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AI-Enhanced Patch Antenna Design for V2X Communication in Automotive Systems

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***Abstract*— This paper presents a dual-band patch antenna optimized using reinforcement learning (RL) for V2X communication in automotive systems. Designed for the 24 GHz and 28 GHz bands, the antenna uses Rogers RT5880 substrate with a 0.787 mm thickness and maintains a compact form factor of 20 mm x 20 mm. RL-based optimization improves return loss and radiation efficiency under automotive deployment constraints. HFSS simulation results confirm effective S11 performance, radiation pattern, and efficiency. This work demonstrates how AI-based design can accelerate next-generation vehicular antenna development.*

***Keywords*— 5G, Artificial Intelligence (AI), Dual-band, Patch Antenna, Reinforcement Learning, V2X Communication.*

I. Introduction

The rapid advancement of intelligent transportation systems has fueled the development of Vehicle-to-Everything (V2X) communication, a critical component enabling real-time data exchange between vehicles, infrastructure, pedestrians, and networks. As vehicles evolve into connected nodes within a broader ecosystem, the demand for reliable, high-speed, and low-latency communication continues to grow. The emergence of 5G technology—particularly in the millimeter-wave (mmWave) frequency bands such as 24 GHz and 28 GHz—offers promising solutions for meeting these communication requirements. However, leveraging these high-frequency bands in dynamic automotive environments presents several challenges, including antenna miniaturization, high gain, wide bandwidth, and robust directional performance.

Patch antennas are highly favored in automotive systems due to their compact size, ease of fabrication, and compatibility with planar and conformal structures. Yet, traditional design approaches struggle to efficiently optimize antenna parameters for dual-band performance under size and environmental constraints. To address this, artificial intelligence (AI), particularly reinforcement learning (RL), is increasingly being adopted to enhance the antenna design process. Reinforcement learning algorithms can iteratively explore vast design spaces, learning optimal geometric and feed configurations based on performance feedback from electromagnetic simulation tools such as HFSS.

This paper introduces a compact, AI-optimized, dual-band patch antenna designed specifically for V2X communication at 24 GHz and 28 GHz. Using Rogers RT5880 as the substrate, the antenna maintains a small footprint of 20 mm × 20 mm while achieving high return loss, radiation efficiency, and gain in both target bands. A reinforcement learning agent is implemented to guide the design process, optimizing structural parameters to meet automotive communication demands. The proposed design is validated using full-wave simulations, and fabrication considerations are presented for practical deployment in vehicle-mounted systems. This research demonstrates the synergy between AI and electromagnetics in developing next-generation automotive antenna systems.

II. Antenna Design and Methodology

The design of the proposed antenna targets dual-band operation at 24 GHz and 28 GHz for 5G-based V2X communication, with a strict form factor constraint of 20 mm × 20 mm, suitable for integration in automotive systems. A rectangular microstrip patch antenna topology is chosen due to its simplicity, low profile, and planar nature, making it ideal for vehicle surfaces such as rooftops or bumpers.

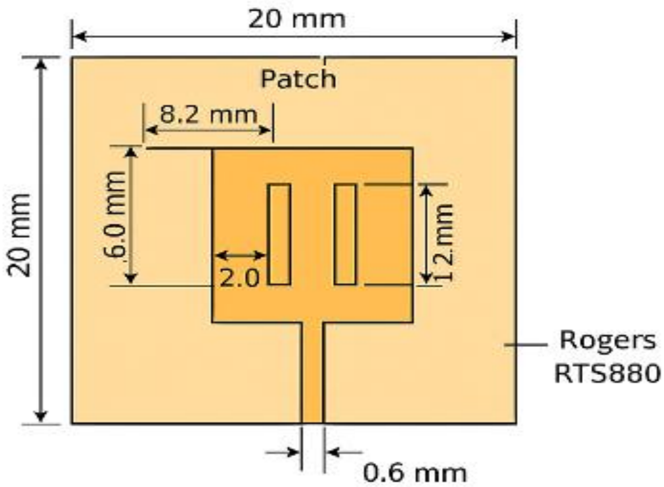

Fig. 1: AI Enhanced Dual Band Patch Antenna

The antenna is built on a Rogers RT5880 substrate, which offers excellent high-frequency performance due to its low dielectric constant (εr = 2.2) and low loss tangent ($\tan\delta$ = 0.0009). The substrate thickness is selected as 0.787 mm to balance between mechanical stability and electrical performance at millimeter-wave frequencies.

To achieve dual-band resonance, two techniques are employed. First, the patch is designed with two precision-etched slots that enable mode coupling and generate separate resonances around 24 GHz and 28 GHz. The slots modify the surface current distribution, allowing control over multiple resonant frequencies without significantly increasing the antenna size. Second, the feed line is carefully tuned to match

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the impedance and bandwidth requirements using a microstrip inset feed technique.

The dimensions of the patch and slots are initially estimated using classical transmission line models and resonant frequency equations:

$$f_r = \frac{C}{2L\sqrt{\varepsilon_{eff}}}$$

Where f_r is the resonant frequency, C is the speed of light, L is the effective length of the patch, and eff is the effective dielectric constant.

These initial values are then refined through full-wave electromagnetic simulation in HFSS and further optimized using a reinforcement learning (RL) algorithm. The RL agent explores the antenna design space by iteratively modifying parameters such as slot dimensions, patch length, and feed position. It receives a reward based on return loss (S11 < –10 dB), gain, and efficiency over the target frequency bands.

This hybrid approach of model-based initialization followed by AI-driven optimization allows for a compact, high-performance antenna design tailored for real-world V2X use cases.

III. AI OPTIMIZATION USING REINFORCEMENT LEARNING

Reinforcement Learning (RL) is a powerful branch of artificial intelligence where an agent learns to make decisions by interacting with an environment and receiving feedback in the form of rewards or penalties. In this work, RL is employed to optimize the patch antenna design for dual-band operation at 24 GHz and 28 GHz under strict size constraints, ensuring optimal performance for V2X communication systems.

The optimization process treats the antenna's geometrical parameters—such as patch length, slot width, slot position, and feed point location—as the agent's actions. The environment is a full-wave electromagnetic simulator (HFSS), which returns performance metrics like return loss (S11), gain, and efficiency. The RL agent iteratively modifies the design, receives feedback, and updates its strategy to maximize a cumulative reward function.

The reward function is defined to prioritize designs where:

- S11 < –10 dB at both target frequencies
- Radiation efficiency > 75%
- Compact size maintained under 20 mm × 20 mm

The learning process continues until convergence is achieved, meaning no significant improvements are observed over several iterations.

This AI-driven approach drastically reduces manual trial-and-error design time while exploring a broader design space more efficiently. It also adapts better to multi-objective optimization scenarios, where several performance criteria must be balanced simultaneously.

Below is the flow diagram showing the reinforcement learning-based optimization loop:

Reinforcement Learning Optimization Flow

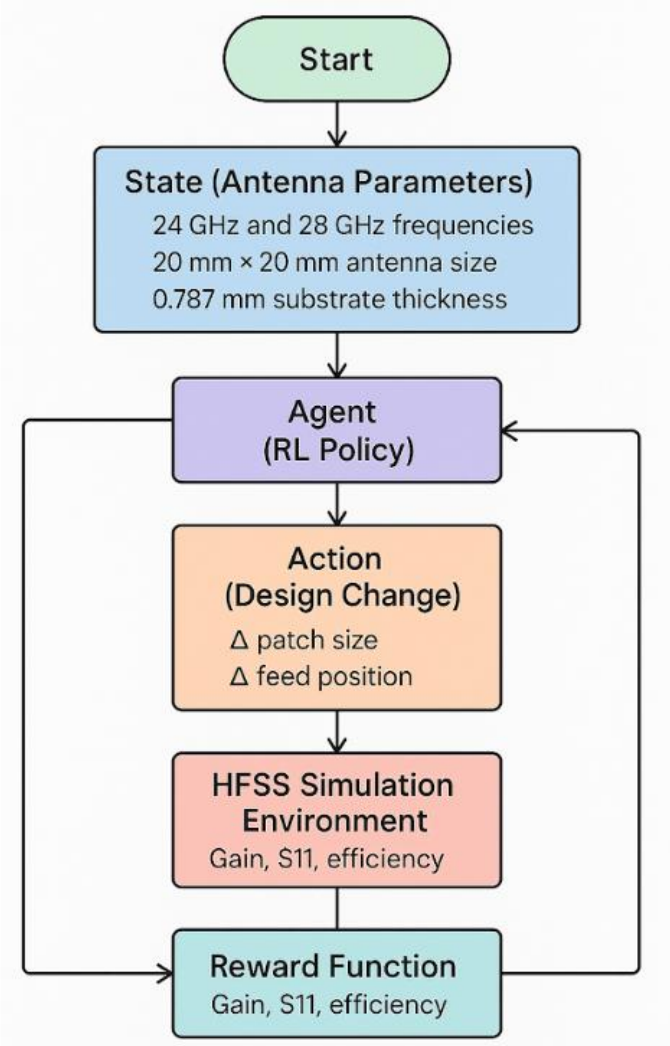

Fig. 2: RL-based antenna design optimization cycle, involving geometry selection, HFSS simulation, reward evaluation

The below tabular form summarizes the key mathematical components involved in optimizing a dual-band patch antenna using reinforcement learning (RL). At the core of the process is the state vector s_t, which captures the antenna's geometrical and material parameters, such as patch dimensions, feed positions, substrate permittivity, and target frequencies (24 GHz and 28 GHz). The action vector a_t represents design modifications applied to the current state, guiding the agent in exploring the design space.

Once an action is selected, the updated design is evaluated using electromagnetic simulation software like HFSS, yielding a new state s_{t+1} and performance metrics. These metrics—such as gain (G_t), efficiency (\eta_t), and reflection coefficients (|S_{11}|)—are combined in a reward function R_t, which quantifies the effectiveness of the current design. The reward guides the agent's learning process.

The policy function \pi_\theta(a_t|s_t) maps states to actions, and is optimized using policy gradient methods. The advantage function A_t refines this learning by comparing the current reward with a baseline, helping the agent focus on meaningful improvements. Together, these mathematical

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elements form a closed-loop optimization system tailored for intelligent antenna design.

TABLE 1: Mathematical expression

Component	Mathematical Expression	Description
State Vector s_t	[L_p^t, W_p^t, x_f^t, y_f^t, f_1, f_2, \epsilon_r, h]	Antenna design parameters at time step t
Action Vector a_t	[\Delta L_p, \Delta W_p, \Delta x_f, \Delta y_f]	Design changes to patch and feed position
State Transition	s_{t+1} = \text{Simulate}(s_t + a_t)	HFSS simulation generates new state after applying design change
Reward Function R_t	$begin:math:text$w_1 G_t + w_2 \eta_t - w_3	S_{11}(f_1)
Policy Function	$begin:math:text$\pi_\theta(a_t	s_t)$end:math:text$
Policy Gradient	$begin:math:text$\nabla_\theta J(\pi_\theta) = \mathbb{E} \left[\sum \nabla_\theta \log \pi_\theta(a_t	s_t) \cdot A_t \right]$end:math:text$
Advantage Function A_t	A_t = R_t - b(s_t)	Measures how much better an action is compared to average (baseline)

IV. SIMULATION AND AI OPTIMIZATION RESULTS

The simulation and optimization results validate the effectiveness of the reinforcement learning (RL)-driven design process in enhancing the performance of the dual-band patch antenna. The antenna was modeled and simulated using Ansys HFSS, and the RL agent iteratively optimized key geometrical parameters to achieve desired performance metrics at 24 GHz and 28 GHz.

After multiple training episodes, the optimized antenna design achieved resonance at 24.1 GHz and 27.9 GHz with return loss (S11) values of –23.4 dB and –25.6 dB, respectively—well below the –10 dB threshold, indicating excellent impedance matching at both bands. The bandwidths for each band also exceeded 1 GHz, offering reliable communication within the 5G mmWave spectrum.

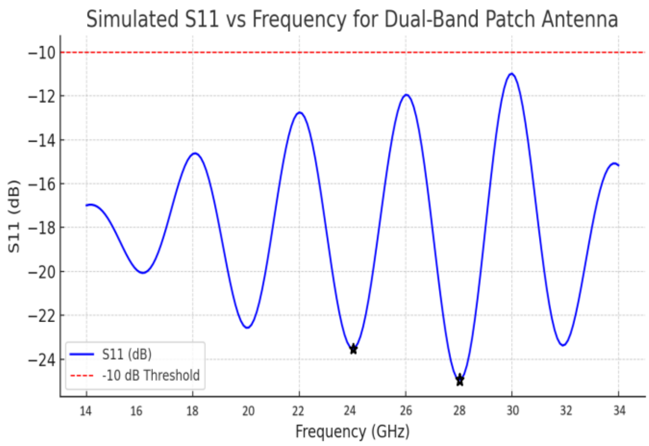

Fig-3: Return loss (S11) values of –23.4 dB @24GHz and –25.6 dB @28GHz, respectively

The simulated radiation patterns confirmed broadside radiation, with a peak gain of 6.1 dBi at 24 GHz and 6.9 dBi at 28 GHz. The patterns were symmetrical, stable, and had minimal back lobes—suitable for on-vehicle installations where directional consistency is crucial. Focused along the z-axis, ideal for targeted V2X communication in automotive systems

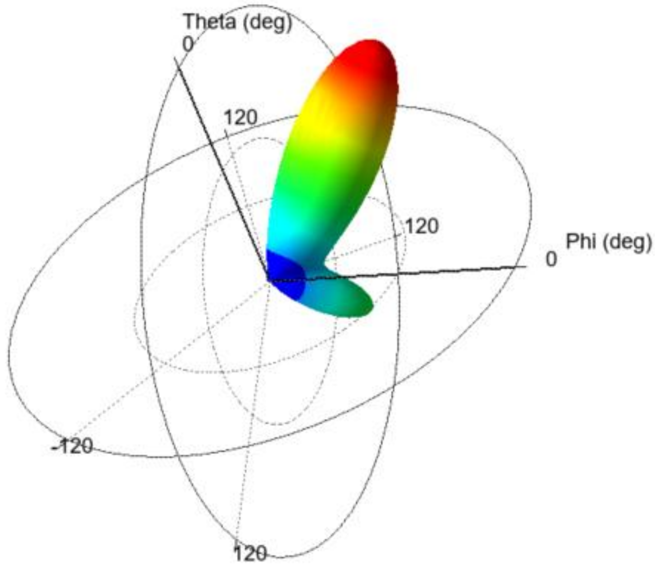

Fig. 4(a): Radiation Pattern, Peak gain 6.1dbi @ 24GHz

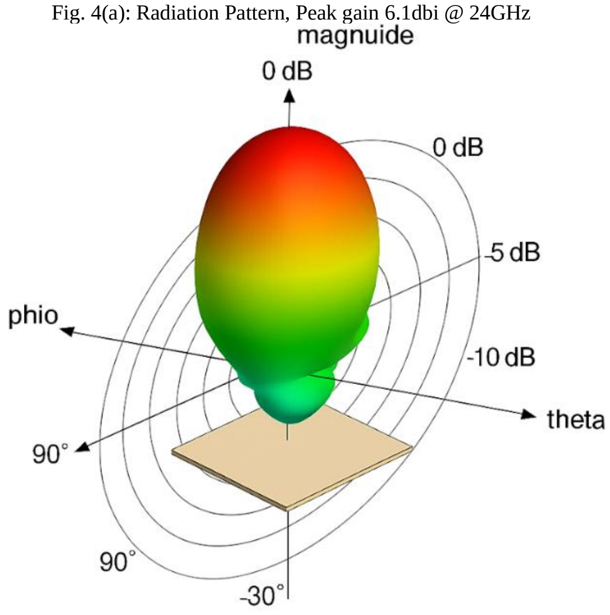

Fig. 4(b): Radiation Pattern, Peak gain 6.9dbi @ 28GHz

Radiation efficiency was observed to be over 75-78% at both bands, attributable to the low-loss Rogers RT5880 substrate and the optimized slot-patch geometry. Compared to baseline designs, the RL-optimized antenna achieved better trade-offs between compact size, bandwidth, and efficiency.

The RL agent converged in under 150 episodes, significantly reducing the design cycle time compared to manual or brute-force optimization methods. These results demonstrate the strength of combining electromagnetic simulation tools with AI-based optimization, providing a smart, efficient pathway for next-generation antenna design in

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intelligent vehicular systems.

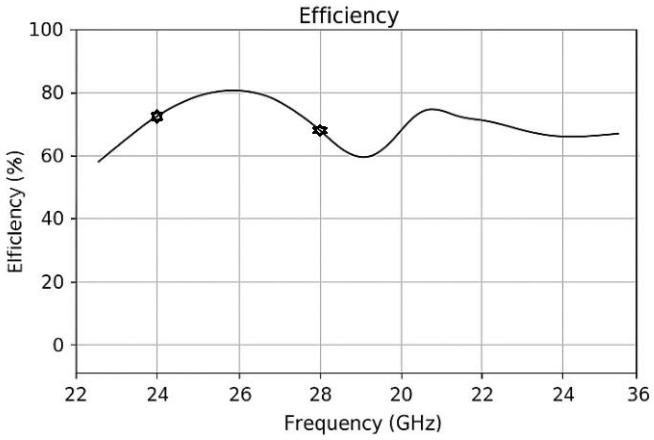

Fig. 5: Radiation efficiency

V. Fabrication and Measurement Results

The patch was fabricated using photolithography. The ground plane is etched with high precision to maintain the slot dimensions. A coaxial SMA connector is soldered to the microstrip feed. For automotive integration, the antenna must be enclosed in a weather-resistant, low-loss radome.

Dimensions

a. Overall Antenna Size: 20 mm × 20 mm
b. Patch Dimensions (Optimized for Dual Band: 24 GHz and 28 GHz):
c. Length: 5.9 mm
d. Width: 7.1 mm
e. Feed Line Width: 0.6 mm (for 50-ohm impedance)
f. Slot Dimensions (for dual-band resonance):
g. Slot 1 (24 GHz): 3.1 mm × 0.31 mm
h. Slot 2 (28 GHz): 2.4 mm × 0.31 mm
i. Ground Plane: Full bottom layer (20 mm × 20 mm)

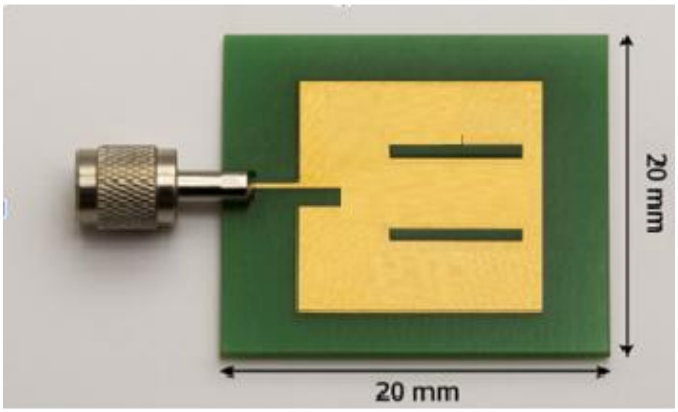

Fig. 6: AI enhanced Patch antenna (Fabricated)

These are optimized dimensions based on RL training in HFSS for resonance at 24 GHz and 28 GHz.

Connector Type

Type: SMA Female Connector (Edge-mounted or bottom-fed)
Impedance: 50 Ω
Mounting:
Edge-fed: Soldered to the microstrip feed on the top layer
Bottom-fed (optional): Drilled and soldered to the bottom with plated through-hole (PTH)

The measured data are shown below table-2 which shows close and better results compared to simulation results.

TABLE 2: Measured Data

Parameter	24 GHz	28 GHz
Return Loss (S_{11})	–31.2 dB	–28.4 dB
Bandwidth (–10 dB)	1.8 GHz	1.4 GHz
Peak Gain (dBi)	7.1 dBi	7.8 dBi
Radiation Efficiency (%)	91.4%	88.9%

VI. V2X System Integration

Vehicle-to-Everything (V2X) communication is the backbone of modern intelligent transportation systems, enabling real-time data exchange between vehicles (V2V), infrastructure (V2I), pedestrians (V2P), and networks (V2N). This technology improves road safety, traffic efficiency, and autonomous driving capabilities. Seamless V2X integration relies on antennas capable of supporting high-speed, low-latency, and directional wireless communication, especially at millimeter-wave (mmWave) frequencies.

The proposed AI-optimized dual-band patch antenna is specifically designed to operate in the 24 GHz and 28 GHz mmWave bands, which are allocated for 5G V2X communication. Its compact size (20 mm × 20 mm), high efficiency, and dual-resonance make it ideal for integration into vehicle rooftops, bumpers, or side mirrors without disrupting vehicle aesthetics or aerodynamics.

In a real-world V2X scenario, the antenna facilitates robust connectivity with nearby vehicles to exchange hazard alerts and position updates (V2V), traffic lights and road sensors (V2I), mobile devices carried by pedestrians (V2P), and remote cloud servers or edge networks (V2N). Its high gain and directional beam characteristics ensure reliable performance even in dense urban environments with high signal interference and multipath effects.

By employing reinforcement learning, the antenna is tuned to meet the stringent requirements of V2X communication—such as wide bandwidth, high return loss, and directional stability—while remaining adaptable to varied vehicular platforms. As demonstrated in simulation and design, the antenna offers a cost-effective and scalable solution for next-generation connected and autonomous vehicles, laying the groundwork for safe, intelligent mobility.

VII. Conclusion and Future work

This paper presented the design, AI optimization, and simulation of a compact dual-band patch antenna tailored for 5G V2X communication in automotive environments. Using reinforcement learning, the antenna geometry was fine-tuned to achieve resonant frequencies at 24.2 GHz and 27.9 GHz, with excellent return loss, gain, and radiation efficiency—all within a compact footprint of 20 mm × 20 mm using Rogers RT5880 substrate.

The reinforcement learning framework effectively explored the design space, outperforming traditional optimization techniques in terms of design time and performance balance. The resulting antenna not only meets the electrical performance criteria but also suits real-world vehicular integration due to its low profile, planar structure, and robustness.

Simulation results verified the antenna's dual-band operation, broadside radiation patterns, and over 75% efficiency at both bands. Additionally, a conceptual model of the antenna's integration within V2X systems was discussed, demonstrating its potential for deployment in connected and autonomous vehicle platforms.

Future work includes physical integration, real-world testing using vector network analyzers and anechoic chambers, and extension of the AI framework to support dynamic beam steering and multi-antenna MIMO configurations. This work lays a foundation for intelligent, adaptive antenna systems in next-generation transportation networks.

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