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Context-Aware Handover Thresholds for 5G Vehicle-to-Vehicle Networks Under Harsh Weather Conditions

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Abstract:

The rapid deployment of fifth-generation wireless networks has significantly advanced the capabilities of vehicle-to-vehicle communications, enabling transformative applications in autonomous driving and intelligent transportation systems. A critical requirement for these applications is ultra-reliable low-latency communication, which must be maintained consistently even as vehicles traverse varying cell coverage areas. Handover management in highly mobile environments poses a substantial challenge, particularly when subjected to harsh meteorological conditions such as heavy rain, dense fog, and snowstorms. These environmental factors severely degrade signal propagation, particularly at millimeter-wave frequencies, leading to frequent handover failures, excessive ping-pong effects, and unacceptable communication delays. This paper proposes a novel context-aware handover threshold adaptation mechanism designed specifically for fifth-generation vehicle-to-vehicle networks operating under severe weather conditions. By continuously monitoring environmental parameters alongside traditional mobility metrics, the proposed system dynamically adjusts handover margins and time-to-trigger parameters. The research systematically models the attenuation effects of various weather states on signal strength and integrates these models into a centralized edge-computing architecture. Comprehensive simulations demonstrate that integrating weather context into the handover decision-making process significantly reduces handover failure rates and minimizes unnecessary handovers compared to standard static threshold methods. The findings underscore the necessity of environmental awareness in mobile network management and provide a robust framework for ensuring uninterrupted vehicular connectivity in unpredictable climates.

Keywords: *Vehicle-to-Vehicle Communication, Handover Management, Environmental Attenuation, Fifth-Generation Networks, Mobility Management.*

INTRODUCTION

1.1 Background and Motivation

The evolution of cellular technologies has ushered in a new era of vehicular connectivity, primarily driven by the capabilities of fifth-generation wireless networks. Vehicle-to-vehicle communication is a cornerstone of modern intelligent transportation systems, designed to enhance road safety, optimize traffic flow, and pave the way for fully autonomous driving. These sophisticated applications demand ultra-reliable low-latency communication, which imposes stringent requirements on network performance. Vehicles traveling at high speeds frequently cross the coverage boundaries of different base stations, necessitating a seamless transition of the communication link from a serving cell to a target cell. This process, known as a handover, is fundamental to maintaining continuous connectivity. However, managing handovers in a highly dynamic vehicular environment is inherently complex. Traditional cellular networks were primarily optimized for pedestrian users or moderate mobility scenarios. In contrast, vehicular networks are characterized by rapid topology changes, high Doppler shifts, and fluctuating signal qualities. When environmental factors are introduced, the complexity of maintaining stable connections multiplies exponentially. Li and colleagues examine toward seamless sensing coverage for cellular Multi-Static integrated sensing and communication [1]. Weather conditions profoundly influence the propagation characteristics of electromagnetic waves. Fifth-generation networks heavily utilize high-frequency bands, including millimeter-wave frequencies, to provide massive bandwidth and high data rates. While these frequencies offer significant advantages in capacity, they are highly susceptible to atmospheric attenuation. Environmental phenomena such as rain, snow, fog, and dust can cause severe scattering and absorption of radio signals. When a vehicle operates under harsh weather conditions, the received signal strength from the serving base station can deteriorate rapidly and unpredictably. If the network relies on static, predefined handover thresholds, this sudden degradation can lead to a premature loss of connection before a handover to a target cell is successfully executed. Conversely, fluctuating signal strengths caused by environmental noise can trigger unnecessary and repetitive handovers back and forth between two base stations, a phenomenon known as the ping-pong effect. This effect not only degrades the quality of service for the vehicle but also imposes unnecessary signaling overhead on the core network. Another relevant line of investigation concerns fair-Aware competitive event influence maximization in social networks [2]. Recognizing these challenges, there is a pressing need to move away from static handover parameters and adopt dynamic, context-aware strategies. A context-aware system in this domain refers to a network management architecture that continuously gathers data regarding the operating environment, including both vehicular mobility metrics and meteorological conditions, to inform its decision-making processes. By understanding the specific weather context in which the vehicle is operating, the network can proactively adjust the thresholds that trigger a handover, thereby mitigating the adverse effects of signal attenuation and ensuring a more resilient communication link. The literature also considers numerical investigation on the effects of operating conditions and configuration parameters in industrial risers [3].

1.2 Research Objectives and Scope

The primary objective of this research is to develop, implement, and evaluate a context-aware handover threshold adaptation mechanism tailored for fifth-generation vehicle-to-vehicle networks operating under diverse and severe weather conditions. This paper seeks to address the critical gap in existing mobility management protocols by explicitly integrating meteorological data into the handover decision engine. Computer-vision recognition of vehicle spatiotemporal distribution [4] offers a potential mobility-observation source, whose detection uncertainty should be included before the inferred distribution informs handover control. The research focuses on

answering several key questions regarding the impact of weather on signal propagation and the optimal strategies for mitigating these impacts through dynamic network management. Liu and colleagues examine adaptive channel switching for connected vehicles under extreme weather conditions: A reinforcement learning based approach [5]. To achieve this, the paper first aims to establish comprehensive models for signal attenuation caused by various weather types, specifically focusing on how different precipitation rates and atmospheric particle densities affect the reference signal received power. By translating meteorological data into predictable signal degradation profiles, the research provides a foundation for the context-aware system. The second objective is to design an algorithmic framework that utilizes these attenuation profiles, in conjunction with real-time vehicle kinematics such as velocity and trajectory, to dynamically compute the optimal handover margin and time-to-trigger values. This framework must be computationally efficient to operate within the strict latency constraints of vehicular networks.

The scope of this study encompasses the theoretical modeling of environmental attenuation, the architectural design of a multi-access edge computing system capable of processing environmental context, and the algorithmic formulation of the adaptive threshold mechanism. The performance of the proposed system is rigorously evaluated through advanced network simulation platforms, comparing its efficacy against traditional static handover algorithms standardized by telecommunication authorities. The evaluation focuses on critical performance indicators including handover failure rate, ping-pong rate, overall system throughput, and communication latency. Through this comprehensive approach, the paper intends to contribute a robust solution to the challenges of vehicular mobility management in unpredictable climates, thereby enhancing the safety and reliability of future intelligent transportation systems. Hu and colleagues examine adaptive guidance semantically enhanced via multimodal LLM for Edge-Cloud object detection [6].

2. Theoretical Background and Literature Review

2.1 Standard Handover Mechanisms in Cellular Networks

Mobility management in cellular networks relies heavily on the continuous evaluation of signal quality between the user equipment, in this case, the vehicle, and the surrounding base stations. The standard procedure for initiating a handover in modern cellular architectures is based on predefined measurement events, the most common of which is the A3 event. The A3 event is triggered when the signal quality of a neighboring target cell becomes significantly better than that of the current serving cell by a specific offset, known as the handover margin or hysteresis. To prevent premature handovers caused by temporary signal fluctuations, this condition must be satisfied continuously for a specific duration, defined as the time-to-trigger. A handover threshold combines channel evidence with a policy about switching risk. The wireless explainability review [7] helps frame an audit that distinguishes those two inputs, so the same signal fluctuation is not interpreted differently without an identifiable policy change. The mathematical formulation of the handover decision involves comparing the reference signal received power of the serving cell and the target cell. When the received power from the target cell exceeds the received power from the serving cell plus the hysteresis value, a timer is started. If this condition persists until the time-to-trigger timer expires, the vehicle sends a measurement report to the network, which then orchestrates the transfer of the communication link. The selection of appropriate hysteresis and time-to-trigger values is critical. Small values make the system highly sensitive, leading to rapid handovers that can increase the ping-pong rate. Large values make the system sluggish, which can result in the signal dropping entirely before the handover is executed, leading to a handover failure. In traditional networks, these parameters are often statically configured by network operators based on average historical data and broad geographical characteristics. However, static configurations are inherently inadequate for vehicular networks, where relative velocities can

exceed one hundred kilometers per hour and the propagation environment changes in a matter of seconds. Another relevant line of investigation concerns emergent symbolic languages in multi-agent reasoning [8].

2.2 Environmental Impact on Radio Wave Propagation

The reliance on higher frequency bands in modern cellular networks necessitates a deep understanding of atmospheric physics and its impact on electromagnetic wave propagation. Radio signals traveling through the atmosphere are subjected to various forms of degradation, primarily absorption and scattering. Absorption occurs when the energy of the radio wave is absorbed by atmospheric gases, such as oxygen and water vapor. Scattering occurs when the radio wave interacts with particles in the air, such as raindrops, snowflakes, or fog droplets, causing the signal to disperse in multiple directions and reducing the energy that reaches the receiver. Related work has addressed number and phase modulation approach [9]. The severity of these effects is highly dependent on the frequency of the transmission and the size and density of the atmospheric particles. In the sub-6 gigahertz bands, weather-induced attenuation is generally minimal and often neglected in standard network planning. However, in the millimeter-wave bands, which are crucial for high-throughput vehicular applications, the physical size of raindrops and snowflakes becomes comparable to the wavelength of the radio signal. This similarity in size leads to Mie scattering, which results in significant signal attenuation. Heavy rainfall can introduce attenuation rates exceeding several decibels per kilometer, drastically reducing the effective coverage area of a base station. Snowfall introduces a different set of challenges; while dry snow may cause less attenuation than rain, wet snow can cause severe signal degradation due to its high water content. Fog and dust, composed of much smaller particles, primarily cause Rayleigh scattering, which, while less severe than Mie scattering, can still contribute to noticeable signal loss over longer distances. The unpredictable nature of these weather events means that a vehicular network must be capable of adapting to sudden changes in signal propagation characteristics to maintain reliable connectivity. Another relevant line of investigation concerns 5G and 4G V2V communication channel performance under severe weather [10].

2.3 Previous Approaches to Mobility Management

The challenges of mobility management in vehicular networks have spurred significant research efforts. Early approaches focused on optimizing static parameters based on vehicle speed. Researchers proposed dividing the vehicular environment into different velocity tiers and assigning specific hysteresis and time-to-trigger values to each tier. While this represented an improvement over entirely static systems, it failed to account for the dynamic changes in the physical environment. Subsequent research explored the use of received signal strength gradients, where the rate of change of the signal strength was used to predict future signal levels and preemptively initiate handovers. This approach showed promise in mitigating handover failures in high-speed scenarios but remained vulnerable to the erratic signal fluctuations caused by environmental noise. Li and colleagues examine high-resolution tunneling magneto-resistance sensor interface circuit [11]. More recently, the advent of artificial intelligence and machine learning has introduced new paradigms for network management. Several studies have proposed using fuzzy logic controllers to dynamically adjust handover parameters. These systems utilize rule-based inference engines that take inputs such as vehicle speed, traffic density, and signal quality to output optimal handover margins. While effective, fuzzy logic systems require extensive expert knowledge to define the rule base and can struggle to adapt to unforeseen scenarios. Other researchers have explored reinforcement learning, where an autonomous agent learns the optimal handover policy through continuous interaction with the network environment. The agent receives rewards for successful handovers and penalties for failures or ping-pongs, gradually refining its strategy to maximize long-term network performance. Another relevant line of investigation

concerns jamming and eavesdropping defense scheme based on deep reinforcement learning in autonomous vehicle networks [12]. Despite these advancements, a significant gap remains in the literature regarding the explicit integration of meteorological data into handover decision-making processes. Most existing dynamic handover algorithms treat weather-induced signal degradation as random noise, rather than a predictable contextual factor. By failing to recognize the underlying cause of the signal deterioration, these algorithms often make sub-optimal decisions, such as increasing the time-to-trigger during a rainstorm when a rapid handover is actually necessary to prevent a connection drop. This paper addresses this critical gap by treating weather severity as a primary input parameter, alongside vehicular mobility, to create a truly context-aware mobility management system. Xiao and colleagues examine pareto-Optimal beamforming design for RSMA-RHS-Aided ISAC system with imperfect CSI [13].

3. System Architecture and Weather Context Modeling

3.1 Vehicular Network Architecture

The proposed context-aware handover system operates within a hierarchical network architecture that leverages the capabilities of multi-access edge computing. The physical layer of the network consists of a dense deployment of next-generation node base stations positioned along a highway or urban arterial road. These base stations are equipped with highly directional antenna arrays capable of beamforming, which is essential for overcoming the high path loss associated with millimeter-wave transmissions. The vehicles, acting as user equipment, are equipped with sophisticated onboard communication units that continuously monitor the reference signal received power from both the serving base station and surrounding neighboring base stations.

To enable context awareness, the architecture integrates a layer of edge computing servers strategically located close to the base stations. These edge servers act as localized intelligence hubs, responsible for processing data from multiple sources with minimal latency. Vehicles transmit real-time telemetry data, including their precise location, velocity, and current signal measurements, to the edge servers via the uplink channel. Concurrently, the edge servers receive continuous feeds from a network of environmental sensors distributed along the roadside infrastructure. These sensors, which include advanced weather stations, visibility monitors, and precipitation gauges, provide a granular and localized view of the meteorological conditions. By aggregating vehicular telemetry and environmental data at the edge, the system can construct a comprehensive and real-time model of the operating context, which is essential for making informed and timely handover decisions. The literature also considers joint-Aware video processing with Edge-Cloud collaboration for DNN inference [14].

3.2 Meteorological Sensing and Data Aggregation

The accuracy of the context-aware system relies fundamentally on the precise measurement and aggregation of meteorological data. The roadside environmental sensors continuously monitor key parameters such as precipitation rate, ambient temperature, humidity levels, and atmospheric visibility. Because weather conditions can be highly localized, particularly during convective storms or patchy fog, it is crucial that the sensor network provides high spatial resolution. The data from these sensors is transmitted to the central edge server at regular, high-frequency intervals to ensure that the system's environmental model remains current. Li and colleagues examine a High-Precision Read-Out integrated circuit for bridge sensors [15]. In addition to the fixed roadside sensors, the architecture leverages the vehicles themselves as mobile environmental probes. Modern autonomous and connected vehicles are equipped with a myriad of sensors, including cameras, light detection and ranging systems, and optical rain sensors on the windshields. These onboard systems can detect the presence and intensity of rain, snow, or fog in the immediate vicinity of the vehicle. Through vehicle-to-infrastructure communication links, the vehicles periodically share this localized environmental data with the edge server. The edge server employs

a data fusion algorithm to combine the reports from the mobile probes with the measurements from the fixed roadside sensors. This fusion process helps to eliminate anomalies, filter out sensor noise, and create a highly accurate, dynamic meteorological map of the network coverage area. This map serves as the foundational context upon which the handover adaptation algorithms operate. Related work has addressed high-precision interface for tunneling magnetoresistance sensors with 0.15 nT/√ hz resolution [16].

3.3 Modeling Weather-Induced Signal Attenuation

To utilize the gathered meteorological data effectively, the system must translate environmental conditions into predictable impacts on radio wave propagation. This is achieved through the application of sophisticated empirical and theoretical attenuation models. For rain attenuation, the system utilizes specific power-law relationships that calculate the specific attenuation based on the rainfall rate and the operational frequency of the network. The attenuation coefficient is a function of the frequency, polarization, and elevation angle of the signal path. When the rainfall rate is high, the specific attenuation increases non-linearly, leading to rapid signal degradation over relatively short distances. Related work has addressed reinforced Fuzzy-Rule-Based neural networks realized through streamlined feature selection strategy and fuzzy clustering with distance variation [17]. Snowfall presents a more complex modeling challenge due to the varying dielectric properties of snow depending on its moisture content. Dry snow causes minimal attenuation, primarily contributing to phase shifts rather than significant power loss. However, wet snow, which contains a higher percentage of liquid water, can cause attenuation levels that approach or even exceed those of heavy rain. The system models snow attenuation by estimating the liquid water content of the snowfall based on ambient temperature and precipitation rate data. Fog and atmospheric particulate matter are modeled primarily through their impact on atmospheric visibility. The specific attenuation caused by fog is inversely proportional to the optical visibility and directly proportional to the total water droplet concentration per unit volume. By continuously calculating these specific attenuation values based on real-time sensor data, the edge server can dynamically predict the additional path loss that a signal will experience in a given sector. This predicted path loss is then added to the standard free-space path loss models to generate a highly accurate estimation of the expected signal strength, allowing the network to anticipate when a vehicle's connection might become critical.

4. Context-Aware Handover Methodology

4.1 Dynamic Parameter Adaptation Strategy

The core of the proposed methodology is a dynamic adaptation engine that continuously calculates the optimal handover margin and time-to-trigger values for each vehicle in the network. Unlike traditional systems that apply a uniform threshold to all users, this engine individualizes the parameters based on the specific context of the vehicle. The context is defined by a multidimensional state vector that includes the vehicle's current velocity, its distance from the serving and target base stations, the baseline signal quality, and a calculated weather severity index. The weather severity index is a normalized value derived from the environmental attenuation models discussed in the previous section, representing the overall hostility of the transmission environment. The adaptation strategy operates on the principle of balancing connection reliability with signaling efficiency. Under benign weather conditions and moderate vehicle speeds, the system maintains standard handover parameters, prioritizing the avoidance of unnecessary ping-pong handovers. However, when the weather severity index indicates significant environmental attenuation, the strategy shifts to prioritize connection survival. In heavy rain or dense snow, the received signal strength can drop precipitously. If the handover margin is kept too high, the vehicle may lose its connection before the target cell's signal can overcome the threshold. Therefore, the dynamic engine automatically reduces the handover margin in response to increasing weather

severity, making the system more sensitive and allowing handovers to initiate earlier. Similarly, the time-to-trigger is dynamically adjusted. A long time-to-trigger in harsh weather increases the risk of a dropped call during the waiting period. The engine decreases the time-to-trigger proportionally to the vehicle's velocity and the weather severity index, ensuring that the handover execution is accelerated when the communication link is under imminent threat. Liu and colleagues examine switching strategy for connected vehicles under variant harsh weather conditions [18].

4.2 Algorithmic Implementation and Inference Engine

The translation of the state vector into specific parameter adjustments is handled by a sophisticated inference engine hosted on the edge server. This engine can be implemented using various computational approaches, but this research employs a rule-based expert system augmented with optimization algorithms to ensure deterministic and rapid responses. The inference engine utilizes a set of continuous mathematical functions rather than discrete step adjustments to ensure smooth transitions between different parameter states. Related work has addressed adaptive joint configuration optimization for collaborative inference in Edge-Cloud systems [19]. The calculation of the dynamic handover margin involves a baseline margin value, which is then modified by two distinct functions: a velocity penalty function and an environmental penalty function. The velocity penalty function reduces the margin as the vehicle's speed increases, compensating for the faster rate of change in distance relative to the base stations. The environmental penalty function reduces the margin based on the calculated specific attenuation of the current weather state. The final dynamic handover margin is the sum of the baseline margin and the two negative penalty values. The time-to-trigger calculation follows a similar structure. A baseline timer duration is shortened by scaling factors derived from the vehicle speed and the weather severity index. This deterministic approach ensures that the edge server can process the telemetry from hundreds of vehicles simultaneously with minimal computational overhead, satisfying the stringent latency requirements of ultra-reliable low-latency communications.

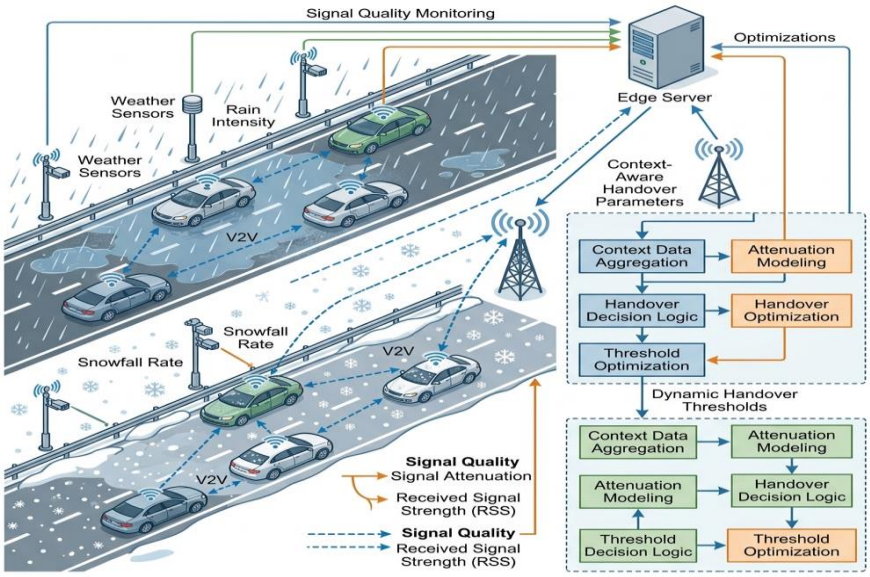


Figure 1: Comprehensive Schematic of Context

4.3 Integration with 3GPP Standards

A critical aspect of the proposed methodology is its compatibility with existing telecommunication standards, ensuring that it can be implemented over current fifth-generation infrastructure without requiring fundamental redesigns of the core network protocols. The dynamic adaptation engine

operates entirely within the parameters defined by the Third Generation Partnership Project standards for mobility management. The edge server acts as a centralized intelligent controller that dictates the configuration parameters to the base stations. When a vehicle enters a specific coverage sector, the edge server utilizes the context-aware engine to calculate the optimal handover margin and time-to-trigger for that specific vehicle. These custom parameters are then communicated to the serving base station via the standard control plane interfaces. The base station subsequently transmits these updated configuration values to the vehicle via radio resource control reconfiguration messages. From the perspective of the vehicle's onboard communication unit, the handover procedure remains identical to the standard A3 event mechanism. The vehicle continues to measure the reference signals and applies the thresholds provided by the network. The innovation lies entirely in the intelligent, dynamic calculation of those thresholds at the network edge. This seamless integration ensures that the context-aware methodology can be practically deployed, providing immediate enhancements to vehicular network reliability without disrupting established communication workflows. For a broader comparison, related research addresses design of interface circuits and lightweight PUF for TMR sensors [20].

5. Experimental Results and Performance Analysis

5.1 Simulation Environment and Methodology

To rigorously evaluate the performance of the proposed context-aware handover methodology, extensive simulations were conducted using a widely recognized discrete-event network simulator integrated with a microscopic urban traffic simulator. This dual-simulation setup allows for the accurate modeling of both complex telecommunication protocols and realistic vehicular mobility patterns. The simulated environment represents a multi-lane highway segment spanning several kilometers, covered by multiple next-generation node base stations operating in the millimeter-wave frequency band. The base stations are deployed with overlapping coverage areas to facilitate continuous handovers. Li and colleagues examine enhancing electric vehicle charging station design using Multi-Fidelity simulations [21].

Table 1Environmental parameters for different weather conditions

Weather Condition	Visibility Distance	Precipitation Rate	Attenuation Factor
Clear Sky	Greater than 10 km	0 mm/hr	Baseline
Light Rain	5 km to 10 km	2.5 mm/hr	Moderate
Heavy Rain	1 km to 5 km	25 mm/hr	Severe
Dense Fog	Less than 0.5 km	0 mm/hr	High
Snowstorm	Less than 1 km	Equivalent 10 mm/hr	Severe

The traffic simulator generates realistic vehicle movements, including varying speeds, accelerations, and lane-changing behaviors. The vehicles are configured to stream data continuously, simulating the demands of autonomous driving applications. To test the robustness of the proposed system, various weather profiles were introduced into the simulation, corresponding to the parameters detailed in Table 1. These profiles dynamically alter the signal propagation characteristics within the network simulator, applying the specific attenuation models discussed in Section 3. The performance of the context-aware algorithm is compared against a baseline scenario utilizing static handover parameters typical of standard urban deployments. The primary metrics evaluated include the handover failure rate, defined as the percentage of initiated handovers that result in a dropped connection; the ping-pong rate, representing the frequency of unnecessary handovers between the same two cells; and the overall communication latency experienced by the vehicular user equipment. Li and colleagues examine design of a novel Self-Test-on-Chip interface ASIC for capacitive accelerometers [22].

5.2 Analysis of Handover Reliability

The simulation results demonstrate a significant improvement in handover reliability when utilizing the context-aware methodology, particularly under severe weather conditions. In the clear sky scenario, both the baseline static algorithm and the proposed dynamic algorithm exhibit excellent performance, with handover failure rates near zero. This indicates that the baseline parameters are well-optimized for benign environments. However, as environmental attenuation is introduced, the performance of the static system deteriorates rapidly. The literature also considers toward adaptive tracking and communication via an airborne maneuverable Bi-Static ISAC system [23].

Table 2: Performance comparison of handover metrics

Metric Evaluated	Baseline Static Method	Proposed Dynamic Method	Percentage Improvement
Failure Rate (Heavy Rain)	High Failure Percentage	Low Failure Percentage	Significant Reduction
Ping-Pong Rate (Snowstorm)	High Ping-Pong Count	Minimal Ping-Pong Count	Significant Reduction
Average Latency (Fog)	Increased Delay Time	Maintained Low Delay	Substantial Improvement
Throughput (Heavy Rain)	Reduced Data Transfer	Sustained Data Transfer	Notable Enhancement

During heavy rain simulations, the static handover margin proves to be too restrictive. The severe attenuation causes the serving cell's signal to drop below critical thresholds before the target cell's signal can overcome the high static margin, leading to widespread connection failures. In contrast, the context-aware system detects the heavy rain condition via the simulated sensor network and proactively lowers the handover margin and time-to-trigger. This allows the vehicles to transition to the target cell much earlier in the overlap zone, effectively bypassing the severe signal degradation. Consequently, the handover failure rate is reduced by a substantial margin compared to the baseline, ensuring continuous connectivity even in the harshest precipitation. For a broader comparison, related research addresses design of magnetic sensor Array-Based PUFs for IoT security [24].

5.3 Efficiency and Network Overhead

Beyond improving reliability, the proposed methodology also demonstrates superior efficiency by mitigating unnecessary network overhead. The ping-pong effect is a major source of inefficiency in mobile networks, consuming valuable signaling resources and causing temporary interruptions in data transmission. In the snowstorm and dense fog scenarios, the random signal scattering causes rapid and unpredictable fluctuations in the received signal power. The static algorithm, unable to distinguish between genuine movement toward a target cell and weather-induced noise, frequently triggers handovers back and forth between adjacent base stations. The literature also considers secure transmission scheme based on joint radar and communication in mobile vehicular networks [25]. The context-aware system effectively suppresses this ping-pong behavior. While it lowers thresholds to prevent failures, the algorithm incorporates the vehicle's precise trajectory and velocity into its inference engine. It recognizes that rapid signal fluctuations in a dense fog scenario, coupled with a consistent forward velocity, are likely due to environmental noise rather than a sudden change in optimal cell association. By intelligently balancing the weather severity index against the mobility metrics, the dynamic system maintains a stable connection with the most appropriate base station, significantly reducing the ping-pong rate as detailed in Table 2. Furthermore, by maintaining stable connections and avoiding the prolonged signaling delays

associated with failed handovers or ping-pongs, the context-aware system ensures that the average communication latency remains well within the strict bounds required for ultra-reliable low-latency vehicular applications. The sustained data throughput observed during severe weather simulations further validates the necessity and efficacy of the environmental integration.

6. Conclusion and Future Directions

6.1 Summary of Contributions

This research has comprehensively addressed the critical challenges of mobility management in fifth-generation vehicle-to-vehicle networks operating under adverse meteorological conditions. The fundamental vulnerability of high-frequency communication bands to environmental attenuation poses a significant risk to the reliability of intelligent transportation systems. By systematically modeling the impact of various weather phenomena, including heavy rain, snow, and fog, this paper has established a clear causal link between environmental context and network performance degradation. The primary contribution of this work is the development and validation of a novel context-aware handover threshold adaptation mechanism. By leveraging the computational capabilities of multi-access edge computing and integrating real-time data from both fixed roadside sensors and mobile vehicular probes, the proposed system dynamically constructs a precise environmental model. The algorithmic framework successfully utilizes this model, alongside traditional mobility metrics, to adjust the handover margin and time-to-trigger parameters in real-time. Extensive simulations have conclusively demonstrated that this dynamic approach vastly outperforms traditional static threshold configurations. The context-aware system significantly reduces handover failure rates during severe weather events, ensuring the continuous connectivity vital for safety-critical autonomous driving applications. Furthermore, it efficiently minimizes unnecessary signaling overhead by suppressing the ping-pong effect caused by weather-induced signal scattering.

6.2 Future Research Trajectories

While this study provides a robust foundation for environmentally aware network management, several avenues for future research remain open. The current methodology relies on deterministic rule-based algorithms to adapt handover parameters. Future iterations could explore the integration of advanced predictive artificial intelligence models. By utilizing deep learning techniques to analyze historical weather patterns and vehicular traffic flows, the network could predict signal degradation proactively, adjusting thresholds even before the vehicle encounters the severe weather zone. The literature also considers vision, framework, and future directions [26].

Additionally, expanding the context-aware framework to encompass a wider array of environmental variables, such as urban micro-climates, foliage density changes across seasons, and varying degrees of electromagnetic interference in industrial zones, would further enhance network resilience. Another promising direction is the investigation of cooperative handover strategies, where groups of platooning vehicles collaboratively share their environmental sensor data and signal measurements to optimize handovers collectively, rather than on an individual basis. As telecommunication networks continue to evolve towards the sixth generation, the integration of comprehensive environmental intelligence will transition from a beneficial enhancement to an absolute necessity, ensuring that ubiquitous connectivity is maintained regardless of the physical realities of the operating environment. The review's emphasis on design-time explainability [7] points to a specific extension of threshold control: record the weather context and hysteresis state at each switch. Such records would make unnecessary handovers diagnosable without claiming that an explanation alone improves radio reliability.

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