

A Computationally Efficient Radar Sensor Modeling Methodology Incorporating Rain-Induced Propagation Attenuation for Virtual Validation of Autonomous Driving Systems

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1. Introduction

Reliable environmental perception is a fundamental prerequisite for safe autonomous driving because perception accuracy directly affects subsequent decision-making and vehicle control. Modern autonomous vehicles employ multiple sensing modalities, including radar, LiDAR, cameras, and inertial measurement units (IMUs), to perceive surrounding objects and estimate their dynamic states. Based on information acquired from these sensing systems, autonomous driving systems identify surrounding objects, predict potential hazards, plan appropriate driving trajectories, and generate steering, acceleration, and braking commands. Consequently, the overall reliability of autonomous driving systems depends largely on the robustness and accuracy of environmental perception [1, 2].

Although recent advances in artificial intelligence and high-performance computing have significantly improved perception algorithms, extensive real-world testing remains indispensable for developing and validating autonomous driving systems. Simulation-based validation has therefore emerged as an attractive alternative because it provides a safe, repeatable, and cost-effective environment for evaluating autonomous driving functions under diverse operating conditions [3]. Nevertheless, achieving realistic perception remains one of the primary challenges in virtual validation.

Most commercial autonomous driving simulators provide idealized ground-truth measurements, including object position, distance, velocity, and orientation. Although these outputs are suitable for algorithm development and functional verification, they cannot reproduce perception degradation caused by adverse weather conditions or stochastic sensing uncertainty. Consequently, virtual validation environments tend to overestimate perception performance and often fail to accurately evaluate the robustness of autonomous driving systems operating under challenging environmental conditions. To overcome these limitations, several studies have investigated physics-based radar models that explicitly simulate electromagnetic wave propagation and environmental effects [4, 5]. Although these approaches provide relatively high physical fidelity, they require substantial computational resources because electromagnetic propagation phenomena must be modeled directly. Such computational complexity limits their applicability to real-time simulation and accelerated virtual validation [6, 7].

Several previous studies have also investigated automotive radar models under adverse weather conditions [8–10]. However, most existing studies focus primarily on sensor-level modeling and rarely consider integration into real-time co-simulation environments for autonomous driving validation. Furthermore, the combined effects of rainfall attenuation, target radar cross section (RCS), stochastic false alarms, roadside infrastructure, and surrounding traffic participants have not been comprehensively represented within a unified simulation framework. Although commercial simulation platforms allow users to configure parameters such as system loss, receiver noise figure, and false alarm probability, these parameters generally remain fixed throughout the simulation and therefore cannot reproduce dynamically varying sensing conditions encountered in real driving environments.

Although measurement-based approaches provide the highest level of physical fidelity, acquiring radar measurements over a wide range of rainfall intensities and safety-critical driving scenarios is both time-consuming and resource-intensive. Moreover, constructing reproducible datasets under identical environmental and traffic conditions is inherently difficult. Consequently, rather than reproducing the characteristics of a specific commercial radar unit through measurement-based calibration, this study focuses on developing a computationally efficient and physically consistent sensing methodology that can be readily integrated into autonomous driving simulation environments. The proposed framework is intended to support simulation-based validation of perception–decision–control algorithms under adverse weather conditions. To address these challenges, this paper proposes a computationally efficient sensing methodology that incorporates rain-induced propagation attenuation into a virtual autonomous driving simulation environment. The proposed framework estimates the reduction in received signal power by combining the classical radar equation with the rainfall attenuation model specified in ITU-R Recommendation P.838-3. Furthermore, a stochastic False Alarm Probability Generation (FAPG) algorithm is introduced to reproduce intermittent target detection caused by environmental uncertainty. The developed framework is implemented in MATLAB/Simulink and integrated with the IPG CarMaker simulation platform through real-time co-simulation. Consequently, it provides a physically consistent and computationally efficient virtual testing environment for evaluating perception degradation under rainfall conditions.

The primary contributions of this study are threefold: First, we propose a computationally efficient sensing methodology that seamlessly integrates rain-induced propagation attenuation into the classical radar equation for virtual autonomous driving environments. Second, we introduce a stochastic False Alarm Probability Generation (FAPG) algorithm capable of faithfully reproducing intermittent target detections governed by user-defined probabilities of false alarm and detection. Finally, we establish a real-time co-simulation framework combining MATLAB/Simulink with the IPG CarMaker platform, thereby providing a robust, physics-consistent environment for the virtual validation of autonomous driving perception systems under adverse weather conditions.

2. Radar Sensor Model Incorporating Rain-Induced Propagation Attenuation

The overall architecture of the radar sensor model incorporating rainfall attenuation phenomena is illustrated in Fig. 1. A brief overview of the input parameters, output signals, and computational processes is as follows. The user defines three primary parameters: rainfall intensity (R_r), the required false alarm probability (P_{fa-des}), and the required probability of detection (P_{d-des}). Subsequently, the user-defined rainfall intensity and the ground-truth physical values provided by the virtual sensor in the simulation environment are utilized to calculate the estimated signal attenuation due to rain ($\hat{L}_r$). During the modeling process, the system computes the estimated radar received signal strength ($\hat{P}_r$) and the estimated distance to the preceding target vehicle ($\hat{R}_t$). To simulate realistic sensor degradation, the estimated object distance ($\hat{R}_a$), which accounts for rainfall attenuation, is processed through a False Alarm Generation Algorithm. By incorporating the defined false alarm probability (P_{fa}), this algorithm introduces stochastic variations, ensuring that the final relative distance output ($\hat{R}_{f-a}$) realistically fluctuates rather than remaining constant.

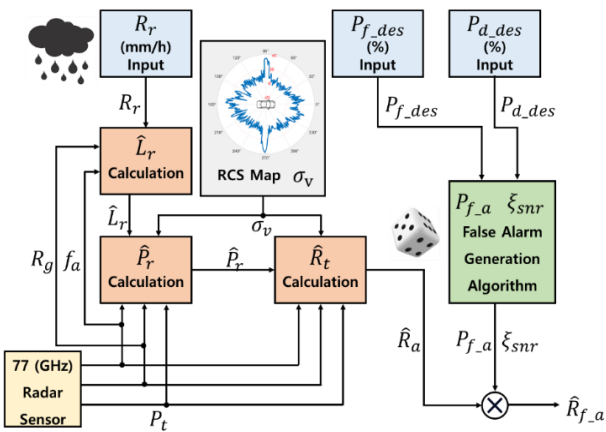


Fig. 1 Diagram of the radar sensor model based on the rain attenuation phenomenon

2.1. Radar sensor modeling

Automotive radar sensors typically operate in the 24 GHz or 77 GHz frequency bands [11]. In the proposed radar sensor model, the received signal power ($\hat{P}_r$) is used to represent the effect of propagation attenuation on the mod-

eled target-distance measurement. According to the standard radar range equation, expressed in Eq. (1), the received signal power is determined by the radar cross-section (RCS, denoted as σ) of the preceding target vehicle and the associated propagation attenuation effects.

$$\hat{P}_r = \frac{P_t G^2 \lambda^2 \sigma}{(4\pi)^3 R_g^4} \times \frac{1}{L_r} \times \frac{1}{L_a}, \quad (1)$$

where $\hat{P}_r$ is a received signal power, P_t is a transmitted signal power (W), G is an antenna gain, λ is a wavelength (m), σ is a radar cross section (m^2), R_g is a ground-truth target distance (m), L_r is a rain-induced propagation attenuation, L_a is an additional system loss.

In this study, only preceding vehicles were considered as target objects. The RCS distribution (σ_v) of a typical vehicle is illustrated in Fig. 2. The plastic materials predominantly used in the front and rear bumpers exhibit relatively low radar reflectivity. Conversely, the metallic components constituting the vehicle doors yield significantly higher radar reflectivity than the fascia regions [12].

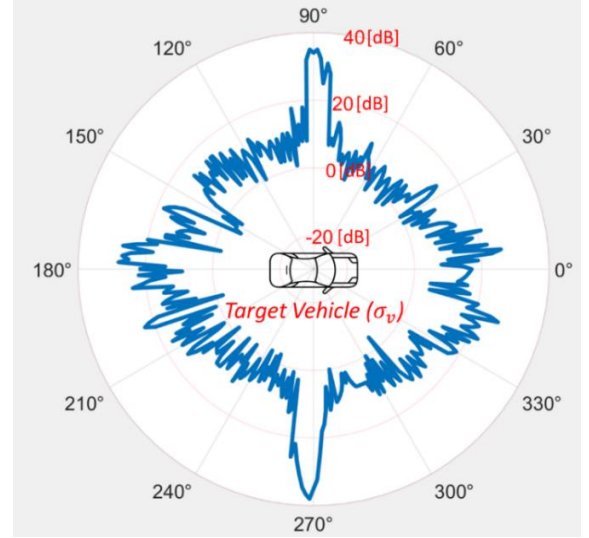


Fig. 2 Representative radar cross-section (RCS) characteristics of a passenger vehicle

Assuming that the fixed internal hardware losses, such as transmitter, receiver, and matching losses, are not explicitly modeled, L_a is set to 0 dB. Here, L_a denotes additional signal losses that are not explicitly considered in the proposed model. Since the present study focuses on rainfall-induced propagation attenuation, an additional loss term without independent measurements or a validated model is not introduced to avoid unnecessary uncertainty. Thus, L_a is set to 0 dB, while the rainfall-induced attenuation is explicitly incorporated into the propagation loss. Accordingly, the estimated distance to the preceding vehicle can be derived by rearranging Eq. (1) into Eq. (2).

$$\hat{R}_t = \left(\frac{P_t G^2 \lambda^2 \sigma}{(4\pi)^3 P_r} \right)^{\frac{1}{4}} \times \left(\frac{1}{L_r} \right)^{\frac{1}{4}}, \quad (2)$$

where $\hat{R}_t$ is an estimated target range.

2.2. Rain attenuation modeling

In rainy weather conditions, the strength of the radio signals received by the radar sensor decreases due to absorption by raindrops and scattering along the propagation path [13]. To quantify this signal degradation, the International Telecommunication Union (ITU) defines a standard specific attenuation model [13-15], as expressed in Eq. (3).

$$\hat{L}_r = A \times R_r^\alpha, \quad (3)$$

where $\hat{L}_r$ is a rain attenuation loss (dB/km), R_r is a rainfall rate (mm/h), A , α are coefficients depending on frequency.

In Eq. (4), the coefficients A and α are determined based on the frequency-dependent characteristics specified in ITU-R Recommendation P.838-3 [14]. To account for arbitrary polarization, A is calculated as the arithmetic mean of its horizontal and vertical components, $(A_h + A_v) / 2$, and α is similarly computed as $(\alpha_h + \alpha_v) / 2$. To improve computational efficiency while preserving the overall attenuation characteristics, the parameters A and α are represented using fixed values based on ITU-R Recommendation P.838-3 [14], as summarized in Table 1.

$$\begin{aligned} \log A &= \sum_{j=1}^4 \left(x_j \exp \left[- \left(\frac{\log f - y_j}{z_j} \right)^2 \right] \right) + \\ &\quad + v_k \log f + \omega_k, \\ \alpha &= \sum_{j=1}^5 \left(x_j \exp \left[- \left(\frac{\log f - y_j}{z_j} \right)^2 \right] \right) + \\ &\quad + v_m \log f + \omega_m, \end{aligned} \quad (4)$$

where A is either A_h (coefficient for horizontal polarization) or A_v (coefficient for vertical polarization); α is either α_h (coefficient for horizontal polarization) or α_v (coefficient for vertical polarization), f is a frequency, v_k and ω_k are the coefficients of polarization; v_m and ω_m are the coefficients of rainfall rate.

Table 1
Simplified attenuation coefficients derived from ITU-R Recommendation P.838-3 [14]

f_a , GHz	A_h	A_v	α_h	α_v
10	0.01217	0.01129	1.2571	1.2156
24	0.1425	0.1404	1.0101	0.9561
35	0.3374	0.3224	0.9047	0.8761
50	0.6600	0.6472	0.8084	0.7871
60	0.8606	0.8515	0.7656	0.7486
77	1.1320	1.1276	0.7177	0.7073
81	1.1827	1.1793	0.7096	0.7004

The operating frequency (f_a) of the radar sensor equipped on the autonomous vehicle is configured to 77 GHz. The propagation path length (D) is defined by the

distance to the target vehicle (R_g) extracted from the simulation environment. Here, R_g serves as the absolute, error-free ground-truth reference distance provided directly by the simulator.

Using Eqs. (1) and (2), the baseline received signal power ($\hat{P}_r$) and the initially estimated distance to the target vehicle ($\hat{R}_t$) are calculated. Subsequently, by integrating Eq. (3) with the coefficients defined in Table 1, the rain-attenuated target distance ($\hat{R}_a$) is derived from the received signal power, which is explicitly degraded to reflect the simulated rainfall conditions.

2.3. False alarm modeling

In dynamic autonomous driving environments, radar measurements are frequently distorted by multipath reflections and environmental clutter. Consequently, the estimated distance to the target fluctuates over time, potentially leading to intermittent target loss (missed detections). Conversely, false alarms (ghost targets) occur when the background noise or clutter power exceeds the predefined detection threshold used to determine the presence or absence of an object. The theoretical probability of a false alarm occurring is determined by integrating the probability density function (PDF) of the noise power envelope, as defined in Eq. (5) [15].

$$\begin{aligned} P_{rob} (P_r < E < \infty) &= \int_{V_t}^{\infty} \frac{E}{\Omega_0} \exp \frac{-E^2}{2\Omega_0} dE = \\ &= \exp \frac{-V_t^2}{2\Omega_0} = P_{fa}, \end{aligned} \quad (5)$$

where E is an amplitude of the output power envelope, V_t is a detection threshold power, Ω_0 is a variance of the noise power, P_{fa} is a false alarm probability.

The false alarm time (T_{fa}) represents the average time interval between successive positive crossings of the detection threshold by the noise power envelope, as conceptually illustrated in Fig. 3 and expressed mathematically in Eq. (6). Alternatively, it can be defined as a time ratio, as shown in Eq. (7).

$$T_{fa} = \lim_{a \rightarrow \infty} \frac{1}{a} \sum_{n=1}^a T_n, \quad (6)$$

where T_{fa} is a false alarm time (average time interval between threshold crossings), T_k is a time between successive crossings of the threshold (P_{th}) by the noise power.

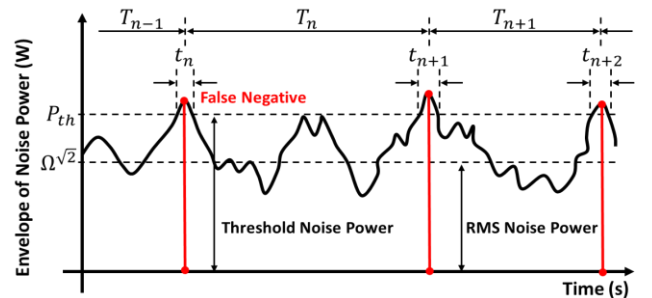


Fig. 3 Relationship between the receiver detection threshold and the probability of false alarm

$$P_{fa} = \frac{\sum_{n=1}^r t_n}{\sum_{n=1}^r T_n} = \frac{\langle t_n \rangle_{avg}}{\langle T_n \rangle_{avg}} = \frac{1}{T_{fa} B}, \quad (7)$$

where T_n is a false alarm occurrence time interval, t_n is a false alarm occurrence time, B is a receiver bandwidth.

Based on the user-defined rainfall intensity (mm/h) and the target false alarm probability (FAP, denoted as P_{fa}), signal attenuation increases the likelihood of missed detections (false negatives). The stochastic occurrence of these missed detections is governed by the False Alarm Probability Generation (FAPG) algorithm. In this study, the FAPG algorithm does not generate additional false-positive or ghost targets; rather, it uses P_{fa} as a statistical parameter to stochastically determine the detection state of a valid target. As illustrated in Fig. 4, when the detection state changes to $S_c = 0$, the system simulates a missed detection by suppressing the distance output for the preceding vehicle.

Given:	t, P_n
Init.:	$t_n = 0, S_c = 0$ $t_{n+1} = \mathcal{R}_n \times \rho_f$
Loop:	1: Measure the current input t and P_{tr} 2: IF $(t - t_n) < t_{n+1}$ 3: → Maintain the current state 4: IF $(t - t_n) \geq t_{n+1}$ 5: → Determine $S_c = 1$ or $S_c = 0$ 6: IF $((P_n - \mathcal{R}_n) > 0) \rightarrow S_c = 1$ 7: ELSE → $S_c = 0$ 8: Determine $t_n = t$ 9: Determine $t_{n+1} = \rho_s + (\mathcal{R}_n \times \rho_f)$ 10: Continue with loop step 1
Result:	$S_c \in \{0, 1\}$

Fig 4. False alarm probability generation algorithm

The operational state variable S_c dictates target visibility based on this stochastic process. Specifically, $S_c = 0$ designates a missed-detection state where the target distance is not output, whereas $S_c = 1$ denotes a successful-detection state where the distance is validly tracked and displayed. Thus, the FAPG algorithm controls the stochastic visibility of an existing target rather than generating additional false-positive or ghost-target coordinates. Although the transition between detection and missed-detection states is stochastic, the generated detection states are determined according to the prescribed P_{fa} , as formalized in Eqs. (8) and (9).

$$F(\mathcal{R}) = \begin{cases} 0 & \mathcal{R} < 0 \\ r & 0 \leq \mathcal{R} \leq 1, \\ 1 & \mathcal{R} > 1 \end{cases}, \quad (8)$$

$$\int_1^b \mathcal{R} f(\mathcal{R}) d\mathcal{R} = 0.5, \quad (9)$$

where S_c is a stochastic target detection state, t_n is a current false-alarm update time, P_n is a normalized received signal power at the n -th update, $\mathcal{R}$ is a random threshold variable, $\mathcal{R}_n$ is a n -th realization of $\mathcal{R}$, ρ_s is a start time parameter for state transition, ρ_f is a final time parameter for state transition.

Ultimately, the rain-attenuated target distance ($\hat{R}_a$) computed from Eqs. (2) and (3), coupled with the stochastic FAP dynamics (P_{fa}) derived from Eq. (5) through (7) and Table 1, are synthesized to determine the final, degraded distance output ($\hat{R}_{fa}$) of the radar sensor. This final calculation incorporates the normalized received signal power (P), mathematically defined as $P_n = (P_r - P_{min}) / (P_{max} - P_{min})$. Fundamentally, the false alarm probability (FAP) of a radar sensor is inversely coupled with its detection reliability: minimizing the FAP enhances the trustworthiness of the reported detections. Concurrently, the probability of detection (PD) denotes the likelihood of the sensor accurately identifying a valid target, serving as the primary metric for overall detection performance. To establish the operational bounds of the simulation, the theoretical P_{fa} defined in Eqs. (5)-(7) is constrained by the user-defined desired false alarm probability (P_{fa-des}). Based on this requirement, along with the desired probability of detection (P_{d-des}), the sensor's minimum required signal-to-noise ratio SNR_{min} , denoted as ξ_{snr} , is strictly dictated. Calculating this baseline ξ_{snr} enables the system to predict the detection thresholds necessary to actively mitigate the signal degradation caused by rainfall attenuation. The mathematical derivation of ξ_{snr} which is integrated into the FAPG block, is formulated in Eqs. (10) and (11).

$$\begin{cases} Z_{fa} = \sqrt{2} \ln \left(\frac{1}{P_{fa-des}} \right) \\ Z_{pd} = \sqrt{2} \ln \left(\frac{1}{1 - P_{d-des}} \right) \end{cases}, \quad (10)$$

$$SNR_{min} = Z_{fa} - Z_{pd} = \sqrt{2} \left[\text{erf}^{-1}(2P_{fa-des}) - \text{erf}^{-1}(2P_{d-des}) \right], \quad (11)$$

where Z_{fa} is a standard normal variable corresponding to the probability of false alarm, Z_{pd} is a standard normal variable corresponding to the probability of detection, $\text{erf}(\cdot)$ is an error function.

3. Verification Environment and Results

The overall architecture of the radar sensor attenuation framework, designed to simulate weather-induced signal degradation, is illustrated in Figure 5. The ego-vehicle's radar sensor is configured to operate at the automotive standard frequency of 77 GHz, with the transmission power set to 14 dBm. The specific simulation scenario is depicted in Fig. 6, where the preceding target vehicle is initialized at a relative distance of 50 m. A median barrier is installed at the end of the road segment to introduce environmental clutter and multipath reflections.

Throughout the simulation, both the ego-vehicle

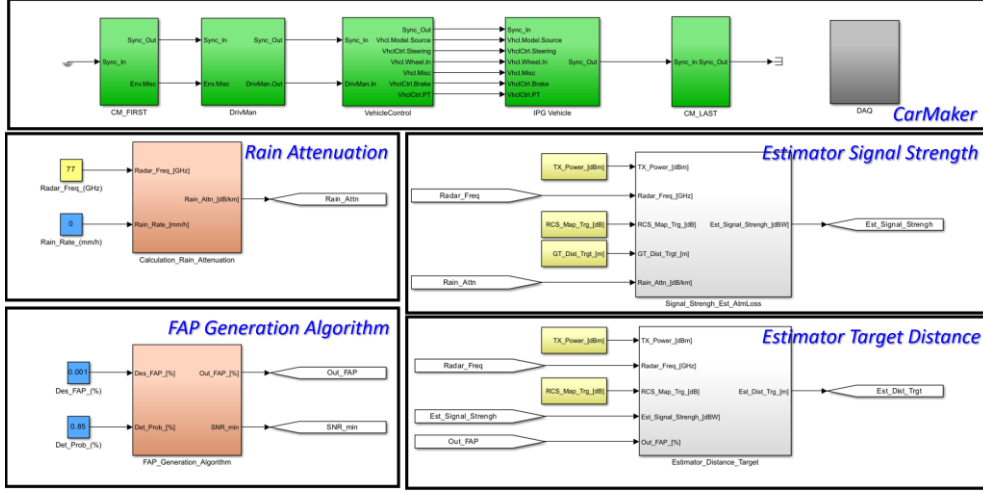


Fig. 5 Co-simulation architecture for rain-attenuated radar sensor modeling using CarMaker and MATLAB/Simulink

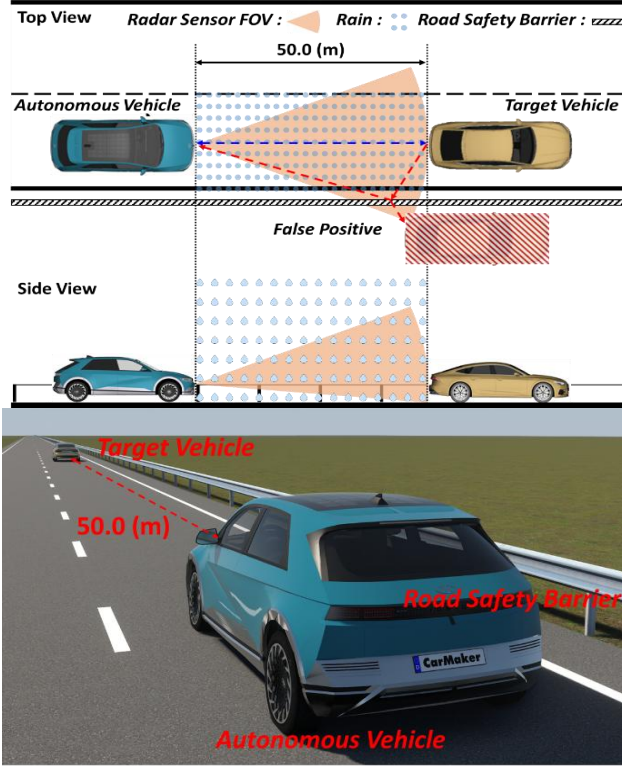


Fig. 6 Virtual test environment and scenario configuration for radar sensor verification

and the target vehicle travel at identical longitudinal velocities, thereby maintaining a constant headway distance under baseline conditions. Notably, to validate the efficacy of the proposed dynamically integrated model, the static default parameters natively provided by the CarMaker environment—such as system loss (dB), noise bandwidth (Hz), noise Fig. (dB), and false alarm probability—were deliberately disabled. This ensures that the simulated perception degradation is governed exclusively by the proposed rainfall attenuation and stochastic failure algorithms.

3.1. Experimental results – clear weather conditions (0 mm/h)

The initial experiment evaluated the proposed radar sensor model under clear weather conditions to establish

a baseline. The specific experimental parameters were configured as follows: a rainfall intensity of 0 mm/h, a target false alarm probability (P_{fa-des}) of 0.1%, and a required probability of detection (P_{d-des}) of 85%. Fig. 7 illustrates the estimated distance ($\hat{R}_a$) versus the ground-truth distance (R_g) between the ego-vehicle and the preceding target vehicle using the proposed stochastic method. While the overall distance estimation error is practically negligible, intermittent signal dropouts (missed detections) are observable. Under the specified P_{fa} setting, the resulting detection-state sequence exhibited a True Positive Rate (TPR) of approximately 99.9%. As depicted in Fig. 8, the TPR reaches approximately 99.9% at the 5.89 s mark, demonstrating the statistical behavior of the proposed probabilistic state-generation algorithm.

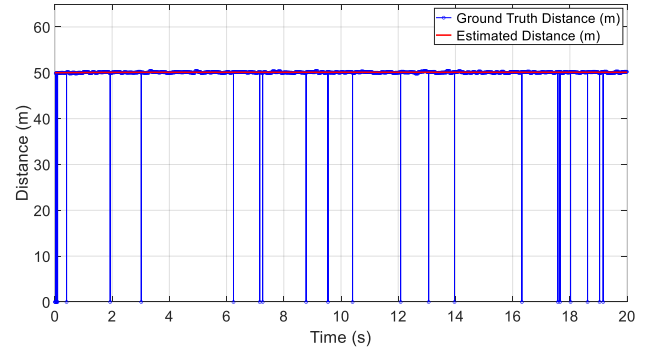


Fig. 7 Estimated distance ($\hat{R}_a$) to the target vehicle under clear weather conditions

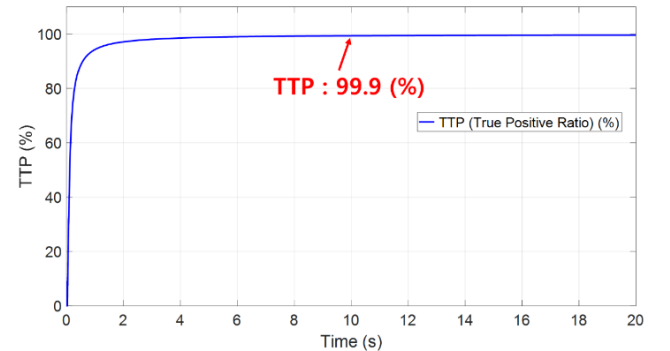


Fig. 8 True positive rate (TPR) evaluation in the absence of rain

3.2. Experimental results - rainfall conditions (10, 30, 120 mm/h)

In the second experiment, the attenuation characteristics of the radar sensor under rainfall conditions were evaluated. The rainfall intensity was set to 10, 30, and 120 mm/h, while the desired probability of false alarm (P_{fa-des}) and probability of detection (P_{d-des}) were maintained at 0.1% and 85%, respectively. The rain-attenuation results obtained from the proposed model were compared with the reference results reported in [16], as shown in Fig. 9.

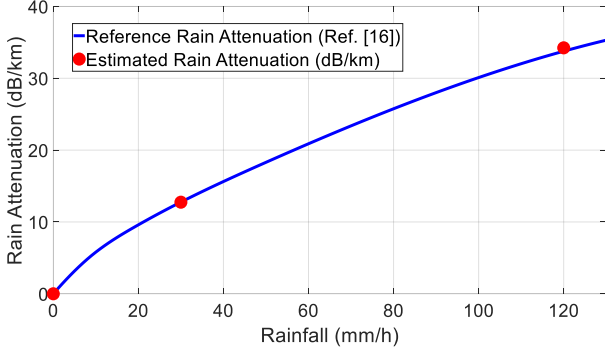


Fig. 9 Comparison of rain attenuation between reference data and the proposed model

To clearly examine the radar sensor response to changes in rainfall intensity and the resulting variation in range measurement, the rainfall intensity was varied step-wise over time: 10 mm/h from 0 to 7 s, 30 mm/h from 7 to 15 s, and 120 mm/h from 15 to 20 s. The rainfall conditions were intentionally varied over a relatively wide range to clearly distinguish the corresponding changes in attenuation and radar sensor response. The rain attenuation was calculated according to Eq. (3). The mean signal strength was -186.446 dBW at 10 mm/h, -188.994 dBW at 30 mm/h, and -189.992 dBW at 120 mm/h, respectively. The corresponding temporal variation in signal strength induced by changes in rainfall intensity is presented in Fig. 10.

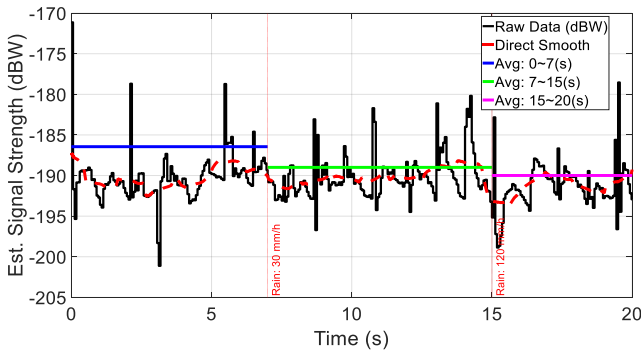


Fig. 10 Time-varying radar signal strength under different rainfall conditions

To examine the transient response of the radar sensor to rainfall, a rainfall intensity of 10 mm/h was first considered as a representative condition. The rainfall intensity was abruptly applied at $t = 7$ s, and the corresponding virtual simulation environment, rain attenuation, received signal strength, and estimated target distance are presented in Figs. 11-14, respectively.

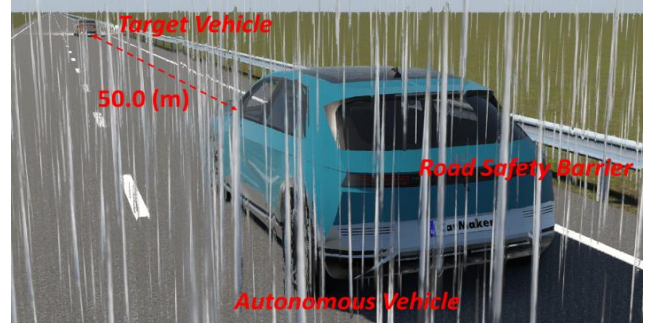


Fig. 11 Virtual simulation environment depicting various rainfall conditions

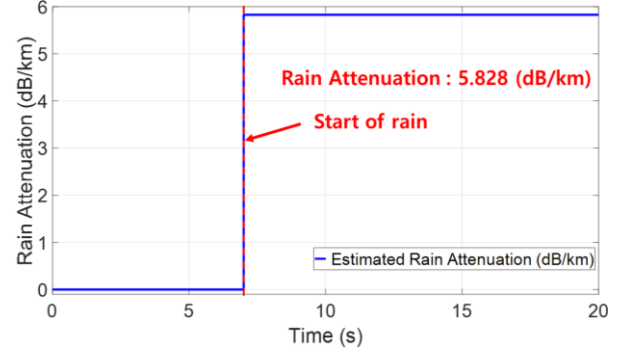


Fig. 12 Estimated specific rain attenuation ($\hat{L}_r$) over time under light rainfall conditions (10 mm/h)

Under the 10 mm/h rainfall condition, the estimated specific rain attenuation was 5.828 dB/km. The corresponding estimated received signal strength ranged from approximately -185 to -178 dBW, as shown in Fig. 13. The resulting target-distance response is presented in Fig. 14.

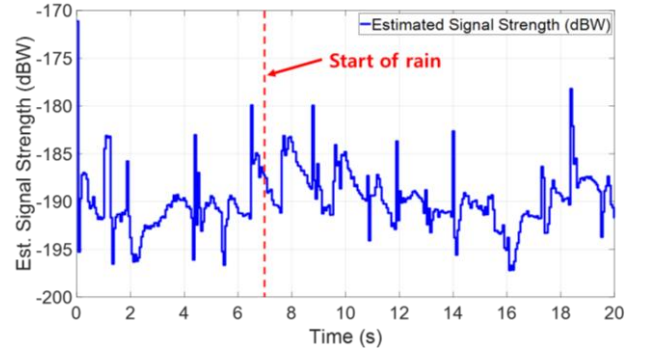


Fig. 13 Estimated radar received signal strength ($\hat{P}_r$) reflecting the impact of rain attenuation (10 mm/h)

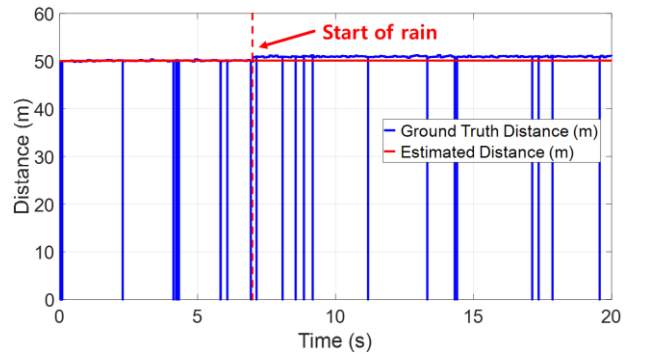


Fig. 14 Estimated distance ($\hat{R}_a$) to the target vehicle during light rainfall conditions (10 mm/h)

To further investigate the effect of increased rainfall intensity, the same simulation was performed under a rainfall intensity of 120 mm/h. The rainfall intensity was similarly applied at $t = 7$ s, and the corresponding simulation results are shown in Figs. 15-17.

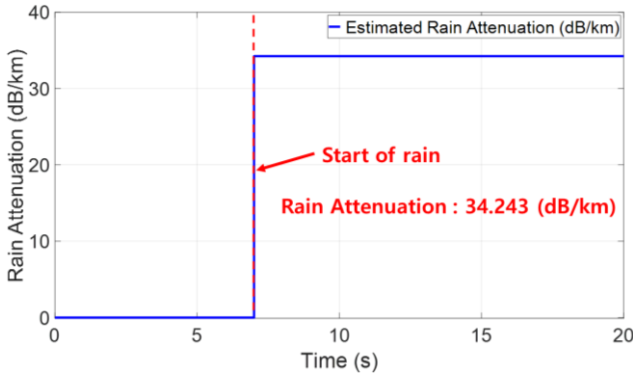


Fig. 15 Estimated specific rain attenuation ($\hat{L}_r$) over time under extreme rainfall conditions (120 mm/h)

Under the 120 mm/h rainfall condition, the estimated specific rain attenuation increased to 34.243 dB/km, resulting in a further reduction in the received signal strength to approximately from -201 to -182 dBW. The corresponding target-distance response is also presented in Fig. 16, showing the effect of increased rain attenuation on radar ranging performance.

The distance to the target vehicle was approximately 55 m, and Fig. 17 shows that a distance error of approximately 5 m was observed.

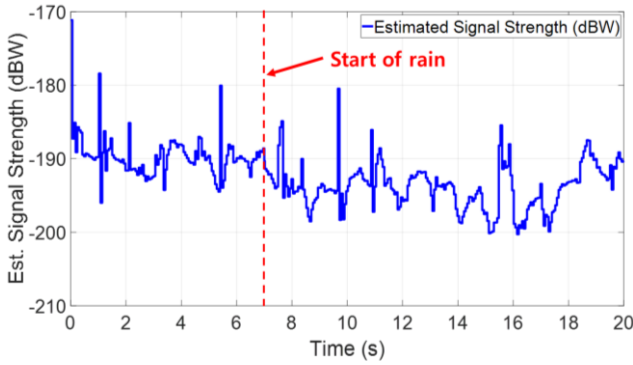


Fig. 16 Estimated radar received signal strength ($\hat{P}_r$) reflecting the impact of rain attenuation (120 mm/h)

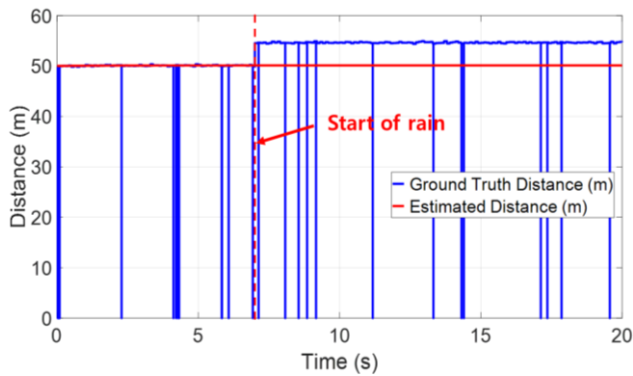


Fig. 17 Estimated distance ($\hat{R}_d$) to the target vehicle during extreme rainfall conditions (120 mm/h)

As summarized in Table 2, the rain attenuation increases substantially with increasing rainfall intensity, from 5.828 dB/km at 10 mm/h to 12.751 dB/km at 30 mm/h and 34.243 dB/km at 120 mm/h. This increase directly reduces the received signal strength and consequently affects the reliability of the radar-based distance measurement. At 10 mm/h, the received signal strength ranges from approximately -185 to -178 dBW, whereas the range extends to approximately from -200 to -176 dBW at 30 mm/h and from -201 to -182 dBW at 120 mm/h. The broader and generally lower signal-strength range under stronger rainfall conditions indicates an increased susceptibility of the received radar signal to rain-induced propagation loss.

Table 2
Summary of radar measurement results under different rainfall intensities

Rain inten., mm/h	Rain atten., dB/km	Rec. Sig. Str., dBW	Dist. meas., m
10	5.828	$-185 \sim -178$	$50.85 \sim 51.11$
30	12.751	$-200 \sim -176$	$51.86 \sim 52.12$
120	34.243	$-201 \sim -182$	$55.2 \sim 55.46$

Correspondingly, the measured distance ranges from 50.85-51.11 m at 10 mm/h, 51.86-52.12 m at 30 mm/h, and 55.20-55.46 m at 120 mm/h. The progressive variation in the measured distance demonstrates that the degradation of the received signal under heavy rainfall can propagate into the radar measurement output. These results indicate that the proposed model captures the coupled relationship between rainfall intensity, propagation attenuation, received signal strength, and radar distance measurement, thereby providing a physically interpretable representation of rain-fall-induced sensing degradation.

3.3. Experimental results - dynamically varying rainfall and target false alarm probability

In the third experimental scenario, the system's dynamic responsiveness — specifically regarding the detection range, True Positive Rate (TPR), and the estimated minimum signal-to-noise ratio $\text{SNR}_{\min}$ was evaluated by varying both the rainfall condition and the target false alarm probability (P_{fa-des}) in real-time. Simulated precipitation is initiated at the onset of the simulation ($t = 0$) and abruptly ceases at $t = 6$ s. The rainfall intensity was deliberately set to an extreme level to explicitly magnify and observe the consequent degradation in received signal power and the resulting detection range errors. Through this aggressive stress-testing scenario, the real-time computational feasibility and the operational robustness of the proposed mathematical formulations and stochastic algorithms were successfully verified.

As anticipated, substantial distance estimation errors were observed as a direct result of this severe precipitation. The direct correlation between these detection range errors and the fluctuation patterns of the estimated received

signal power ($\hat{P}_r$) was also validated. To evaluate the probabilistic algorithm's dynamic adaptability, the target false alarm probability (P_{fa-des}) was maintained at an artificially high rate of 80% from $t = 0.0$ s to 7s, after which it was abruptly constrained to a stringent 0.1%. Corresponding fluctuations and intermittent dropouts in the target vehicle's distance output were explicitly observed, accurately reflecting this stochastic transition.

Furthermore, these dynamic adjustments to the FAP directly influenced the operational bounds of the required probability of detection (P_{d-des}), thereby inducing proportional variations in the required SNR_{min}. The comprehensive results of these dynamic observations are presented in Figs 18 through 21.

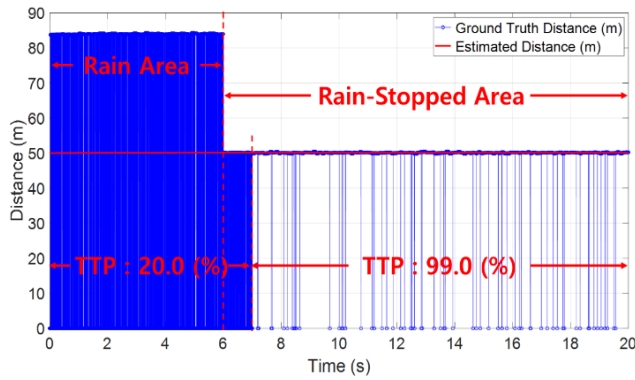


Fig. 18 Final estimated distance ($\hat{R}_{fa}$) to the target vehicle under dynamically varying rain conditions

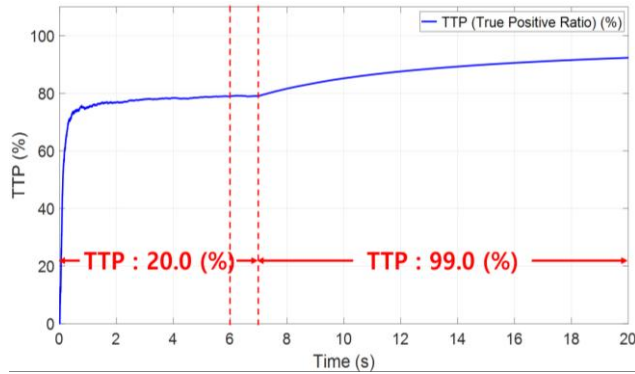


Fig. 19 True positive rate (TPR) response to dynamic adjustments in the target false alarm probability

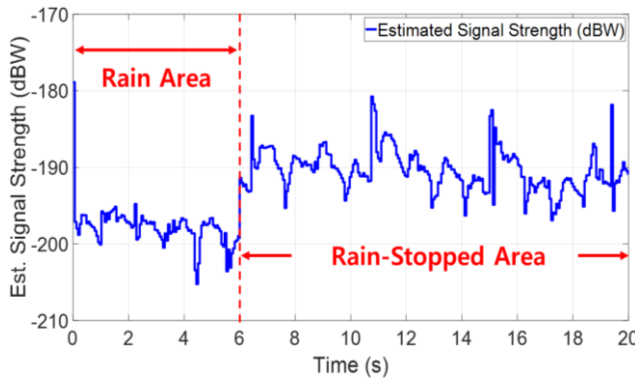


Fig. 20 Estimated radar received signal strength ($\hat{P}_r$) over time under varying rain conditions

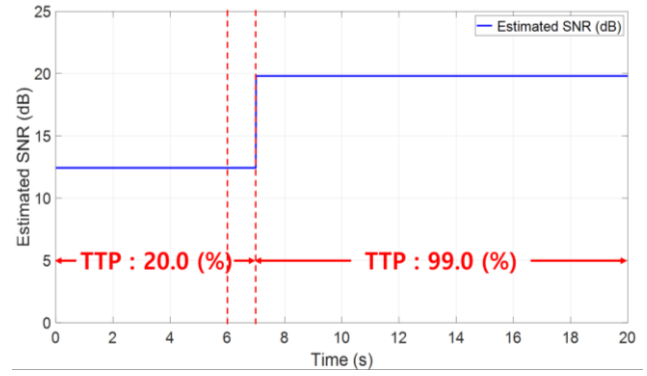


Fig. 21 Variations in the estimated minimum signal-to-noise ratio (ξ_{snr}) induced by dynamically changing FAP settings

4. Conclusions

This study proposed a physics-based and computationally efficient radar sensor modeling method for virtual validation of autonomous driving systems under rainfall conditions. The proposed model incorporates rainfall-induced signal attenuation into a radar propagation model and employs the False Alarm Probability Generation (FAPG) algorithm to reproduce stochastic target dropouts and intermittent detection failures. The results demonstrated that increasing rainfall intensity causes greater propagation loss and corresponding degradation in received signal strength and radar distance estimation.

The proposed framework was implemented through a co-simulation architecture integrating IPG Car-Maker and MATLAB/Simulink, enabling the coupled modeling of vehicle dynamics, target behavior, and rainfall-affected radar sensing. Across repeated 100-s driving simulations, the proposed framework consistently completed the simulations in approximately 14.5 s of wall-clock time on average, corresponding to an average real-time factor of approximately 6.9 $\times$. This result demonstrates that the proposed model can operate faster than real time, supporting accelerated simulation and virtual validation.

The current study focused on vehicle detection using vehicle-specific radar cross-section (RCS) map data. Future work will extend the framework by incorporating geographically dependent precipitation characteristics and empirical RCS data for pedestrians, cyclists, and heavy commercial vehicles. The proposed rainfall attenuation and FAPG modeling approaches will also be investigated for other perception sensors, including LiDAR and ultrasonic sensors, to further improve the applicability of the framework to comprehensive virtual validation of autonomous driving systems.

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A COMPUTATIONALLY EFFICIENT RADAR SENSOR MODELING METHODOLOGY INCORPORATING RAIN-INDUCED PROPAGATION ATTENUATION FOR VIRTUAL VALIDATION OF AUTONOMOUS DRIVING SYSTEMS

Summary

This paper presents a computationally efficient radar sensor modeling methodology incorporating rain-induced propagation attenuation for simulation-based validation of autonomous driving systems. The proposed framework combines the classical radar equation with the rain attenuation model specified in ITU-R Recommendation P.838-3 to estimate received signal power degradation and target-range estimation errors under rainfall conditions. A stochastic False Alarm Probability Generation (FAPG) algorithm is also introduced to reproduce intermittent target detection according to user-defined probabilities of false alarm and detection. The proposed methodology was implemented through real-time co-simulation between MATLAB/Simulink and IPG CarMaker. Simulation results demonstrated that the proposed framework successfully reproduced rain-induced propagation attenuation, target-range estimation errors, received signal power degradation, and stochastic target detection behavior while maintaining computational efficiency suitable for real-time simulation.

Keywords: radar sensor model, rainfall attenuation, autonomous driving, virtual validation, sensor modelling, co-simulation.

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