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Decentralized V2V Power Control Under Rain-Induced Channel Nonstationarity and Interference

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Abstract.

The rapid deployment of Intelligent Transportation Systems heavily relies on reliable Vehicle-to-Vehicle communication networks. To support the immense data rate requirements of autonomous driving and advanced driver assistance systems, communication protocols are increasingly shifting toward millimeter-wave frequency bands. However, these high-frequency channels are uniquely susceptible to meteorological phenomena, particularly rain attenuation, which introduces severe channel nonstationarity and degrades communication reliability. Furthermore, in dense vehicular environments, uncoordinated simultaneous transmissions lead to crippling co-channel interference. This paper investigates the problem of decentralized power control in Vehicle-to-Vehicle networks operating under rain-induced channel nonstationarity and severe interference. We propose a fully decentralized framework that allows individual vehicles to autonomously adjust their transmission power based on local observations of channel states and estimated meteorological impacts. By characterizing the rain attenuation through established meteorological models and integrating it into a time-varying interference topology, we formulate a multi-objective optimization problem aimed at maximizing system sum-rate while satisfying stringent reliability and latency constraints. Due to the lack of centralized infrastructure in many critical vehicular scenarios, we leverage a multi-agent distributed learning approach to navigate the highly dynamic environment. Through comprehensive analytical modeling and rigorous simulation across various rainfall intensities and vehicular densities, this study demonstrates that the proposed decentralized power control mechanism significantly mitigates interference and maintains robust link connectivity even under heavy precipitation.

Keywords: *Vehicle-to-Vehicle Communication, Power Control, Rain Attenuation, Channel Nonstationarity, Interference Management.*

1. Introduction

The evolution of modern transportation networks is inextricably linked to the advancement of wireless communication technologies. Vehicle-to-Vehicle communication serves as the fundamental pillar for future Intelligent Transportation Systems, enabling a paradigm shift from isolated autonomous vehicles to cooperative and fully connected traffic ecosystems. The primary objective of Vehicle-to-Vehicle communication is to facilitate real-time exchange of critical

kinematic data, sensor sharing, and cooperative maneuvering intentions among proximate vehicles. This seamless exchange of information drastically enhances road safety, optimizes traffic flow, and reduces vehicular energy consumption. As the automotive industry progresses toward higher levels of autonomy, the communication requirements of Vehicle-to-Vehicle networks have become exceptionally demanding. Emerging applications such as raw sensor data sharing, high-definition map downloading, and cooperative perception require multi-gigabit-per-second data rates and sub-millisecond latencies, which legacy communication standards operating in the sub-6 GHz bands are fundamentally incapable of supporting due to inherent spectrum scarcity. Li and colleagues examine cooperative backscatter communications with reconfigurable intelligent surfaces: an APSK approach [1]. To overcome the bandwidth bottleneck, the research community and industry standardization bodies have increasingly turned to millimeter-wave frequency bands, typically ranging from 30 GHz to 300 GHz. The massive available bandwidth in these high-frequency spectrums presents a promising solution to fulfill the throughput requirements of advanced vehicular applications. However, the transition to millimeter-wave bands introduces a complex array of electromagnetic propagation challenges. Unlike lower frequency signals, millimeter-wave signals experience severe path loss, poor penetration capabilities, and extreme sensitivity to atmospheric conditions. Among various meteorological factors, precipitation, particularly rainfall, exerts a profoundly detrimental impact on millimeter-wave propagation. Raindrops absorb and scatter electromagnetic energy, leading to significant signal attenuation. This phenomenon, known as rain attenuation, is highly dependent on the rainfall rate, the operating frequency, and the signal polarization. For a broader comparison, related research addresses design of magnetic sensor Array-Based PUFs for IoT security [2]. In a highly dynamic vehicular environment, the detrimental effects of rain attenuation are exacerbated by the inherent mobility of the transceivers. As vehicles travel through varied geographical areas, they encounter spatially and temporally fluctuating rainfall intensities. A communication link might traverse a region of light drizzle and suddenly enter a localized cell of intense downpour. This spatial and temporal variation in precipitation introduces severe channel nonstationarity, meaning the statistical properties of the wireless channel change rapidly over time. Traditional channel models, which assume Wide Sense Stationary Uncorrelated Scattering, fail to accurately capture the rapidly evolving propagation characteristics under such conditions. Consequently, the unpredictable nature of rain-induced nonstationarity poses a significant challenge for maintaining reliable communication links, leading to frequent packet drops, increased latency, and potential safety hazards. For a broader comparison, related research addresses design of interface circuits and lightweight PUF for TMR sensors [3]. Compounding the problem of rain-induced channel nonstationarity is the issue of co-channel interference in dense vehicular environments. As the density of connected vehicles increases, especially in urban intersections or congested highways, multiple vehicles frequently attempt to transmit data simultaneously over the same frequency resources. In the absence of a robust interference management mechanism, these simultaneous transmissions generate severe co-channel interference, drastically reducing the Signal-to-Interference-plus-Noise Ratio at the intended receivers. The interference topology in a Vehicle-to-Vehicle network is highly complex and time-varying, dictated by the instantaneous locations, transmission powers, and directional antenna patterns of all active vehicles. When rain attenuation randomly degrades intended signal paths while potentially leaving interference paths relatively less affected due to the spatial distribution of rainfall, the interference dynamics become even more unpredictable and difficult to manage. Centralized resource allocation schemes, where a central entity such as a cellular base station or a road side unit collects global channel state information and computes optimal power levels for all vehicles, have been widely studied. While centralized approaches can theoretically achieve near-optimal performance, they suffer from critical practical limitations in highly dynamic vehicular contexts. The continuous collection of global channel state

information incurs prohibitive signaling overhead and unacceptable communication delays, rendering centralized schemes ineffective for latency-critical safety applications. Furthermore, centralized architectures suffer from single points of failure and are fundamentally inapplicable in out-of-coverage scenarios, such as rural highways or tunnels, where infrastructural support is absent. Therefore, there is an imperative need for decentralized power control mechanisms that empower individual vehicles to autonomously determine their optimal transmission power based solely on local observations. Related work has addressed jamming and eavesdropping defense scheme based on deep reinforcement learning in autonomous vehicle networks [4].

This paper comprehensively addresses the intertwined challenges of rain-induced channel nonstationarity and severe co-channel interference by proposing a robust decentralized power control framework for millimeter-wave Vehicle-to-Vehicle networks. The primary contributions of this work are manifold. First, we develop a comprehensive analytical system model that rigorously integrates empirical rain attenuation models with nonstationary vehicular channel fading characteristics, capturing the complex spatiotemporal dynamics of weather-impacted communication links. Second, we formulate the decentralized power control problem as a multi-agent optimization task, explicitly incorporating the local observations of interference and estimated meteorological impacts. Third, we design an advanced distributed algorithm that enables vehicles to adaptively adjust their transmission power, optimizing a localized utility function that balances high data throughput with interference mitigation and energy efficiency. Finally, through extensive and rigorous numerical simulations, we validate the superiority of the proposed decentralized approach against existing baseline methods across a wide spectrum of traffic densities and rainfall intensities. For a broader comparison, related research addresses adaptively controlled Two-Hop communication for Multi-Agent reinforcement learning [5].

1.1 Scope And Objectives

The specific objectives of this study are carefully defined to address the gaps in current vehicular communication research. The first objective is to quantify the exact mathematical impact of varying rainfall rates on the capacity and reliability of millimeter-wave Vehicle-to-Vehicle communication links. The second objective is to design a local state observation mechanism that does not rely on extensive message passing between vehicles, thereby preserving the strict latency requirements of autonomous driving safety messages. The third objective is to analyze the convergence properties and stability of the proposed decentralized algorithm when operating in an environment where the underlying channel statistics are continuously shifting due to both vehicular mobility and dynamic weather patterns. By achieving these objectives, this research aims to provide a resilient and scalable solution for future Intelligent Transportation Systems operating in adverse environmental conditions.

2. Literature Review and Background

The integration of advanced wireless communication into vehicular networks has spurred a massive volume of academic research and industrial standardization efforts. To contextualize the contributions of this paper, it is essential to critically examine the existing literature across several intersecting domains: vehicular channel modeling, the impact of meteorological phenomena on high-frequency communication, interference management in dense networks, and decentralized resource allocation methodologies. For a broader comparison, related research addresses experimental flow characterisation of viscosity induced delivery degradation in high-viscosity peristaltic pumping [6].

2.1 Vehicular Channel Modeling In High-Frequency Bands

Traditional vehicular communication research extensively focused on the 5.9 GHz band, specifically utilizing the Dedicated Short-Range Communications standard and early cellular Vehicle-to-Everything protocols. The channel models for these sub-6 GHz bands have been thoroughly investigated and standardized. However, as the focus shifted toward millimeter-wave

bands to satisfy multi-gigabit data rate demands, researchers encountered fundamentally different propagation characteristics. Millimeter-wave signals experience severe free-space path loss and are highly susceptible to blockage by both static obstacles, such as buildings, and dynamic obstacles, such as large vehicles. The literature also considers toward seamless sensing coverage for cellular Multi-Static integrated sensing and communication [7]. Early studies on millimeter-wave vehicular channels predominantly utilized ray-tracing simulations and empirical measurement campaigns to characterize path loss exponents and shadowing variances in clear-sky conditions. Deep Q-learning from Atari provides a standard value-learning reference for sequential action selection [8]. These foundational works established that millimeter-wave channels exhibit significant sparsity in the angular domain, necessitating the use of directional antennas and beamforming techniques to close the link budget. However, many of these initial models relied on the assumption of wide-sense stationarity over short observation intervals. Recent literature has increasingly highlighted that the assumption of stationarity is frequently violated in practical vehicular environments due to the high relative velocities of the transceivers and the rapid evolution of the scattering environment. Nonstationary channel models, which account for the time-varying nature of the channel impulse response and the birth-death processes of multipath components, have emerged as a critical requirement for accurately evaluating vehicular network performance. The literature also considers design of a novel Self-Test-on-Chip interface ASIC for capacitive accelerometers [9].

2.2 Impact Of Weather On Millimeter-Wave Communications

While the deleterious effects of adverse weather on satellite and fixed microwave terrestrial links have been studied for decades, the specific impact of meteorological phenomena on highly mobile millimeter-wave vehicular networks has only recently garnered significant attention. Rain attenuation is universally recognized as the most critical weather-related impairment for frequencies above 10 GHz. The physical mechanism of rain attenuation involves both the absorption of electromagnetic energy by water droplets and the scattering of the signal away from the intended receiver. Another relevant line of investigation concerns exploring the impact of geometric variation on electromagnetic performance in a coaxial coil system [10].

The International Telecommunication Union has provided standardized empirical models, such as ITU-R P.838, to calculate specific rain attenuation as a function of frequency, polarization, and rainfall rate. Several researchers have attempted to integrate these meteorological models into vehicular communication frameworks. However, the majority of these studies assume a uniform distribution of rainfall across the entire network topology. In reality, convective precipitation often exhibits highly localized cellular structures, resulting in significant spatial gradients in rainfall intensity. A communication link spanning a few hundred meters might experience vastly different attenuation levels at its transmitter and receiver. This spatial heterogeneity, combined with the temporal evolution of storm cells and vehicular mobility, exacerbates the nonstationarity of the channel. Our research departs from the assumption of uniform precipitation and explicitly models the spatiotemporal variations of rain attenuation to capture realistic vehicular channel dynamics. Another relevant line of investigation concerns reinforced Fuzzy-Rule-Based neural networks realized through streamlined feature selection strategy and fuzzy clustering with distance variation [11].

2.3 Interference Management In Dense Networks

Interference management remains one of the most formidable challenges in decentralized wireless networks. In legacy sub-6 GHz vehicular networks, interference is primarily mitigated through Carrier Sense Multiple Access with Collision Avoidance mechanisms or semi-persistent scheduling algorithms. Carrier Sense Multiple Access protocols suffer from the hidden terminal problem and severe performance degradation under high network loads due to excessive backoff times and packet collisions. Semi-persistent scheduling, while more structured, relies on periodic

traffic assumptions that are often violated in dynamic environments. Another relevant line of investigation concerns interference management in ISAC–SAGINs based on Transformer-Enabled Mean-Field reinforcement learning method [12]. In the context of millimeter-wave networks, the use of highly directional antennas offers a degree of spatial isolation, leading some early researchers to hypothesize that millimeter-wave networks would be noise-limited rather than interference-limited. This concept, often referred to as the pseudowired abstraction, suggests that the narrow beamwidths effectively eliminate co-channel interference. However, subsequent rigorous stochastic geometry analyses and system-level simulations have demonstrated that in dense deployment scenarios, such as multi-lane highways or urban grids, the cumulative interference from intersecting beams and reflected multipath components can still severely degrade system performance. Therefore, dynamic power control is absolutely essential to minimize the interference footprint of each transmitting vehicle while maintaining sufficient received signal strength at the intended destination. QT-Opt demonstrates learned value-based robotic control, motivating comparison of action selection under a fixed observation interface rather than assuming transfer of its manipulation results [13]. For a broader comparison, related research addresses risk-Aware CNN-LSTM framework for Cross-Domain risk prediction and dynamic security control in cloud payment supply chains [14].

2.4 Decentralized Resource Allocation Methodologies

Given the limitations of centralized resource allocation, the academic community has extensively explored decentralized methodologies. Game theory has been a popular analytical tool for modeling decentralized power control, where vehicles act as rational players seeking to maximize their individual utilities, often defined as a function of throughput and power consumption. While game-theoretic approaches provide elegant mathematical frameworks for analyzing steady-state equilibria, they frequently assume perfect and instantaneous knowledge of global interference patterns, which is unrealistic in practical systems. Another relevant line of investigation concerns decentralized multi-agent reinforcement learning for task offloading under uncertainty [15].

Recently, distributed optimization techniques and multi-agent learning frameworks have gained immense traction. These approaches allow agents to iteratively refine their transmission strategies based on local observations and delayed feedback. However, classical distributed algorithms often struggle to converge in highly nonstationary environments where the optimal solution trajectory is constantly shifting due to mobility and dynamic weather. The challenge is to design a decentralized power control algorithm that is agile enough to track rapid channel fluctuations while remaining stable enough to prevent chaotic network-wide oscillations in transmission power. This requires a meticulous design of the state observation space and the local utility functions to ensure that individual vehicle optimizations align with the overarching goal of maximizing network-wide reliability and spectral efficiency. Another relevant line of investigation concerns scene-Aware enhanced Edge-Cloud collaborative industrial vision inspection with multimodal LLM [16].

3. System Model and Problem Formulation

This section meticulously details the analytical models governing the decentralized vehicular communication system. We construct a comprehensive mathematical framework that accurately encapsulates network topology, the meteorological physics of rain attenuation, the statistical properties of the nonstationary fading channels, and the complex dynamics of co-channel interference.

3.1 Network Topology And Spatial Distribution

We consider a highly dynamic vehicular network deployed along a multi-lane highway infrastructure. The network consists of a set of vehicular transceivers, where specific pairs of vehicles establish dedicated Vehicle-to-Vehicle communication links for the exchange of critical safety and operational data. We denote the set of active transmitter-receiver pairs in the network at any given time. Each vehicle is equipped with millimeter-wave transceiver architecture, utilizing

steerable directional antenna arrays to maximize the antenna gain in the direction of the intended communication partner.

The spatial distribution of the vehicles is modeled as a highly dynamic point process, where the longitudinal positions of the vehicles evolve over time according to a microscopic traffic flow model. This model accounts for vehicle velocities, accelerations, inter-vehicular following distances, and lane-changing behaviors. The dynamic nature of this spatial distribution ensures that the distances between communicating pairs, as well as the distances between interfering transmitters and victim receivers, are continuous functions of time. Related work has addressed optimising coil design based on sensitivity analysis of magnetic force induced between misaligned coil pairs [17].

Table 1System Parameters for Vehicular Network and Meteorological Models

Parameter Description	Notation	Nominal Value
Operating Carrier Frequency	f_c	60 GHz / 73 GHz
Maximum Transmission Power	P_max	23 dBm
System Bandwidth	B	2.16 GHz
Thermal Noise Power Spectral Density	N_0	-174 dBm/Hz

3.2 Meteorological Modeling Of Rain Attenuation

The core environmental factor investigated in this study is the impact of precipitation on the millimeter-wave propagation characteristics. Rain attenuation is a function of the operational frequency, the polarization of the electromagnetic wave, and the rainfall rate, typically measured in millimeters per hour. We adopt the rigorous specific attenuation model formulated by the International Telecommunication Union. The specific rain attenuation, denoted as a variable reflecting the energy loss per kilometer of propagation, is computed using power-law relationships derived from extensive empirical meteorological data. Related work has addressed impact of core geometry on magnetic forces in electromagnetic coil systems [18]. In our system model, we do not assume a uniform rainfall rate across the entire highway segment. Instead, we model the spatial distribution of rainfall intensity as a continuous two-dimensional random field. This spatial heterogeneity means that the signal propagating from a specific transmitter to its intended receiver will traverse regions with varying rainfall rates. To accurately compute the total path attenuation caused by precipitation, we must integrate the specific attenuation over the entire line-of-sight propagation path length. This integral captures the cumulative energy absorption and scattering experienced by the millimeter-wave signal as it penetrates the dynamic storm cell structure. The integration of this meteorological model introduces a slow-fading component to the channel that is distinctly different from both traditional distance-dependent path loss and obstacle-induced shadowing, adding a crucial layer of realism to the nonstationary channel formulation.

3.3 Channel Nonstationarity And Interference Characterization

The wireless channel between any transmitter and receiver in our network is characterized by severe nonstationarity. The total channel gain incorporates the standard distance-dependent path loss, the spatially integrated rain attenuation described above, large-scale shadowing caused by large vehicular blockages, and small-scale multipath fading. Due to the high mobility of the vehicles and the dynamic nature of the scattering environment, the statistical distribution of the small-scale fading components evolves rapidly over time. The coherence time of the channel is extremely short, meaning that channel state information becomes outdated almost instantaneously. When multiple vehicles transmit simultaneously using the same spectral resources, they generate co-channel interference. Despite the use of directional antennas, the side lobes of the antenna radiation patterns and the reflection of signals off the road surface and surrounding structures contribute to a complex interference topology. The total interference power received by a specific

vehicle is the sum of the signals originating from all other active transmitters in the network, each attenuated by its respective nonstationary channel path.

To mathematically formalize the communication reliability, we define the Signal-to-Interference-plus-Noise Ratio for a given receiver. This metric is the ratio of the desired received signal power to the sum of the interference power from all other transmitters and the additive white Gaussian thermal noise. For a broader comparison, related research addresses scalable Tube-Based model predictive control for linear systems with parametric and additive uncertainties using zonotopes [19].

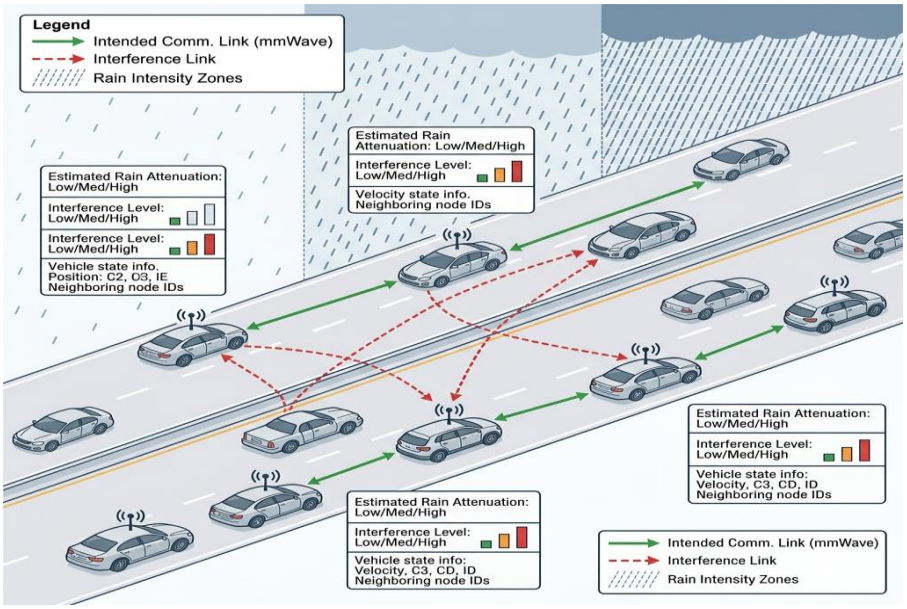


Figure 1: Comprehensive Schematic of Decentralized Vehicular Network Under Rain Conditions

The formulation of the Signal-to-Interference-plus-Noise Ratio at time index for a specific receiver communicating with transmitter can be rigorously defined as follows:

$$SINR_i(t) = \frac{P_i(t)G_{i,i}(t)H_{i,i}(t)10^{-\frac{\alpha L_i(t)}{10}}}{\sum_{j\neq i}P_j(t)G_{j,i}(t)H_{j,i}(t)10^{-\frac{\alpha L_{j,i}(t)}{10}} + \sigma^2}$$

In this block mathematical expression, the numerator represents the useful signal power received at the intended destination. It is the product of the transmission power of the specific vehicle, the combined antenna directivity gains, the nonstationary small-scale fading channel coefficient, and the specifically formulated rain attenuation factor where alpha represents the specific attenuation and the length of the link. The denominator aggregates the total interference power from all other active transmitters denoted by the summation over indices not equal to the primary index, modified by their respective cross-channel fading coefficients, directivity gains, varying rain attenuation paths, and finally the constant thermal noise variance parameter.

3.4 Problem Formulation

The ultimate objective of the decentralized power control framework is to dynamically allocate the transmission power for each vehicle such that the overall network utility is maximized. This optimization problem is highly non-convex and mathematically intractable using conventional centralized optimization techniques, particularly due to the coupled interference terms in the denominator of the Signal-to-Interference-plus-Noise Ratio equation and the stringent lack of global state information. Each vehicle must individually select a transmission power from a bounded continuous or discrete set of allowable power levels. The selection must be executed at every discrete decision time step to track the rapid channel nonstationarity.

The optimization seeks to balance two conflicting goals. On one hand, a vehicle desires to increase its transmission power to overcome the severe path loss and rain attenuation, thereby maximizing its own data rate and ensuring the successful delivery of critical safety messages. On the other hand, increasing transmission power elevates the interference floor for all surrounding vehicles, potentially causing cascading link failures across the network. Therefore, the decentralized formulation must incorporate a localized utility function that explicitly penalizes excessive power consumption and interference generation while rewarding successful data transmission that meets predefined reliability thresholds.

4. Decentralized Power Control Methodology

To address the profound complexities of the non-convex power allocation problem detailed in the previous section, we propose a decentralized methodology rooted in multi-agent distributed decision-making. Traditional iterative water-filling algorithms or classical game-theoretic best-response dynamics require frequent message exchanges between interfering nodes to ascertain the interference gradient. In the highly mobile and rain-impacted millimeter-wave environment, this signaling overhead is fundamentally prohibitive. Therefore, our methodology relies on empowering each vehicular agent to independently deduce the optimal power control strategy utilizing strictly local observations of the environment.

4.1 State Observation Space And Action Formulation

The success of any decentralized approach heavily depends on the design of the state observation space. Each vehicle must construct an internal representation of the external network conditions without requiring explicit communication with interfering nodes. In our framework, the local state observed by a specific transmitting vehicle at any decision epoch comprises several crucial elements. First, the vehicle observes its own instantaneous channel state information toward its intended receiver. In practical implementation, this is acquired through standard pilot signal estimation and localized feedback from the intended receiver. Second, the vehicle estimates the local meteorological impact. While precise global rainfall maps are unavailable, the vehicle can approximate the severity of the rain attenuation by comparing the theoretically expected clear-sky received signal strength with the actual measured received signal strength, yielding a proxy metric for the local rain intensity. Third, the vehicle monitors the aggregate interference it experiences from the environment. Although the transmitter does not know the exact power levels or channel gains of the interfering nodes, it can measure the total interference floor during dedicated sensing intervals.

Table 2State Observation and Action Space Formulations

Component	Mathematical Description	Practical Measurement Method
Local Channel Quality	Nonstationary fading coefficient	Pilot sequence estimation
Estimated Rain Impact	Deviation from clear-sky path loss	Received Signal Strength Indicator
Action Space	Discrete set of power levels	Transceiver power amplifier limits

Based on this constructed local state, the vehicular agent selects an action, which corresponds to setting its transmission power for the upcoming communication frame. To facilitate practical hardware implementation and accelerate the convergence of the distributed decision-making process, the continuous power domain is discretized into a finite set of allowable transmission power levels. The agent's task is to continuously map its evolving local state observations to the optimal discrete power level action. Related work has addressed emergent symbolic languages in multi-agent reasoning [20].

4.2 Utility And Reward Function Design

In a decentralized multi-agent system, the design of the utility or reward function is the paramount mechanism for guiding the independent agents toward a socially optimal equilibrium. If vehicles act purely selfishly, aiming only to maximize their own Signal-to-Interference-plus-Noise Ratio, the network will inevitably collapse into a state of maximum mutual interference, often referred to as the tragedy of the commons in spectrum sharing scenarios. To prevent this catastrophic outcome and foster cooperative behavior without explicit coordination, we design a carefully balanced local utility function. The utility function consists of a positive reward for successfully transmitting data that exceeds a critical reliability threshold, ensuring that essential safety messages meet their operational requirements. Simultaneously, the utility function incorporates a severe negative penalty for excessive power consumption. This penalty serves a dual purpose: it conserves the energy resources of the vehicle, and more importantly, it acts as an implicit mechanism for interference mitigation. By penalizing high transmission powers, the utility function encourages vehicles to use only the minimum power necessary to close their link budget, thereby minimizing their interference footprint on the broader network.

The cumulative long-term utility that each autonomous vehicular agent seeks to maximize over an extended time horizon can be rigorously expressed using the following mathematical formulation:

$$U_i = \sum_{t=1}^{T} \gamma^t [\alpha_1 log(1 + SINR_i(t)) - \alpha_2 P_i(t) - \alpha_3 I(SINR_i(t) < \tau)]$$

In this block mathematical equation, the total accumulated utility for an individual vehicle over a temporal horizon is calculated as the discounted sum of instantaneous rewards. The discount factor gamma ensures mathematical convergence and emphasizes the importance of near-term performance. The instantaneous reward bracket contains three heavily weighted components. The first term represents the Shannon capacity approximation of the communication link, weighted by a coefficient to reward high data throughput. The second term introduces a linear penalty for the absolute transmission power utilized at that time step, strictly enforcing energy efficiency and interference reduction. The final component employs an indicator function that applies a massive structural penalty if the achieved link quality falls below the critical safety threshold, forcing the decentralized algorithm to prioritize baseline reliability above all other metrics. Zhao and colleagues examine trajectory-level reward shaping for formulaic alpha mining [21].

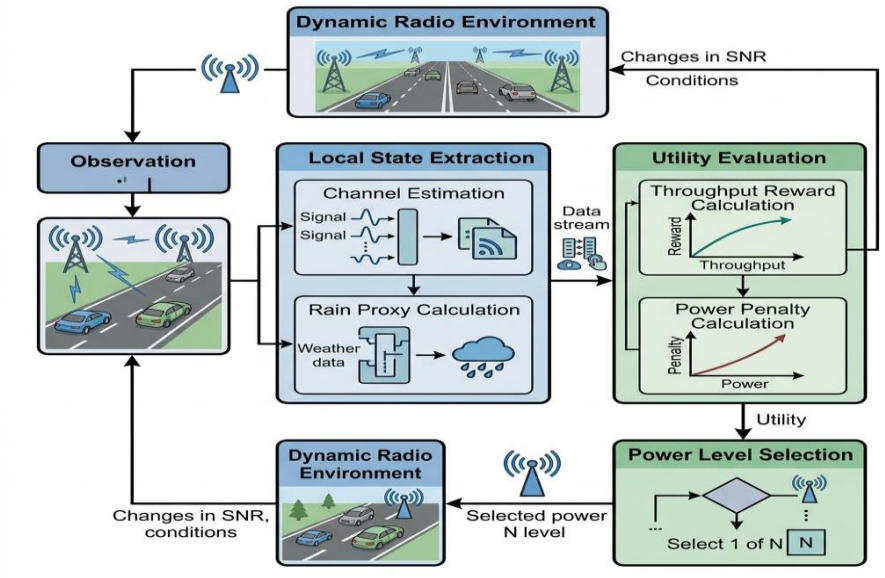


Figure 2Architectural Flowchart of the Decentralized Multi

5. Algorithmic Implementation and Protocol Design

The theoretical methodology established in the previous section must be translated into a practical, implementable algorithmic structure and an associated communication protocol. The transition from mathematical abstraction to engineering implementation requires careful consideration of signaling overhead, computational latency, and the physical limitations of vehicular hardware.

5.1 Distributed Decision Execution

The core of the implementation is the algorithm executed independently by the onboard processing unit of each vehicle. Because the environment is profoundly nonstationary due to mobility and shifting weather patterns, classical static optimization tables are entirely ineffective. The algorithm must continuously adapt. We utilize a decentralized iterative learning approach where each vehicle maintains a localized value function mapping its observed states to expected utilities. Yang and colleagues examine joint-Aware video processing with Edge-Cloud collaboration for DNN inference [22]. During operational deployment, at the beginning of each scheduling interval, the vehicle samples its local state observation vector. Utilizing its internally maintained value function, it selects the transmission power level that currently predicts the highest cumulative utility. After executing the transmission, the vehicle receives an acknowledgment or negative acknowledgment from its receiver, along with a quantized report of the actual achieved Signal-to-Interference-plus-Noise Ratio. Using this immediate feedback, the vehicle computes the instantaneous utility realized during that time step. The most critical phase of the algorithmic execution is the update mechanism. The vehicle uses the realized utility to iteratively update its internal value function, refining its future decision-making capabilities. In a nonstationary environment, older experiences rapidly become obsolete as the spatial topology and rainfall distribution evolve. Therefore, the learning rate and the memory retention factors of the update algorithm are dynamically tuned. When the vehicle detects rapid changes in the environment—for example, a sudden drop in received signal strength indicative of entering a heavy rain cell—the algorithm automatically increases the learning rate, discarding outdated state-action mappings and rapidly adapting to the new meteorological reality.

5.2 Signaling Protocol And Overhead Analysis

A primary advantage of the proposed decentralized architecture is the drastic reduction in signaling overhead compared to centralized or cooperative distributed schemes. In a centralized architecture, every active vehicle must continuously transmit high-resolution channel state information back to a central controller, which then computes the global optimum and transmits the power commands back to the vehicles. In a rapidly fading millimeter-wave channel, this process requires immense bandwidth and incurs latency that frequently exceeds the coherence time of the channel, rendering the power commands entirely obsolete by the time they are executed. Related work has addressed aI-Driven visual End-Edge-Cloud architecture for 6G in Low-Carbon smart cities [23].

Our protocol design intentionally eliminates the need for global state reporting and inter-vehicle interference coordination messages. The only signaling required overhead is the localized feedback strictly between the intended transmitter and receiver pair. This feedback consists of an extremely short control message appended to standard acknowledgment frames, containing a heavily quantized representation of the measured link quality.

Table 3Communication Protocol Overhead Comparison

Architecture Type	Required Signaling Messages	Latency Implication	Scalability in Dense Networks
Purely Centralized	Global Channel State Updates	High Delay	Extremely Poor
Cooperative Distributed	Inter-vehicle Interference Reports	Medium Delay	Moderate

Proposed Decentralized	Local Intended Receiver Feedback	Minimal Delay	Highly Scalable

This localized protocol design guarantees that the signaling overhead scales linearly with the number of active communication pairs, rather than exponentially with the density of the network. Furthermore, because the decision-making is executed locally at the transmitter, the computational latency is negligible, allowing the power control mechanism to operate at the microsecond timescales required to track the fast-fading components of the nonstationary vehicular channel. For a broader comparison, related research addresses prescribed-time tracking control of MIMO nonlinear systems with nonvanishing uncertainties [24].

6. Simulation Results and Performance Evaluation

To rigorously validate the efficacy of the proposed decentralized power control framework, we conduct extensive numerical simulations. The simulation environment is meticulously constructed to faithfully replicate the complex interplay of vehicular mobility, millimeter-wave propagation physics, and dynamic meteorological phenomena.

6.1 Simulation Environment Setup

The mobility of the vehicular network is generated using established microscopic traffic simulators, modeling a heavily congested multi-lane highway scenario. Vehicles are injected into the simulation at varying densities to evaluate the algorithms under different interference regimes. The wireless communication parameters are configured according to standardized millimeter-wave specifications, operating at a high carrier frequency with realistic directional antenna radiation patterns that include main lobe gains and side lobe leakage.

The meteorological environment is a critical component of the simulation. We model dynamic storm cells moving across the highway infrastructure. The rainfall intensity within these cells ranges from zero millimeters per hour, representing clear-sky conditions, to excessive downpours exceeding fifty millimeters per hour. As the simulated vehicles traverse the highway, they dynamically enter and exit these varying precipitation zones, experiencing severe and uncoordinated rain attenuation that accurately reflects the nonstationary channel conditions described in the theoretical models. We benchmark the performance of our proposed decentralized algorithm against three standard baselines. The first baseline is a Maximum Power scheme, where all vehicles constantly transmit at their maximum allowable power, representing a naive approach focused solely on overcoming path loss. The second baseline is a Random Power scheme, where vehicles select their transmission power uniformly at random from the discrete action space. The third baseline is a computationally heavy Centralized Allocation scheme that assumes perfect, instantaneous global knowledge of all channels and interference paths, serving as a theoretical upper bound for network performance. Another relevant line of investigation concerns a three-axis digital tunneling resistance-type magnetic sensor [25].

6.2 Impact Of Rainfall Rate On Network Performance

The initial phase of the performance evaluation focuses on the impact of varying rainfall intensities on the overall network sum-rate and link reliability. Under clear-sky conditions, the primary challenge is pure co-channel interference. In this regime, the Maximum Power baseline performs exceptionally poorly. While individual links attempt to maximize their signal strength, the aggregate interference floor rises exponentially, leading to a catastrophic drop in the Signal-to-Interference-plus-Noise Ratio for the majority of the network. Our proposed decentralized algorithm successfully learns to throttle transmission powers, establishing a cooperative equilibrium that significantly outperforms the naive baselines by minimizing mutual interference. As the simulation introduces varying degrees of precipitation, the dynamics shift dramatically. Under moderate rain conditions, the path loss increases significantly. The proposed algorithm intelligently detects this environmental change through the local rain impact estimation state

variable. In response, the vehicular agents autonomously increase their transmission powers to compensate for the rain attenuation, while still carefully balancing the interference penalty.
Under severe rain conditions, characterized by intense localized downpours, the nonstationarity of the channel reaches its peak. Vehicles inside the storm cell require maximum power just to maintain baseline connectivity, while vehicles just outside the cell must avoid overwhelming the weakened signals of those inside. The results clearly demonstrate that the proposed decentralized algorithm maintains a highly stable network sum-rate even under these extreme conditions.

Table 4Comparative Performance Metrics Under Severe Rain Conditions (50 mm/hr)

Algorithmic Approach	Average Network Sum-Rate	Link Reliability (Outage Probability)	Average Power Consumption
Maximum Power Baseline	1.2 Gigabits/second	28.4 Percent	23.0 dBm
Random Power Baseline	0.8 Gigabits/second	45.1 Percent	15.0 dBm
Proposed Decentralized	3.4 Gigabits/second	4.2 Percent	12.5 dBm
Theoretical Centralized	3.9 Gigabits/second	1.5 Percent	11.2 dBm

The data in Table 4 illustrates the robust performance of the proposed methodology. While the Maximum Power baseline suffers a massive outage probability due to uncontrollable interference, and the Random Power baseline fails entirely to maintain link budgets through the heavy rain, the proposed decentralized algorithm achieves an average network sum-rate that approaches the theoretical centralized upper bound. Crucially, it accomplishes this while maintaining an exceptionally low outage probability, ensuring that critical safety messages are reliably delivered despite the severe weather. Furthermore, the average power consumption metric reveals the high energy efficiency of the decentralized approach. Related work has addressed weather-aware power control for decentralized V2V communication [26].

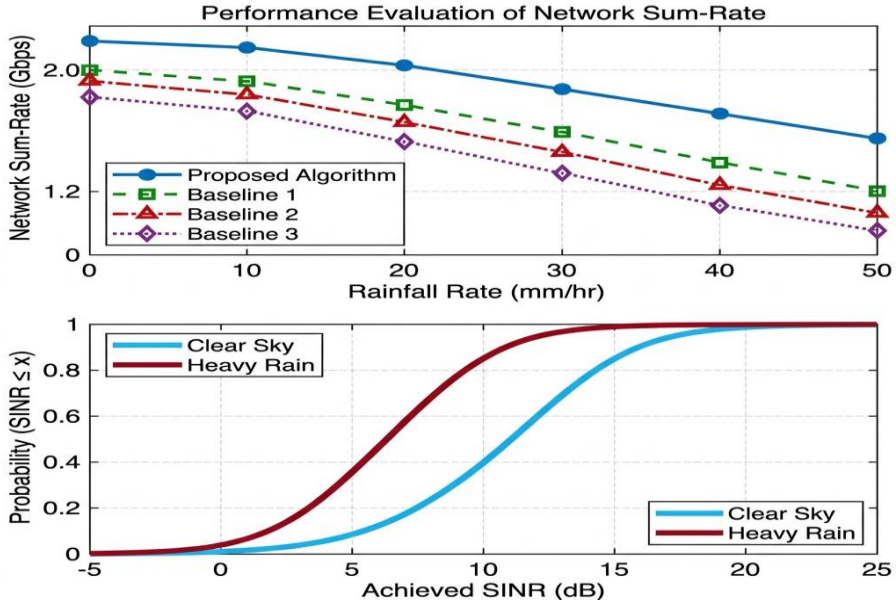


Figure 3Performance Evaluation Graphs

6.3 Convergence And Interference Mitigation Analysis

Beyond static performance metrics, the transient behavior and convergence properties of the decentralized algorithm are critical for practical implementation in fast-fading vehicular

environments. We analyze the convergence speed by tracking the evolution of the network sum-rate from the initialization of the simulation. Wei and colleagues examine toward adaptive tracking and communication via an airborne maneuverable Bi-Static ISAC system [27].

The analysis reveals that the proposed algorithm achieves a stable power allocation strategy within a highly compressed timeframe, requiring only a few dozen iterations to reach near-optimal performance. This rapid convergence is directly attributed to the carefully engineered localized state space and the explicit penalty structures within the utility function. By relying strictly on local observations and avoiding the delays of inter-vehicle signaling, the algorithm adapts almost instantaneously to macroscopic changes in the environment, such as a vehicle suddenly merging into a dense traffic cluster or entering the boundary of a severe rain cell. Furthermore, an analysis of the interference distribution across the network demonstrates the profound effectiveness of the implicit coordination mechanism. The decentralized algorithm successfully reshapes the interference topology, forcing vehicles in dense clusters to aggressively reduce their transmit powers to the minimum threshold required for successful communication, thereby creating spatial interference-free zones that allow neighboring links to operate efficiently. This emergent cooperative behavior, achieved entirely without explicit communication between competing agents, confirms the theoretical robustness of the proposed methodology under severe rain-induced nonstationarity.

7. Conclusion

This comprehensive study has rigorously investigated the complex and highly dynamic problem of power control in decentralized millimeter-wave Vehicle-to-Vehicle networks operating under the severe constraints of rain-induced channel nonstationarity and dense co-channel interference. As Intelligent Transportation Systems increasingly rely on high-frequency spectrums to support massive data requirements, the susceptibility of these communication links to meteorological phenomena fundamentally challenges traditional network optimization paradigms. Related work has addressed 5G and 4G V2V communication channel performance under severe weather [28].

We developed a robust analytical framework that intricately integrated empirical meteorological models of rain attenuation with the rapid spatiotemporal fading characteristics inherent to vehicular mobility. Recognizing the insurmountable latency and overhead limitations of centralized architectures in such dynamic environments, we formulated the power allocation challenge as a multi-agent decentralized optimization problem. By meticulously designing a localized state observation mechanism and a carefully balanced utility function that strictly penalizes excessive power consumption and rewards threshold-based reliability, we enabled individual vehicular agents to autonomously deduce highly efficient transmission strategies. Yao and colleagues examine secure transmission scheme based on joint radar and communication in mobile vehicular networks [29]. Extensive numerical simulations across a wide spectrum of traffic densities and extreme rainfall intensities definitively validated the superiority of the proposed framework. The results demonstrated that the decentralized algorithm rapidly converges to a stable, cooperative equilibrium, drastically mitigating network-wide interference while ensuring the reliable delivery of critical communication payloads even under heavy precipitation. By achieving performance metrics that closely rival theoretical centralized upper bounds without requiring any global state information or inter-vehicle coordination, this methodology presents a highly scalable, resilient, and practical solution for the deployment of next-generation vehicular communication networks in adverse environmental conditions.

References

Li, Q., Feng, Y., Wen, M., Wen, J., Alexandropoulos, G. C., Basar, E., & Poor, H. V. (2024). Cooperative backscatter communications with reconfigurable intelligent surfaces: An APSK approach. IEEE Transactions on Wireless Communications, 23(11), 16218-16233.

Wang, S., Zhang, X., Wang, P., & Li, X. (2026). Design of Magnetic Sensor Array-Based PUFs for IoT Security. IEEE Transactions on Instrumentation and Measurement, 75, 1-9.

Li, X., Wang, P., Li, G., Ni, L., & Zhang, Y. (2023). Design of interface circuits and lightweight PUF for TMR sensors. IEEE Sensors Journal, 23(11), 11754-11761.

Yao, Y., Zhao, J., Li, Z., Cheng, X., & Wu, L. (2023). Jamming and eavesdropping defense scheme based on deep reinforcement learning in autonomous vehicle networks. IEEE Transactions on Information Forensics and Security, 18, 1211-1224.

Wang, X., Li, X., Shao, J., & Zhang, J. (2023). AC2C: Adaptively controlled two-hop communication for multi-agent reinforcement learning. arXiv preprint arXiv:2302.12515.

Yang, Y., & Zanj, A. (2026). Experimental flow characterisation of viscosity induced delivery degradation in high-viscosity peristaltic pumping. Flow Measurement and Instrumentation, 112, 103572.

Li, R., Xiao, Z., & Zeng, Y. (2023). Toward seamless sensing coverage for cellular multi-static integrated sensing and communication. IEEE Transactions on Wireless Communications, 23(6), 5363-5376.

Mnih, V., Kavukcuoglu, K., Silver, D., Graves, A., Antonoglou, I., Wierstra, D., & Riedmiller, M. (2013). Playing Atari with deep reinforcement learning. arXiv preprint arXiv:1312.5602.

Li, X., Wang, P., Li, G., & Zhang, Y. (2023). Design of a novel self-test-on-chip interface ASIC for capacitive accelerometers. IEEE Transactions on Circuits and Systems I: Regular Papers, 70(7), 2834-2843.

Yang, Y., Jafari, A., Robertson, W., & Arjomandi, M. (2025). Exploring the impact of geometric variation on electromagnetic performance in a coaxial coil system. Current Science (00113891), 128(7), 657.

Wang, Z., Kim, E. H., Oh, S. K., Pedrycz, W., Fu, Z., & Yoon, J. H. (2024). Reinforced fuzzy-rule-based neural networks realized through streamlined feature selection strategy and fuzzy clustering with distance variation. IEEE Transactions on Fuzzy Systems, 32(10), 5674-5686.

Yao, Y., Lu, Z., Chen, G., Huang, C., Feng, C., & Quek, T. Q. (2026). Interference Management in ISAC-SAGINs Based on Transformer-Enabled Mean-Field Reinforcement Learning Method. IEEE Transactions on Wireless Communications.

Kalashnikov, D., Irpan, A., Pastor, P., Ibarz, J., Herzog, A., Jang, E., et al. (2018). QT-Opt: Scalable deep reinforcement learning for vision-based robotic manipulation. arXiv preprint arXiv:1806.10293.

Hao, Y., Xu, J., & Liao, S. (2026). RAPS-Net: A Risk-Aware CNN-LSTM Framework for Cross-Domain Risk Prediction and Dynamic Security Control in Cloud Payment Supply Chains. Economics and Management Innovation, 3(2), 18-27.

Xu, Yuanchao, Amal Feriani, and Ekram Hossain. "Decentralized multi-agent reinforcement learning for task offloading under uncertainty." arXiv preprint arXiv:2107.08114 (2021).

Tian, Y., & Yang, Z. (2026, May). SAEC: scene-aware enhanced edge-cloud collaborative industrial vision inspection with multimodal LLM. In ICASSP 2026-2026 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) (pp. 19747-19751). IEEE.

Yang, Y., Robertson, W. S., Jafari, A., & Arjomandi, M. (2025). Optimising coil design based on sensitivity analysis of magnetic force induced between misaligned coil pairs. Electrical Engineering, 107(12), 15317-15328.

Yang, Y., Robertson, W. S., Jafari, A., & Arjomandi, M. (2025, August). Impact of Core Geometry on Magnetic Forces in Electromagnetic Coil Systems. In 2025 IEEE International Workshop on Electromagnetics: Applications and Student Innovation Competition (iWEM) (pp. 323-326). IEEE.

Zhang, Y., Pleus, A., & Althoff, M. (2026, July). Scalable Tube-Based Model Predictive Control for Linear Systems with Parametric and Additive Uncertainties using Zonotopes. In 2026 European Control Conference (ECC) (pp. 509-516). IEEE.

Pei, Z., Huang, Q., & Wang, S. (2026). When LLMs develop languages: Symbolic communication for efficient multi-agent reasoning. arXiv preprint arXiv:2606.29354.

Zhao, J., Zhang, C., Wang, C., & Yang, P. (2025). Learning from expert factors: Trajectory-level reward shaping for formulaic alpha mining. arXiv preprint arXiv:2507.20263.

Yang, Z., Ji, W., Guo, Q., & Wang, Z. (2023, October). Javp: Joint-aware video processing with edge-cloud collaboration for dnn inference. In Proceedings of the 31st ACM International Conference on Multimedia (pp. 9152-9160).

Yang, Z., Hu, D., Guo, Q., Zuo, L., & Ji, W. (2023). Visual E 2 C: AI-driven visual end-edge-cloud architecture for 6G in low-carbon smart cities. IEEE Wireless Communications, 30(3), 204-210.

Ye, H.; Song, Y. Prescribed-time tracking control of MIMO nonlinear systems with nonvanishing uncertainties. IEEE Trans. Autom. Contr. 2023, 68, 3664–3671.

Li, X., Yin, L., Chen, W., Liu, X., & Fu, Q. (2016). Study of a three-axis digital tunneling resistance-type magnetic sensor.IEICE Electronics Express,13(13), 20160319-20160319.

Liu, J., & Huang, C. T. (2025, August). Weather-aware power control for decentralized V2V communication. In 2025 34th International Conference on Computer Communications and Networks (ICCCN) (pp. 1-9). IEEE.

Wei, M., Li, R., Wang, L., Chang, Z., Xu, L., & Han, Z. (2026). Toward Adaptive Tracking and Communication via an Airborne Maneuverable Bi-Static ISAC System. IEEE Transactions on Vehicular Technology.

Liu, J., Nazeri, A., Zhao, C., Abuhdima, E., Comert, G., Huang, C. T., & Pisu, P. (2022, October). Investigation of 5G and 4G V2V communication channel performance under severe weather. In 2022 IEEE International Conference on Wireless for Space and Extreme Environments (WiSEE) (pp. 12-17). IEEE.

Yao, Y., Shu, F., Li, Z., Cheng, X., & Wu, L. (2023). Secure transmission scheme based on joint radar and communication in mobile vehicular networks. IEEE transactions on intelligent transportation systems, 24 (9), 10027-10037.