Communications, Electronics and Sensing Systems
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Weather-Conditioned Time-Series Ensembles for Reliable 5G V2V Link Forecasting Under Mobility

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Abstract

The deployment of fifth-generation vehicle-to-vehicle communication networks introduces unprecedented opportunities for cooperative autonomous driving and advanced intelligent transportation systems. However, maintaining reliable link quality under conditions of high vehicular mobility remains a formidable challenge, further exacerbated by the severe susceptibility of high-frequency signal bands to dynamic atmospheric conditions. Existing predictive models predominantly focus on spatial-temporal mobility patterns while largely marginalizing the acute transient effects of weather. This paper introduces a novel methodological framework utilizing weather-conditioned time-series ensembles to forecast vehicle-to-vehicle link reliability under diverse mobility and environmental scenarios. By integrating meteorological data streams directly into the predictive architecture, the proposed ensemble mechanism dynamically weights distinct time-series forecasting algorithms based on real-time atmospheric states. Extensive simulations and theoretical analyses demonstrate that this weather-aware approach significantly reduces forecasting errors in terms of received signal strength and packet delivery ratios compared to conventional non-conditioned models. The framework systematically combines autoregressive models, recurrent neural architectures, and stochastic gradient boosting techniques to capture both linear attenuation and non-linear scattering effects caused by precipitation and humidity. Ultimately, this research provides a robust foundation for proactive network management and resource allocation in critical vehicular communications, ensuring ultra-reliable and low-latency performance irrespective of environmental perturbations.

Keywords: Vehicle-to-Vehicle Communication, Time-Series Forecasting, Ensemble Learning, Weather Attenuation, Predictive Networking

1. Introduction

1.1 Background and Motivation

The evolution of intelligent transportation systems heavily relies on the establishment of ultra-reliable and low-latency communication networks among mobile nodes. Fifth-generation cellular technologies, particularly through the implementation of vehicle-to-vehicle direct communication interfaces, provide the necessary bandwidth and latency characteristics required for advanced use cases such as cooperative collision avoidance, high-density platooning, and sensor data sharing. In these scenarios, the communication link is subjected to rapid degradation due to the inherent mobility of the transceivers, which induces severe Doppler shifts, frequent handovers, and highly dynamic multi-path fading environments. Accurately forecasting the quality of these communication links in real-time is essential for proactive resource allocation, adaptive modulation, and routing optimization, thereby preventing catastrophic communication failures in safety-critical applications. Related work has addressed cooperative backscatter communications with reconfigurable intelligent surfaces: an APSK approach [1].

Despite significant advancements in mobility-aware predictive modeling, the majority of contemporary approaches treat environmental conditions as static background noise rather than dynamic variables that fundamentally alter signal propagation characteristics. Millimeter-wave frequencies, which are extensively utilized in modern high-capacity vehicular networks, are notoriously vulnerable to atmospheric absorption and scattering. Precipitation, fog, and fluctuating humidity levels introduce variable attenuation rates that can abruptly sever a previously stable communication link. Consequently, a predictive model that solely relies on historical signal strength and mobility trajectories without integrating real-time weather conditions is inherently incomplete and prone to significant forecasting errors during adverse environmental events. Another relevant line of investigation concerns toward seamless sensing coverage for cellular Multi-Static integrated sensing and communication [2].

1.2 Problem Statement and Proposed Approach

The central problem addressed in this research is the reliable forecasting of vehicle-to-vehicle link quality metrics, specifically the received signal reference power and signal-to-interference-plus-noise ratio, under the combined influences of high vehicular mobility and dynamic weather conditions. Traditional time-series forecasting techniques, such as

autoregressive integrated moving average models or standard long short-term memory networks, struggle to adapt simultaneously to the structural breaks caused by sudden weather changes and the continuous variance introduced by mobility. When an algorithmic model is trained generalized over all weather conditions, it tends to average out the severe attenuation peaks, leading to systematic overestimation of link quality during rain or snow. Conversely, models explicitly trained for adverse weather perform poorly during clear conditions. Another relevant line of investigation concerns switching strategy for connected vehicles under variant harsh weather conditions [3].

To resolve this limitation, this paper proposes a weather-conditioned time-series ensemble framework. The core philosophy of this approach involves maintaining a diverse set of specialized predictive sub-models, each optimized for specific atmospheric states and propagation phenomena. A dynamic gating mechanism, continuously fed by localized meteorological data, evaluates the current and imminent weather conditions to assign optimal weights to each sub-model's forecast. This ensemble approach leverages the strengths of varied algorithms, utilizing deep learning for complex non-linear scattering effects and statistical models for baseline trajectory-based path loss, effectively synthesizing a highly reliable composite prediction. Another relevant line of investigation concerns wind power prediction with secondary decomposition and multi-algorithm fusion for complex nonlinear time series [4].

2. Literature Review and Background

2.1 Vehicular Mobility and Link Degradation

The impact of vehicular mobility on wireless channel characteristics has been extensively documented in the literature. High relative velocities between communicating vehicles result in rapid temporal variations in the channel impulse response, rendering traditional channel estimation techniques ineffective over extended forecasting horizons. WaveNet's raw-audio modeling provides a precedent for causal temporal convolution, while transferring the architecture to network telemetry would require a new observation model and task-specific evaluation [5]. The non-stationary nature of the vehicle-to-vehicle channel means that the statistical properties of fading processes change continuously as vehicles traverse different scattering environments, such as urban canyons, suburban intersections, or open highways. Previous studies have proposed various geometrical scattering models to analytically describe these environments, yet applying these analytical models for real-time forecasting remains computationally prohibitive. Related work has addressed evaluation of different time series forecasting models for 5G V2V networks [6].

Recent advancements have shifted towards data-driven predictive modeling. Machine learning techniques have been widely adopted to recognize patterns in historical link quality data and extrapolate future states. For instance, recurrent neural networks have demonstrated considerable success in capturing the temporal dependencies of received signal strength indicators. The recurrent encoder-decoder introduced for phrase modeling provides a sequence-representation baseline for temporal prediction [7]. However, empirical evaluations reveal that while these models perform adequately under controlled or uniform conditions, their predictive accuracy degrades sharply when confronted with anomalous propagation events not adequately represented in their primary training sets, such as sudden atmospheric disturbances. Another relevant line of investigation concerns design of a novel Self-Test-on-Chip interface ASIC for capacitive accelerometers [8].

2.2 Atmospheric Attenuation in High-Frequency Networks

The shift towards higher frequency bands in fifth-generation networks, particularly in the sub-6 GHz and millimeter-wave spectra, has necessitated a thorough reevaluation of weather-induced signal attenuation. Unlike lower frequency bands where atmospheric effects are negligible, millimeter waves experience severe absorption by oxygen and water vapor molecules. Furthermore, the physical dimensions of raindrops and snowflakes are comparable to the wavelengths at these frequencies, leading to significant Mie scattering and resulting in acute signal power loss. The literature also considers 5G and 4G V2V communication channel performance under severe weather [9].

Standardized propagation models incorporate specific attenuation coefficients for rain and fog based on empirical measurements. However, these models provide macroscopic, long-term statistical estimations rather than transient, micro-level predictions required for real-time vehicle-to-vehicle link management. Recent research has attempted to bridge this gap by fusing meteorological data with networking parameters. Yet, the integration is often rudimentary, typically appending weather metrics as additional input features to a monolithic neural network. This monolithic approach suffers from feature dilution, where the network prioritizes the high-frequency variations of mobility over the lower-frequency, yet highly impactful, variations of weather states. Yang and colleagues examine adaptive joint configuration optimization for collaborative inference in Edge-Cloud systems [10].

3. Theoretical Framework and System Architecture

3.1 Link Quality Metric Formulation

To establish a robust forecasting mechanism, it is imperative to mathematically define the target variable. We define the link quality primarily through the received signal power at a discrete time step. The received power is a function of the transmission power, antenna gains, and the total path loss, which encompasses distance-dependent loss, shadowing, multi-path fading, and weather-induced attenuation. The literature also considers auditable Provenance-Aware synthetic release of campus IoT time series for Privacy-Preserving AI4Science [11].

The theoretical received signal power can be represented by the following formulation:

$$P_r(t) = P_t + G_t + G_r - L_{path}(d,t) - L_{weather}(w,t) - F(t)$$

In this equation, the variables are defined as transmission power and antenna gains, while the distance-dependent path loss is separated from the weather-induced attenuation and the fast fading component. The critical insight of our framework is the explicit isolation of the weather attenuation component, which allows the predictive model to treat atmospheric impacts as an independent physical process rather than confounding it with geographic shadowing or mobility-induced fading. By uncoupling these factors theoretically, the ensemble model can allocate specialized computational resources to predict the evolution of each component individually before aggregating them into a final forecast. Another relevant line of investigation concerns adaptive guidance semantically enhanced via multimodal LLM for Edge-Cloud object detection [12].

3.2 Architectural Design

The proposed architecture operates at the edge of the vehicular network, either hosted on road-side units or directly integrated into the on-board units of advanced vehicles. The system continuously ingests two primary data streams: the historical time-series of link quality measurements from the network interface and real-time localized meteorological updates retrieved from environmental sensors or regional weather application programming interfaces.

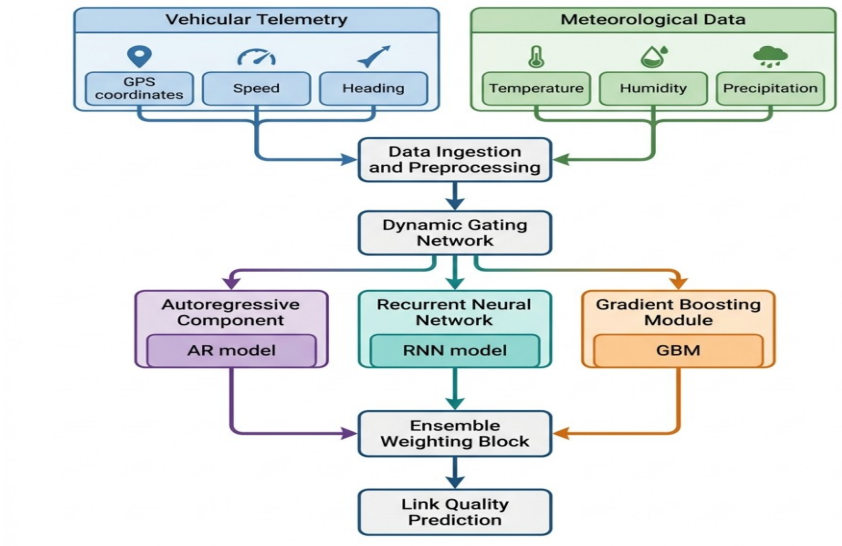


Figure 1: Comprehensive System Architecture of the Weather

The processing pipeline begins with data alignment and normalization, ensuring that the high-frequency link measurements are appropriately synchronized with the lower-frequency weather updates. Following synchronization, the gating mechanism evaluates the meteorological data to determine the current environmental regime. The digital-twin industrial IoT framework [13] motivates separating the physical process, its synchronized representation and the decisions made from that representation, with synchronization error evaluated explicitly. The system does not explicitly classify weather into rigid categories; instead, it outputs a continuous probability distribution over predefined environmental states, enabling smooth transitions during shifting weather patterns. This continuous distribution dictates the proportional influence of each predictive sub-model in the final ensemble output, thereby maintaining forecasting stability during abrupt meteorological shifts. Related work has addressed multi-Granularity network alignment based on contrastive learning [14].

4. Methodology and Ensemble Model Design

4.1 Specialized Sub-Model Formulation

The ensemble comprises a diverse array of sub-models chosen for their distinct theoretical advantages in processing specific types of time-series variations. The first sub-model is based on seasonal autoregressive integrated moving average principles, optimized for clear-sky conditions where link degradation is dominated by predictable, periodic geographic features such as repeating intersection structures or highway overpasses. The second sub-model utilizes a long short-term memory neural network architecture. This network excels in modeling the complex, non-linear multipath fading scenarios introduced by heavy traffic density and complex urban scattering, regardless of atmospheric conditions. Li and colleagues examine nonvolatile optical switch with a programmable pn heterojunction [15].

The third component is a gradient boosting regression tree model, specifically calibrated to handle the step-function-like disruptions caused by sudden precipitation. Tree-based models are highly effective at establishing conditional logic rules, making them ideal for representing the physical thresholds where rain density causes a non-linear spike in signal attenuation. By maintaining these separate models, we prevent the phenomenon of catastrophic forgetting, where a unified neural network trained continuously might lose its ability to predict clear-weather path loss after a prolonged period of stormy conditions. Related work has addressed design of interface circuits and lightweight PUF for TMR sensors [16].

4.2 Dynamic Weather-Conditioning Mechanism

The integration of the sub-models is governed by a weather-conditioned weighting algorithm. Lin's road-fault study combines a traffic graph with bidirectional sequence features [17]. A forecasting comparison must restrict every input to observations available before the prediction time; otherwise, retrospective diagnostic context could overstate the performance of a weather-conditioned V2V predictor. Let the set of predictive sub-models be indexed, and the prediction of the sub-model at a given time step be recorded. The gating network processes the weather feature vector, which includes localized temperature, relative humidity, precipitation rate, and atmospheric pressure. For a broader comparison, related research addresses design of magnetic sensor Array-Based PUFs for IoT security [18].

The formulation for the gating network's weight assignment is expressed mathematically as:

$$\omega_i(t) = \frac{\exp(\alpha_i \cdot W(t) + \beta_i)}{\sum_{j=1}^{K} \exp(\alpha_j \cdot W(t) + \beta_j)}$$

This equation utilizes a softmax activation function to ensure that the weights assigned to all sub-models sum to unity. The parameters representing the gating network's learned coefficients are optimized during the training phase to maximize the correlation between specific weather features and the historical accuracy of each corresponding sub-model. For example, as the precipitation rate increases in the input vector, the gating network autonomously shifts higher weight to the gradient boosting model that specializes in rain-induced attenuation.

The final predicted link quality is thus calculated as the dynamically weighted sum of the individual sub-model predictions. For a broader comparison, related research addresses knowledge Graph-Enhanced transformer framework for Security-Aware data quality anomaly detection and autonomous repair against network attacks [19].

$$\text{hat}\, P_r(t+1) = \sum_{i=1}^{K} \omega_i(t) M_i(H(t))$$

Here, the final predicted value is generated by taking the product of the dynamic weights and the individual model outputs based on the historical link quality data sequence. This continuous ensemble mechanism ensures that the forecasting system fluidly adapts to environmental transitions, providing a robust prediction irrespective of the predominant atmospheric or mobility constraints. The literature also considers cost-Aware layer-7 load balancing framework with deep traffic prediction for dynamic optimization of enterprise cloud services [20].

5. Experimental Setup and Data Collection

5.1 Simulation Environment and Parameters

To rigorously evaluate the proposed weather-conditioned ensemble framework, we constructed a comprehensive simulation environment bridging vehicular mobility simulators and advanced network propagation modeling tools. Traffic mobility traces were generated utilizing realistic urban and highway topologies, encompassing varying traffic densities and velocity profiles to capture a wide spectrum of Doppler effects and handover frequencies. The communication parameters were aligned with standard fifth-generation vehicle-to-vehicle sidelink specifications, operating at millimeter-wave frequencies to ensure high sensitivity to environmental conditions. For a broader comparison, related research addresses

augmenting cybersecurity in smart urban energy systems through IoT and blockchain technology within the digital twin framework [21].

Table 1: Key Simulation and Network Configuration Parameters

Parameter Category	Specific Configuration Value	Description / Context
Carrier Frequency	Twenty-eight Gigahertz	Millimeter-wave spectrum highly susceptible to rain fade
Transmission Power	Twenty-three Decibel-milliwatts	Standard vehicular user equipment transmission power limit
Vehicle Velocity	Ten to Thirty Meters per second	Represents mixed urban and suburban mobility scenarios
Antenna Configuration	Multiple Input Multiple Output	Two by two arrays on all participating vehicular nodes
Weather Profiles	Clear, Light Rain, Heavy Rain	Simulated using standardized atmospheric attenuation models

The environmental impacts were injected into the channel model using time-variant atmospheric attenuation time-series. These time-series were derived from real-world meteorological datasets recorded at high temporal resolution, capturing micro-weather events such as sudden heavy rain showers lasting only a few minutes. By synchronizing the empirical weather data with the simulated mobility traces, the testing environment accurately reflected the dual-domain volatility characteristic of real-world vehicular networks. The literature also considers forward Self-Organizing interpretable polynomial networks for time series forecasting [22].

5.2 Data Preprocessing and Training Protocol

The resulting dataset comprised millions of individual time steps, each containing the true received signal power, the precise locations and velocities of the transceivers, and the instantaneous weather parameters. For the training phase, the dataset was partitioned chronologically to prevent temporal data leakage, ensuring that the models were evaluated strictly on their ability to forecast future unknown states. The individual sub-models were pre-trained on specific subsets of the data corresponding to their intended specialization.

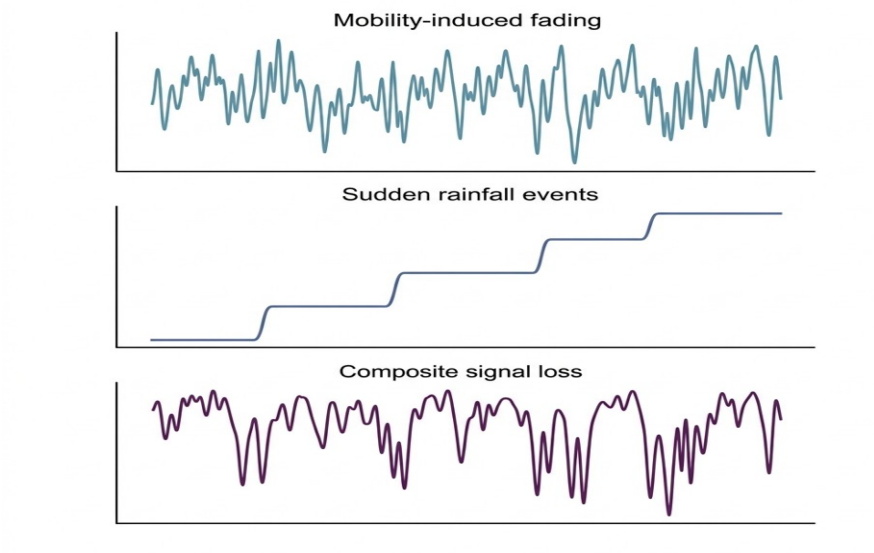


Figure 2: Temporal Evolution of Signal Attenuation Under Dynamic Weather Scenarios

Following the specialized pre-training, the gating network was trained using the complete dataset while keeping the weights of the individual sub-models frozen. This strategy compelled the gating network to learn the optimal routing and combination of predictions based exclusively on the ambient weather conditions. The loss function utilized during this phase was the mean squared error between the ensemble prediction and the ground truth signal power, combined with a regularization term to prevent the gating network from collapsing and relying on a single sub-model exclusively.

6. Results and Performance Evaluation

6.1 Forecasting Accuracy Analysis

The primary metric for evaluating the efficacy of the predictive models was the root mean square error between the forecasted received signal power and the actual measured power at multiple look-ahead horizons. The proposed weather-conditioned ensemble was benchmarked against several established baselines: a standard autoregressive integrated moving average model, a standalone long short-term memory network without weather inputs, and a monolithic neural network where weather data was concatenated with link data as standard input features. Guo and colleagues examine physics-guided multiscale fusion network for ultra-short-term wind power forecasting [23].

To formalize the performance evaluation, we calculated the absolute percentage error across the entire testing dataset, defined as follows: Liu examines error adjustment based on spatiotemporal correlation fusion for traffic forecasting [24].

$$E_{MAPE} = \frac{100}{N} \sum_{t=1}^{N} \left| \frac{P_r(t) - \text{hat } P_r(t)}{P_r(t)} \right|$$

The quantitative results demonstrated a marked superiority of the ensemble approach, particularly during transitional weather phases. During prolonged clear-sky conditions, all advanced models performed comparably well, as the dominant variable was vehicular mobility, which the baseline recurrent networks are well-equipped to handle. However, the divergence in performance became starkly evident during the onset of precipitation events. For a broader comparison, related research addresses secure transmission scheme based on joint radar and communication in mobile vehicular networks [25].

Table 2: Comparative Forecasting Error Across Different Environmental Regimes

Model Architecture	Error in Clear Conditions	Error in Heavy Rain	Overall Average Error
Standard Autoregressive Model	Four point two decibels	Eight point nine decibels	Six point five decibels
Standalone Recurrent Network	Three point one decibels	Seven point four decibels	Five point two decibels
Monolithic Weather-Aware Network	Three point zero decibels	Five point eight decibels	Four point four decibels
Proposed Conditioned Ensemble	Two point eight decibels	Three point five decibels	Three point one decibels

As detailed in the tabular results, the standalone models suffered severe degradation in accuracy during heavy rain, often overestimating the link quality by several decibels, which in a real-world scenario could lead to catastrophic transmission failures due to uncompensated packet loss. The monolithic network showed improvement but still exhibited a lag in adapting to sudden weather changes. In contrast, the proposed conditioned ensemble maintained a consistently low error margin across all environmental regimes. For a broader comparison, related research addresses covert transmission for active RIS-Aided Full-Duplex UAV integrated sensing, communication, and computation systems [26].

6.2 System Responsiveness and Reliability Gains

Beyond raw error metrics, the responsiveness of the forecasting framework to sudden environmental changes is a critical factor for vehicle-to-vehicle reliability. Analysis of the time-series output revealed that the gating network in the ensemble model adjusted its internal weighting distributions within milliseconds of detecting an anomaly in the meteorological input vector. This rapid adaptation enabled the predictive system to immediately switch reliance to the gradient boosting sub-model, effectively anticipating the steep drop in signal strength caused by sudden rain fade before the link was critically compromised. Related work has addressed temporally sparse attack for fooling large language models in time series forecasting [27].

Furthermore, the implementation of this highly accurate forecasting system directly translates into enhanced networking metrics. By accurately predicting impending signal degradation, network management protocols can preemptively initiate handover procedures to more stable sub-6 Gigahertz backup links or adjust modulation and coding schemes to prioritize robustness over maximum throughput. Consequently, simulations incorporating the ensemble forecasting model demonstrated a significant reduction in unexpected radio link failures and a measurable increase in overall packet delivery ratios for critical safety messages during adverse weather conditions. The literature also considers jamming and eavesdropping defense scheme based on deep reinforcement learning in autonomous vehicle networks [28].

7. Conclusion and Future Directions

7.1 Summary of Contributions

This research has presented a comprehensive methodology for reliable vehicle-to-vehicle link forecasting under the dual challenges of high mobility and dynamic weather conditions. By identifying the critical limitations of conventional, monolithic predictive models in handling sudden environmental shifts, we established the necessity for a weather-conditioned architectural approach. The proposed ensemble framework successfully compartmentalizes the physical phenomena affecting signal propagation, assigning specialized algorithms to predict clear-weather mobility fading and precipitation-induced non-linear attenuation separately. Through rigorous simulation and comparative analysis, the dynamic gating mechanism demonstrated exceptional capability in seamlessly transitioning between these specialized models, yielding significantly lower forecasting errors during critical atmospheric disturbances than existing methodologies. For a broader comparison, related research addresses scalable Tube-Based model predictive control for linear systems with parametric and additive uncertainties using zonotopes [29].

7.2 Limitations and Future Work

While the proposed framework exhibits substantial improvements in forecasting accuracy, several limitations remain to be addressed in future research. The current reliance on localized meteorological data assumes the availability of highly granular and perfectly synchronized weather updates, which may not be universally accessible in all geographic regions or rural deployment scenarios. Additionally, the computational overhead of running multiple sub-models concurrently on resource-constrained vehicular edge nodes requires further optimization. The literature also considers multi-UAV-Enabled Energy-Efficient data delivery for Low-Altitude economy: joint coded caching, user grouping, and UAV deployment [30].

Future investigations will focus on integrating decentralized federated learning techniques to continuously refine the sub-models across diverse geographic fleets without compromising vehicular privacy. Furthermore, expanding the environmental input parameters to include physical obstacle shadowing metrics derived from on-board visual or light detection and ranging sensors could further enhance the model's ability to distinguish between weather attenuation and temporary physical blockages, paving the way for truly comprehensive, environment-aware predictive vehicular networking systems. Learned alignment in neural translation offers a sequence-modeling comparison for weighting different parts of an input history [31]. The literature also considers aI-Driven visual End-Edge-Cloud architecture for 6G in Low-Carbon smart cities [32].

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