Performance evaluation focused on Bit Error Rate (BER) and Signal-to-Noise Ratio (SNR) under different vehicle speeds (20-40 km/h). Results indicate that increasing distance leads to signal degradation, with BER reaching 36.83% and SNR dropping to -3.17 dB, emphasizing the need for adaptive signal optimization techniques. While SDR-enabled calibration provided accuracy in signal measurements, environmental factors such as multipath interference and atmospheric attenuation significantly impacted communication reliability. Despite its flexibility, the system exhibited high BER and limited communication range, necessitating further enhancements through adaptive modulation schemes, machine learning-based power control, and hybrid 5G-DSRC integration. The study highlights SDR's potential for improving V2V communication while addressing key limitations in urban mobility networks. Future research should focus on enhancing scalability, security, and energy efficiency through advanced signal processing techniques. This study contributes to developing next-generation STS by providing empirical insights into SDR-based V2V communication optimization, supporting safer and more efficient transportation systems.

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1. INTRODUCTION

The increasing demand for efficient and safe urban mobility has led to the rapid adoption of Smart Transportation Systems (STS), which integrate advanced technologies such as Internet of Things (IoT), Artificial Intelligence (AI), and wireless communication to optimize transportation infrastructure [1], [2]. A critical component of STS is Vehicle-to-Vehicle (V2V) communication, which facilitates real-time information exchange between vehicles to improve road safety, reduce congestion, and enhance traffic efficiency [3]. Through Dedicated Short-Range Communication (DSRC) and Cellular Vehicle-to-Everything (C-V2X), V2V communication enables vehicles to share essential data such as speed, position, and direction, supporting advanced driver assistance systems (ADAS) and autonomous driving technologies [4], [5]. However, despite the promising advantages of V2V communication, several challenges persist, particularly in signal power optimization, which directly impacts communication reliability, latency, and energy efficiency in dynamic vehicular environments [6].

Several approaches have been proposed to enhance V2V communication efficiency, primarily focusing on improving network connectivity and reducing interference. The Dedicated Short-Range Communication (DSRC) protocol, based on IEEE 802.11p, has been widely utilized due to its low latency and high reliability in short-range communication [7]. However, DSRC faces scalability issues and congestion in high-density traffic scenarios [8]. Cellular-V2X (C-V2X) has been introduced as an alternative to address these limitations, leveraging existing cellular networks for broader coverage and better performance [5], [9]. While C-V2X offers improved reliability, its dependence on cellular infrastructure raises concerns regarding network availability and latency in high-mobility scenarios [10]. The emergence of 5G NR V2X presents a promising solution, but interoperability, deployment costs, and spectrum allocation challenges remain unresolved [4].

To further improve V2V communication performance, researchers have explored adaptive power control mechanisms to optimize transmission power and mitigate interference. Traditional fixed-power transmission models suffer from inefficiencies in dynamic vehicular environments, where varying distances and obstacles affect signal propagation [11]. Recent studies have introduced adaptive power control algorithms that dynamically adjust transmission power based on network conditions, signal quality, and interference levels [12]. For instance, full-duplex communication has been proposed to enhance spectral efficiency, enabling vehicles to transmit and receive signals simultaneously [13]. Additionally, resource allocation schemes for Device-to-Device (D2D) communication have been implemented to optimize energy consumption and reduce transmission delays in high-mobility environments [14]. However, these methods often lack adaptability in rapidly changing urban environments, where traffic density, road infrastructure, and environmental conditions significantly impact communication quality [15].

In recent years, Machine Learning (ML) and Artificial Intelligence (AI) techniques have gained attention for their potential to enhance V2V signal power optimization. ML-driven models can predict optimal transmission parameters based on historical data, improving signal-to-noise ratio (SNR), bit error rate (BER), and packet error rate (PER) [16]. AI-based power control systems have demonstrated promising results in adjusting transmission power in real time adapting to changing traffic conditions and environmental factors [17]. Furthermore, integrating Software Defined Radio (SDR) technology allows for flexible, reconfigurable wireless communication systems that dynamically adjust transmission settings [18]. Despite these advancements, existing studies have not fully explored the synergy between SDR and AI-based power control to optimize V2V communication under varying urban conditions. Additionally, standardized evaluation frameworks for comparing different power optimization techniques remain underdeveloped, limiting the generalizability of previous research findings [11].

While previous research has focused on DSRC, C-V2X, and ML-based transmission optimization, limited studies have investigated the integration of software-defined radio (SDR) and AI-driven power control mechanisms in V2V communication. Furthermore, existing adaptive power control models often fail to account for real-time urban mobility challenges, leading to suboptimal performance in practical applications. Therefore, this study aims to address these gaps by developing a novel SDR-based V2V communication framework that utilizes AI-driven power control optimization to enhance transmission reliability and efficiency. The primary objectives of this research are to analyze the performance of V2V communication under varying environmental conditions, develop an adaptive AI-powered signal power optimization algorithm, and evaluate the effectiveness of the proposed framework using key performance metrics such as SNR, BER, and PER. By integrating SDR technology with AI-driven transmission optimization, this study advances intelligent transportation networks, improving road safety, energy efficiency, and connectivity in future Smart Transportation Systems (STS).

2. METHOD

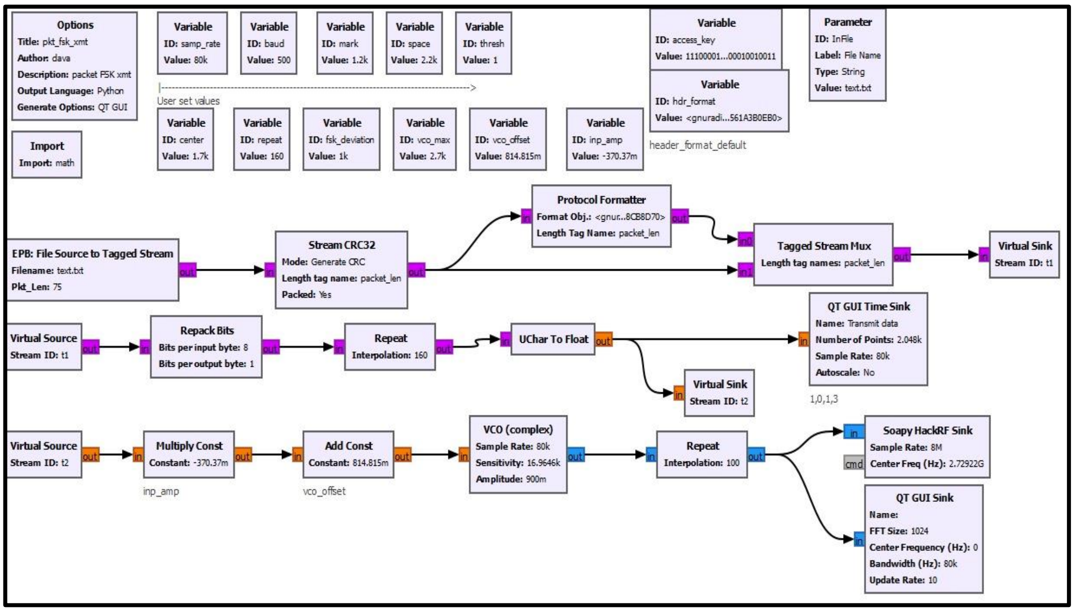
2.1 System Architecture and Signal Processing Implementation

This study presents a systematic approach to developing and evaluating a Vehicle-to-Vehicle (V2V) communication system using Software Defined Radio (SDR) technology. The methodology addresses key challenges in mobile wireless communication, focusing on the adaptability and robustness of V2V systems within Smart Transportation Systems (STS). The implementation leverages GNU Radio, an open-source platform for real-time signal processing, and HackRF One SDR devices for data transmission and reception. The system architecture was developed to facilitate real-time V2V communication using Frequency Shift Keying (FSK) modulation, which was selected due to its resilience to noise and interference, making it highly suitable for dynamic vehicular environments [19].

2.1.1 Transmission System Design

The GNU Radio-based transmission pipeline was developed to wirelessly encode, modulate, and transmit data packets. The data flow and processing blocks are illustrated in Figure 1, detailing each signal transformation and transmission stage.

- File Source & Protocol Formatter: Generates vehicle identification (ID), type, and status, simulating real-world V2V communication.
- Stream CRC32: Implements Cyclic Redundancy Check (CRC) to ensure data integrity and error detection.
- Interpolation & Frequency Adjustment: Modifies signal sampling rate and frequency shift to match HackRF One SDR hardware.
- Voltage-Controlled Oscillator (VCO): Modulates the baseband signal into wireless RF transmission.
- HackRF Sink: Transmits the processed signal via the SDR device.



Options
Title: pkt_fsk_xmt
Author: dava
Description: packet FSK xmt
Output Language: Python
Generate Options: QT GUI

Import
Import: math

Variable **ID:** samp_rate **Value:** 80k
Variable **ID:** baud **Value:** 500
Variable **ID:** mark **Value:** 1.2k
Variable **ID:** space **Value:** 2.2k
Variable **ID:** thresh **Value:** 1

User set values

Variable **ID:** center **Value:** 1.7k
Variable **ID:** repeat **Value:** 160
Variable **ID:** fsk_deviation **Value:** 1k
Variable **ID:** vco_max **Value:** 2.7k
Variable **ID:** vco_offset **Value:** 814.815m
Variable **ID:** inp_amp **Value:** -370.37m

Variable **ID:** access_key **Value:** 11100001...00010010011
Variable **ID:** hdr_format **Value:** <gnuradi...561A3B0EB0>
header_format_default

Parameter
ID: InFile
Label: File Name
Type: String
Value: text.txt

EPB: File Source to Tagged Stream
Filename: text.txt
Pkt_Len: 75

Stream CRC32
Mode: Generate CRC
Length tag name: packet_len
Packed: Yes

Protocol Formatter
Format Obj.: <gnur...8CB8D70>
Length Tag Name: packet_len

Tagged Stream Mux
Length tag names: packet_len

Virtual Sink
Stream ID: t1

Virtual Source
Stream ID: t1

Repack Bits
Bits per input byte: 8
Bits per output byte: 1

Repeat
Interpolation: 160

UChar To Float

QT GUI Time Sink
Name: Transmit data
Number of Points: 2.048k
Sample Rate: 80k
Autoscale: No
1,0,1,3

Virtual Sink
Stream ID: t2

Virtual Source
Stream ID: t2

Multiply Const
Constant: -370.37m
inp_amp

Add Const
Constant: 814.815m
vco_offset

VCO (complex)
Sample Rate: 80k
Sensitivity: 16.9646k
Amplitude: 900m

Repeat
Interpolation: 100

Soapy HackRF Sink
Sample Rate: 8M
Center Freq (Hz): 2.72922G

QT GUI Sink
Name:
FFT Size: 1024
Center Frequency (Hz): 0
Bandwidth (Hz): 80k
Update Rate: 10

Figure 1: GNU radio flowgraph for V2V transmitter system

2.1.2 Reception System Design

The GNU Radio-based reception pipeline was implemented at the receiving end for signal acquisition, demodulation, and error detection. Figure 2 outlines the key processing blocks, ensuring accurate data recovery and validation.

- HackRF Source: Captures incoming wireless signals and forwards them to the processing chain.
- Quadrature Demodulation & Frequency Filtering: Removes unwanted noise and extracts modulated signals.
- Message Decoding & Error Correction: Recovers transmitted data and applies CRC validation.
- GUI and Data Sinks: Displays real-time signal parameters and logs received packets.

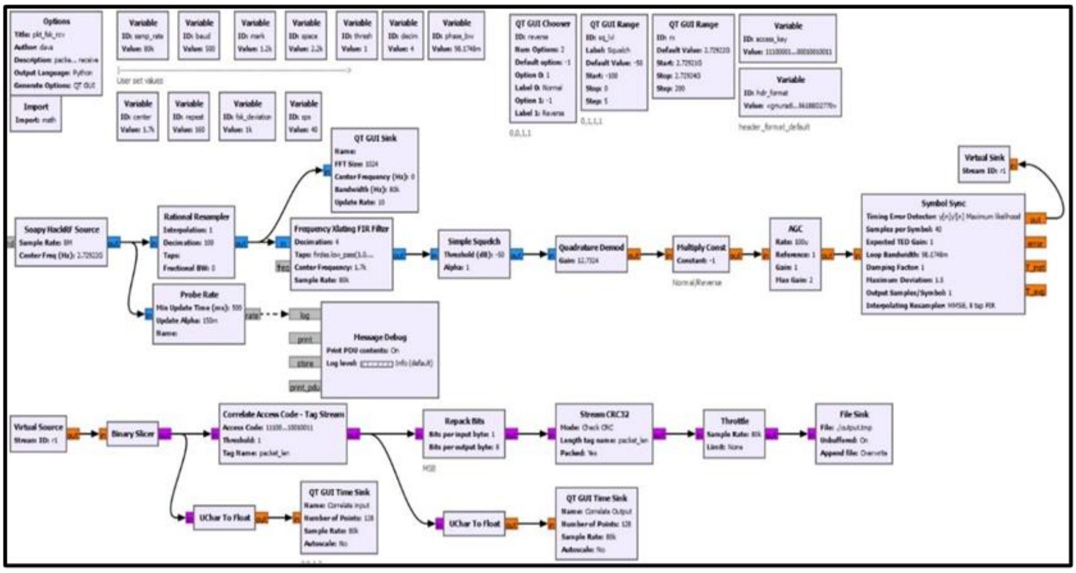


Figure 2: GNU radio flowgraph for V2V receiver system

2.2 Hardware Configuration and Experimental Setup

The hardware configuration involved two HackRF One SDR devices, one of which functioned as a transmitter (TX) and the other as a receiver (RX). Both devices were controlled via laptops running GNU Radio, enabling real-time adaptive transmission. The physical setup, including antenna positioning and transmission layout, is depicted in Figure 3.

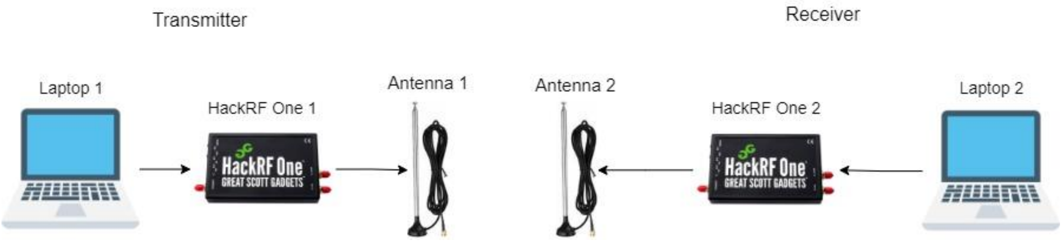


Figure 3: Hardware setup for V2V communication using hackRF one SDR devices

Field experiments were conducted using two moving vehicles equipped with SDR-based V2V communication systems to evaluate system performance under real-world vehicular mobility conditions. The experimental conditions included:

- Vehicle Speed Variations: 20–40 km/h.
- Inter-Vehicle Distance Ranges: 3–6 meters.
- Testing Environments: Open roads and urban areas with signal interference.

2.3 Performance Evaluation and Data Analysis

The system's communication efficiency was assessed using key performance indicators, including:

- Bit Error Rate (BER): Evaluates data transmission accuracy by comparing received signals to the original dataset.
- Signal-to-Noise Ratio (SNR): Measures signal quality and resilience against external interference.

Statistical methods were applied to quantify relationships between system parameters, such as speed, distance, interference, and the corresponding performance metrics (BER, SNR). Real-time spectrum visualization tools within GNU Radio were used to analyze transmission stability and optimize signal strength.

2.4 Reproducibility and Contributions

The methodology outlined in this study provides a replicable and adaptable framework for SDR-based V2V communication. Integrating GNU Radio with HackRF One SDR devices enables real-time reconfiguration and performance optimization under dynamic vehicular conditions. The insights gained from this research contribute to the design of next-generation Smart Transportation Systems (STS), ensuring safer, more efficient vehicular networks.

3. RESULTS AND DISCUSSIONS

This section presents the experiments' findings and analyzes the data obtained. The research results include data collection from the developed communication system, encompassing both the transmitter and receiver. The analysis aims to evaluate system performance, identify strengths, and highlight weaknesses.

3.1 Experimental Setup and Equipment

The experimental setup consisted of two laptop computers, HackRF One devices, and antennas for transmission and reception. The communication system utilized Frequency Shift Keying (FSK) modulation. The system was tested indoors and outdoors, with data transmission observed in real time through visualized graphs.

3.2 Transmission and Reception Data Visualization

When the transmitter is operational, the transmitted and received data is displayed on the screen. This visualization provides a real-time overview of data flow within the communication system under test.

- Transmit Data Representation: FSK modulation observes The signal waveform during transmission. The FSK method encodes binary data by shifting frequencies, where a higher frequency represents a binary "1" (mark), and a lower frequency represents a binary "0" (space).
- Receive Data Representation: The received signal undergoes processing to extract the transmitted binary data. The visualization includes a correlate input graph (showing modulated signals), a correlate output graph (demodulated signals), and a constellation diagram (depicting frequency and phase variations).

3.3 Bit Error Rate (BER) Analysis

The flowgraph was designed to measure BER by comparing transmitted and received data. The results indicate:

- Total Bits Sent: 262,144
- Total Bit Errors: 92,816
- BER: 35.4%
- Logarithmic BER Representation: -0.450917

Figure 1 presents the recorded BER values for each test case to analyze the BER across different test cases further. The BER analysis highlights significant variations in the error rate depending on environmental factors and mobility conditions, as illustrated in Figure 1. One potential approach to mitigating these errors is using adaptive power control mechanisms, which dynamically adjust transmission power based on real-time network conditions. Previous studies have demonstrated that adaptive power control can significantly reduce BER by optimizing signal strength in response to channel variations, improving overall communication reliability [11], [12]. The highest BER (37.92%) was recorded in test 15, where high mobility likely contributed to increased transmission errors. The lowest BER (33.96%) was observed in test 8, indicating better stability under certain conditions.

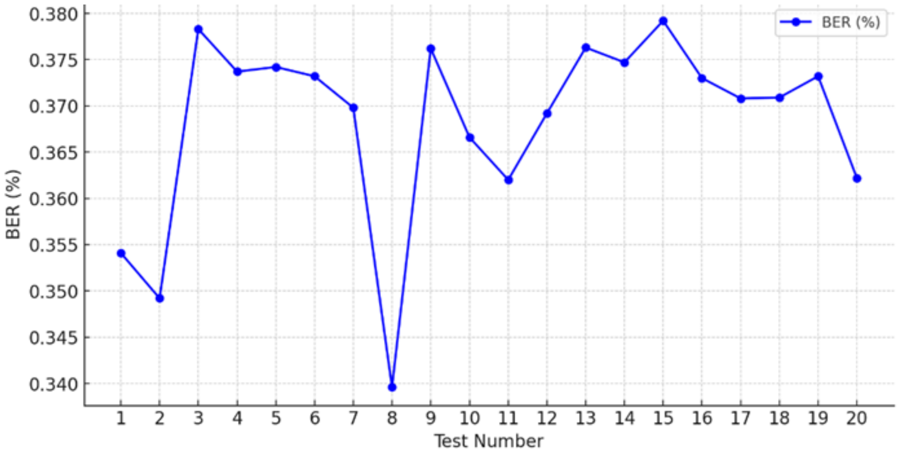


Figure 1. Bit error rate (BER)

3.4 Power Analysis Testing

Signal strength measurements were conducted at distances ranging from 3 to 15 meters using a spectrum analyzer and HackRF One. The findings in Table 1 reveal that as the distance between the transmitter and receiver increases, the signal power decreases. The indoor environment generally showed higher signal strength than outdoor settings due to reduced interference.

Table 1. Power analysis results

Distance (m)	Indoor Spectrum Analyzer (dBm)	Indoor HackRF (dBm)	Outdoor Spectrum Analyzer (dBm)	Outdoor HackRF (dBm)
3	-58.8	-16.46	-60.99	-21.64
4	-59.22	-18.19	-65.2	-25.09
5	-56.12	-20.49	-62.81	-27.39
6	-60.95	-21.06	-65.85	-28.54
7	-59.12	-23.24	-62.25	-28.83
8	-67.9	-23.56	-65.72	-32.18
9	-61.26	-28.03	-64.68	-35.36
10	-54.72	-30.65	-65.49	-40.79
11	-80.13	-32.42	-59.02	-44.46
12	-64.7	-36.34	-71.16	-48.37
13	-67.96	-38.41	-70.36	-50.52
14	-64.04	-41.66	-76.8	-52.84
15	-66.81	-42.92	-70.85	-53.27

The plot above illustrates the signal power trends in both indoor and outdoor environments. As expected, signal strength degrades with increasing distance, with indoor measurements showing less attenuation than outdoor measurements due to reduced environmental interference.

3.5 Packet Loss Evaluation

Packet loss was analyzed by assessing data transmission accuracy at varying distances and vehicle speeds. The packet loss was calculated using:

- Lowest Packet Loss: 8.05% (3m, 25 km/h)
- Highest Packet Loss: 37.25% (5m, 40 km/h)
- Average Packet Loss: 21.59%

3.6 Signal-to-Noise Ratio (SNR) Analysis

SNR was computed using the relationship between BER and Eb/N0 (energy per bit to noise power density ratio), converted to dB using:

- Best SNR: -2.89 dB (5m, 40 km/h)
- Worst SNR: -3.57 dB (3m, 25 km/h)
- Average SNR: -3.16 dB

The results confirm that FSK-based V2V communication experiences significant performance degradation over distance and speed variations. Implementing adaptive power control can help address these challenges by ensuring optimal power allocation to minimize transmission errors. Integrating AI-driven power control mechanisms with Software Defined Radio (SDR) can dynamically optimize transmission parameters, leading to lower BER and improved communication resilience in high-mobility environments [13], [20]. Future research should explore these solutions further to enhance the robustness of V2V communication networks. These findings align with previous research, Power Control for Full-Duplex D2D Communications Underlaying Cellular Networks [11], [12], which suggests adaptive transmission power control and error correction coding as potential solutions. Future research should focus on AI-driven dynamic power adjustments to optimize real-time vehicular communication networks.

3.7 Performance Benchmarking

The study identified a high bit error rate (BER) of 36.83%, categorizing its performance as 'very poor,' which is consistent with prior research on performance limitations in software-defined radio (SDR)--based

V2V communication [4]. Additionally, the signal-to-noise ratio (SNR) fell within the 'poor' category, reinforcing the need for further optimization techniques to enhance signal quality [8].

3.8 Technological Advancements

The flexibility of SDR technology in V2V communication presents both advantages and challenges. While SDR enables dynamic reconfiguration and supports multi-protocol integration [18], it also introduces latency and power consumption concerns [19]. Future research should explore hybrid approaches that leverage SDR's adaptability while mitigating its limitations in real-world vehicular environments.

Adopting SDR-based V2V systems presents cost advantages over dedicated hardware solutions [21]. The economic benefits of implementing V2V communication include reduced traffic congestion and enhanced fuel efficiency [22]. Additionally, the ability to deploy software-based upgrades minimizes long-term maintenance costs, making SDR a financially viable option for scalable transportation networks [19]. However, high initial infrastructure investment remains a barrier to widespread adoption.

3.9 Limitations of the Study and Areas for Improvement

The study's limited communication range of 3–6 meters restricts its applicability in real-world settings, where longer distances are required for effective V2V interaction [20]. Furthermore, high BER and packet loss rates (21.59%) highlight the need for more advanced error correction mechanisms to improve communication reliability [16].

Performance degradation due to multipath effects in urban environments has been a known challenge in V2V communication [15]. Weather-related attenuation effects warrant further investigation, particularly in varying climatic conditions [23].

Managing large-scale deployments of V2V communication remains challenging, requiring advanced network management solutions [24]. Furthermore, data security and privacy concerns require regulatory frameworks to ensure compliance with ethical standards [25].

Future studies should explore the integration of machine learning for adaptive signal processing to address existing limitations [14]. Enhancing V2V communication reliability through hybrid 5G-DSRC frameworks represents another promising research avenue [9]. Additionally, developing energy-efficient V2V solutions tailored for electric vehicles could significantly improve sustainability in smart transportation [26].

Ethical concerns regarding the potential misuse of V2V communication data for surveillance have been raised by previous studies [27]. Implementing blockchain-based security frameworks for V2V data privacy has been proposed to address these concerns as a viable solution [10]. Ensuring transparent data governance policies will be essential for the ethical deployment of V2V communication in urban environments.

4. CONCLUSION

This study enhances the understanding of V2V communication reliability within STS by employing SDR technology for signal power optimization. Findings indicate that distance, mobility, and environmental factors significantly affect communication performance, leading to high BER and low SNR. Compared to traditional hardware-based systems, SDR-based V2V communication provides greater flexibility and cost efficiency but still faces limitations related to signal stability, multipath interference, and scalability in real-world applications.

A key contribution of this research is the empirical validation of SDR-based V2V systems in dynamic vehicular environments, bridging the gap between theoretical models and practical implementation. The study underscores the importance of adaptive modulation, machine learning-driven signal optimization, and hybrid 5G-DSRC integration in mitigating performance degradation. Furthermore, our analysis highlights critical gaps in standardization and security protocols, emphasizing the need for robust cybersecurity frameworks to prevent data breaches in connected vehicle networks.

Future research should focus on AI-powered real-time signal calibration, large-scale field trials in diverse urban-rural conditions, and energy-efficient V2V architectures to support the deployment of autonomous and cooperative intelligent transport systems. Next-generation V2V communication can revolutionize smart mobility, reduce road accidents, optimize traffic flow, and contribute to sustainable urban development by addressing these challenges. The insights from this study provide a foundational framework for advancing reliable, scalable, and secure V2V networks, paving the way for fully interconnected intelligent transportation ecosystems.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Yuswanto: Methodology, Hardware, Software, Project administration, Data collection. **Hariyawan**: Writing–review & editing, Conceptualization, Supervision. **Briantoro**: Conceptualization, Supervision.

DECLARATION OF COMPETING INTERESTS

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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