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A Link Quality Indicator (LQI) Based Closed-Form Localization Framework for Vehicular Ad Hoc Networks (VANETs)

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ABSTRACT: Accurate vehicle localization is essential for safety-critical vehicular ad hoc networks (VANETs), including emergency response, navigation, traffic monitoring, and cooperative driving. However, conventional GPS/GNSS positioning systems have often shown degradation in tunnels, dense urban corridors, and non-line-of-sight (NLOS) environments, where satellite visibility and signal reliability are limited. This paper proposes a calibrated Link Quality Indicator (LQI)-based closed-form localization framework for partially connected Roadside Unit (RSU)-assisted VANETs. The proposed framework first calibrates the LQI-to-range relationship using numerical regression parameters and then converts accepted LQI observations into distance estimates. The distances are processed through a variance-aware weighted least squares (WLS) estimator, after which scalar consistency refinement is applied to improve the geometric consistency of the final position estimate. Partial connectivity is explicitly modeled using communication radius, LQI-threshold, and packet-reception constraints, rather than assuming that all vehicles and anchors are fully connected. The proposed method is evaluated against least squares (LS), WLS, RSSI-WLS, Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF), Particle Filter (PF), cooperative localization, hybrid GNSS/INS/RSS fusion, and machine-learning-based localization baselines. The evaluation includes Monte Carlo simulations under shadowing, fading, packet loss, anchor-geometry, and NLOS conditions, together with confidence interval, statistical-significance, runtime, ablation, and sensitivity analyses. In addition, trace-driven validation is performed using the NGSIM US-101 real-world vehicle trajectory dataset. The NGSIM dataset provides real vehicle mobility traces, while LQI observations are generated using the calibrated LQI-distance model because the dataset does not contain physical LQI measurements. In the 100-vehicle case, throughput improves from 0.614 to 1.169 successful localizations/s compared with LS, corresponding to a 90.39% gain and from 0.591 to 1.169 successful localizations/s compared with WLS, corresponding to a 97.80% gain. In the NGSIM trace-driven experiment, the proposed method achieves RMSE values of 2.39, 2.55, and 3.14 m for 10, 50, and 100 vehicles, respectively. These results indicate that calibrated LQI-based localization provides a low-cost, infrastructure-compatible, and computationally efficient positioning framework for ITS and safety-critical VANET applications.

KEYWORDS: Vehicle localization; link quality indicator; vehicular ad hoc networks; intelligent transportation systems; Cramer-Rao lower bound

1 Introduction

A vehicular ad hoc network (VANET) enables communication between vehicles and roadside infrastructure [1]. It uses vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I) and vehicle-to-everything (V2X) communication. These links form a key part of Intelligent Transportation Systems (ITS). ITS services include safety alerts, route guidance, traffic monitoring, cooperative driving, and emergency response. Each service depends on vehicle position information that is accurate, timely and reliable [2]. GPS/GNSS positioning performs well in open-sky areas. The situation changes in dense urban roads. Its accuracy drops in urban corridors, tunnels, underground roads, and non-line-of-sight (NLOS) environments. In these places, satellite signals are often blocked, reflected, or weakened by surrounding obstacles [3]. For this reason, infrastructure-assisted wireless localization becomes a useful option for VANET positioning. Roadside Units (RSUs), anchor nodes, and inter-vehicle links can provide measurements such as Time of Arrival (TOA), Time Difference of Arrival (TDOA), Round Trip Time (RTT), Received Signal Strength (RSS), and Link Quality Indicator (LQI) [4].

Among these measurements, LQI is attractive because it is obtained at the communication layer and does not require separate ranging hardware. Even so, practical limitations are still faced by LQI-based, RSS-based, and RSU-assisted localization methods. Many studies assume ideal network conditions or fully connected topologies. Real VANET communication is less predictable. Link quality changes with communication range, packet reception probability, interference, fading, shadowing, and temporary obstruction [5]. Reproducibility is another concern, where some studies have converted LQI values into distance estimates but do not report the numerical calibration parameters used in that conversion. In addition, several evaluations depend mainly on synthetic mobility and compare the proposed approach only with basic LS and WLS estimators. This gives a narrow view of performance when the method must also be compared with filtering, cooperative, fusion-based, and learning-based localization baselines [6]. To address these issues, this study presents a calibrated LQI-based closed-form localization method for partially connected RSU-assisted VANETs. The method accepts only links that satisfy range, LQI, and packet-reception requirements. It then calibrates the LQI-to-range model using numerical regression parameters. Accepted LQI samples are then converted into distance estimates and are passed to a variance-aware weighted least squares estimator. A scalar consistency refinement step then improves the geometric agreement of the estimated position, while the Cramér-Rao Lower Bound is derived and used as a theoretical accuracy reference for evaluating the final estimate.

The proposed method is evaluated in two settings. First, it uses Monte Carlo simulations to study wireless impairments, anchor availability, RSU geometry, and traffic density. Secondly, it uses the NGSIM US-101 real-world mobility trace; here, the actual vehicle trajectories are used as ground truth. Calibrated model-generated LQI observations are then used for localization testing [7]. These settings examine the estimator under controlled wireless conditions and realistic freeway mobility patterns.

1.1 Vehicle to Vehicle

V2V communication allows vehicles to exchange position, speed, heading, and driving-status information through a dedicated wireless network [8]. This information can reduce collision risk by supporting driver warnings and protective actions. These actions include braking and deceleration when hazardous situations are detected [9,10]. For this reason, V2V communication is widely treated as a key safety component in connected-vehicle and ITS programs [11].

1.2 Vehicle to Infrastructure (V2I)

In the V2I paradigm, vehicles communicate with roadside infrastructure. This infrastructure may include RSUs, RFID-enabled systems, smart parking infrastructure, traffic lights, street lighting, traffic signage, and roadside cameras or sensors [12,13]. This bidirectional communication supports traffic monitoring, safety services, navigation assistance, and infrastructure-supported localization [14,15]. Short-range V2V and V2I communication commonly relies on DSRC-based vehicular communication in the 5.9 GHz band [16], as illustrated in Fig. 1.

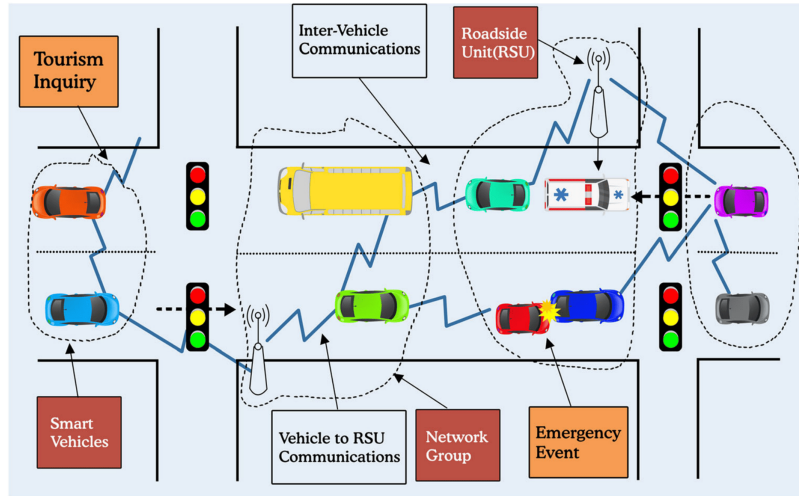


Figure 1: Conceptual structure of VANETs adapted from Cui et al. [17].

1.2.1 Localization Background

Localization determines a vehicle's position in two- or three-dimensional space. In VANETs, manual localization is impractical because of high mobility, changing network topology, vehicle density, and scalability constraints [18]. Automated localization is therefore required, especially when GPS/GNSS is unreliable. In infrastructure-supported scenarios, vehicles can estimate or refine their positions using RSUs or anchors with known coordinates. This process can also be strengthened through measurements shared by neighboring vehicles [19]. VANET localization methods are commonly classified as centralized or distributed and as range-based or range-free, as illustrated in Fig. 2.

1.3 Primary Contributions

This study presents a calibrated LQI-based closed-form localization framework for partially connected RSU-assisted VANETs. The main contributions are as follows:

- A reproducible LQI-to-range calibration model is developed using numerical regression parameters. It also reports residual statistics and confidence intervals.
- A practical VANET localization model is formulated for partial connectivity. It uses communication-radius, LQI-threshold, and packet-reception constraints.
- A closed-form localization estimator is derived by combining LQI-based ranging, variance-aware WLS, and scalar consistency refinement. The CRLB is used as the theoretical accuracy benchmark.
- The framework is validated through Monte Carlo simulations and NGSIM US-101 trace-driven testing. It is compared with classical, filtering, cooperative, fusion-based, and learning-based localization baselines.

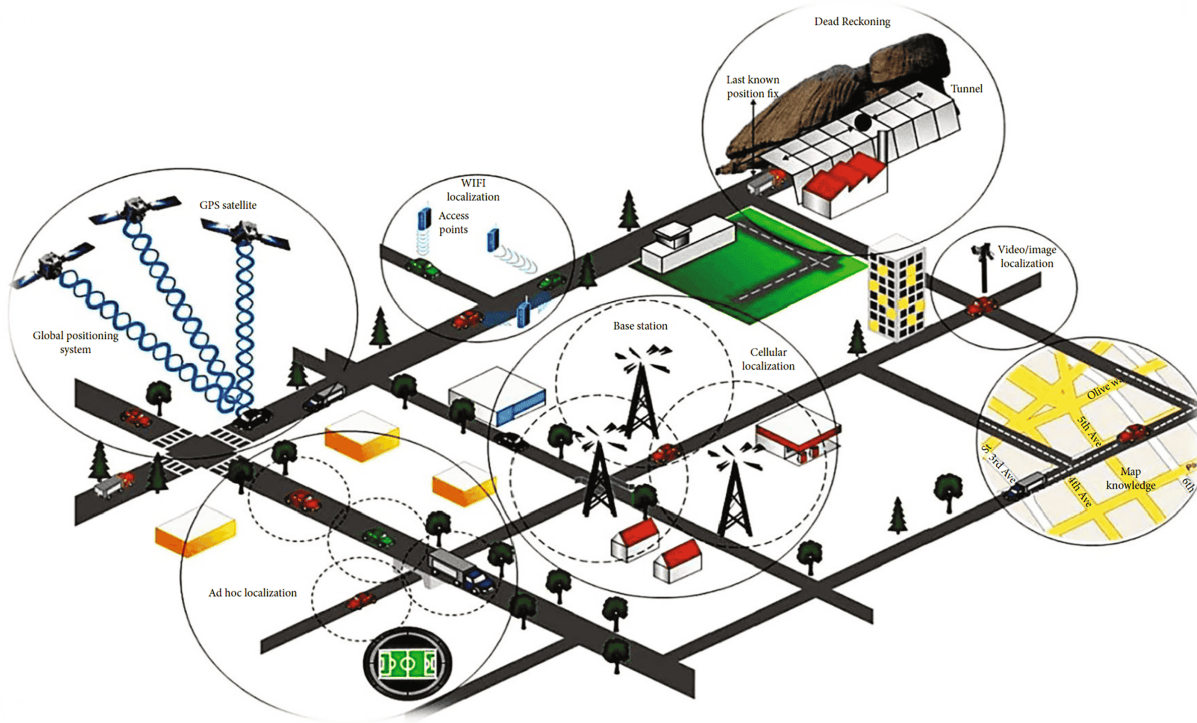


Figure 2: Localization in VANETs (Source: Ahmad et al. [20]; reproduced/adapted with permission under CC BY 4.0).

2 Background Study

2.1 Localization in VANETs

Vehicle localization in VANETs generally involves three stages: measurement acquisition, ranging, and position estimation. When GPS or GNSS is degraded or unavailable, RSU-assisted localization can provide an alternative. It uses infrastructure nodes with known positions and radio measurements collected from vehicular communication links [21]. These measurements may include TOA, TDOA, RTT, RSS, LQI, or combinations of multiple indicators.

Recent VANET localization methods can be grouped into RSU-assisted radio localization, cooperative V2V/V2I localization, filtering-based localization, multi-sensor fusion, learning-based localization, and emerging V2X or 5G/6G positioning [22]. RSU-assisted RSS or LQI localization is cost-effective because it uses communication-layer measurements. However, its accuracy depends on calibration quality, RSU placement, link availability, and propagation conditions. Cooperative localization improves spatial diversity by using neighboring vehicles and infrastructure. However, it increases message exchange and depends on reliable communication links.

Filtering-based methods, such as EKF, UKF, and particle filtering, improve temporal continuity. Their performance depends on the accuracy of the motion and noise models [23]. Multi-sensor fusion combines GNSS, INS, RSS, camera, LiDAR, or map information to improve robustness. However, this improvement is often accompanied by higher hardware cost and greater computational complexity. Learning-based methods can model nonlinear measurement-position relationships, but their performance depends on representative training data and may generalize poorly across different road layouts, RSU deployments, and propagation environments [24].

Real-time localization systems usually operate over short discrete update intervals. They are often supported by Kalman filtering, map matching and sensor fusion. When GNSS becomes unreliable, localization reliability, availability, and continuity can be improved through multi-sensor fusion and EKF-based methods [25]. Wireless positioning systems may also estimate distance to reference nodes through round-trip-time measurements [26]. In cooperative tracking scenarios, V2V and V2I information sharing can further refine state estimates. This is effective when neighboring nodes are reliable, and communication links are stable.

2.2 Roadside Unit Telemetry

RSU-assisted localization uses roadside infrastructure with known coordinates to support vehicle positioning in VANET environments. Its effectiveness depends on RSU density, anchor geometry, communication range, and propagation conditions [27]. When RSUs are not carefully deployed, the anchor layout can become less favorable, and localization accuracy may suffer. Poor RSU placement can also increase the likelihood of geometric dilution of precision. In addition, biased distance estimates for the connections are often introduced by NLOS propagation and multipath effects [28]. The factors discussed make reliable vehicle localization more challenging in practical deployments.

Cooperative localization combines positioning methods, data fusion, and V2V or V2I communication to improve vehicle positioning accuracy in dynamic VANET scenarios. By sharing these measurements between vehicles and infrastructure, cooperative methods increase the available positioning information and support more stable localization in vehicles [29]. They can also help them to reduce local measurement errors when communication links remain stable. Recent cooperative and optimization-based methods further improve localization through shared observations, distance constraints, and anchor-geometry optimization [30]. Still, their performance can drop in sparse traffic, high packet-loss conditions, or cases where neighboring vehicles have uncertain positions.

RSU placement remains an important design issue because infrastructure geometry directly affects localization accuracy, but when RSUs or anchor nodes are poorly distributed, the estimation problem becomes less well-conditioned, and the resulting position estimates can become less reliable [31]. For this reason, GDOP-type measures are commonly used to describe how reference-node geometry influences positioning performance [32]. Closed-form GDOP analyses and deployment-focused formulations have also been used to guide base-station and anchor placement. These methods help improve localization when received signals are strongly affected by deployment geometry [33]. However, many RSU-assisted localization studies still rely on simplified connectivity assumptions or ideal anchor availability. Such assumptions limit their applicability in dense, sparse, and partially connected VANET environments.

2.3 VANET Location Estimation

Accurate vehicle location data is essential for safety warnings, navigation, traffic management, and cooperative driving applications [34,35]. Modern vehicle positioning systems update state estimates in real time over short intervals [36]. Cooperative vehicle localization can be solved using distance constraints and convex optimization. Vehicle positions can also be estimated from trusted neighboring nodes or infrastructure with known locations. In addition, GNSS/GPS errors can be reduced through fused V2V and V2I information [29,31,37]. In such settings, V2V and V2I fusion can improve positioning performance [31].

Recent cooperative localization methods combine shared measurements, prior information, and collaboration among nearby vehicles. These methods can improve position estimates when neighboring vehicles exchange useful localization evidence [38]. They also exploit data correlation, multiple localization cues, and different vehicular communication modes. However, their main weakness remains the strong dependence

on communication reliability. In dense VANETs, additional message exchange may also reduce scalability and increase communication overhead [39,40].

Hybrid GNSS/INS and multi-sensor localization methods have also received considerable research attention, while INS/GNSS integrations can preserve localization continuity during short periods of GNSS unavailability. Yet inertial drift still needs correction from GNSS or another external measurement source [41]. Visual and map-based localization methods have the ability to convert camera and map information into useful localization cues. These methods can support reliable pose estimation in complex road environments [42]. Multi-sensor fusion can still support accurate positioning when signal conditions become degraded [43]. In difficult environments such as underground parking areas and obstacle-rich roads, localization can be improved through semantic-map and topological frameworks [44]. These approaches offer strong robustness, although additional sensors, synchronization, and computational resources are usually required.

Machine-learning and deep-learning-based localization methods can improve robustness in nonlinear and noisy environments [45]. They are useful when radio behavior is difficult to model analytically; however, they require representative training data to retrain the need when road geometry, RSU placement, or propagation conditions change. High-accuracy localization can also be supported by emerging 5G/6G, NR-V2X, and advanced V2X positioning methods. These methods are especially useful when combined with cooperative sensing and infrastructure support [2,16]. However, they may require upgraded infrastructure, dense deployment, specialized devices, or accurate synchronization. In contrast, calibrated LQI-based localization can use low-cost link-quality information already available from communication hardware.

2.4 Validation Approaches in VANET Localization

Validation methods in VANET localization can be grouped into simulation-only validation, trace-driven validation, and hardware/testbed validation. Simulation-only validation is useful for controlled testing. It can evaluate channel noise, fading, packet loss, NLOS propagation, anchor failure, RSU placement, and traffic density. However, purely synthetic simulations may not fully capture real vehicle movement. They may also miss lane-changing behavior, acceleration patterns, and traffic-density variation.

Trace-driven validation improves realism by using real vehicle trajectories collected from road environments. Datasets such as NGSIM provide real vehicle positions, speeds, acceleration, and lane information. These data make it possible to test localization algorithms under realistic mobility patterns. In this work, controlled Monte Carlo simulations evaluate wireless impairments and deployment conditions. NGSIM US-101 trace-driven validation then tests the proposed framework under real freeway vehicle movement. Since NGSIM does not include physical LQI/RSS packet measurements from RSUs or onboard units, only the vehicle trajectories are taken from the real-world dataset. The LQI observations are generated using the calibrated LQI-distance model.

Hardware/testbed validation provides the strongest experimental realism. It uses physical RSU/OBU devices, measured LQI/RSS packet logs, and field experiments under real propagation conditions. Such validation is especially important for highway, urban-canyon, tunnel, and NLOS environments. However, hardware-based experiments require deployment cost, device synchronization, and controlled field access. These requirements make large-scale hardware validation difficult.

2.5 Summary of Existing Gaps

Table 1 summarizes the main localization categories used in VANETs. Existing studies provide useful foundations for GPS/GNSS localization, RSU-assisted positioning, cooperative localization, filtering, sensor

fusion, INS/GNSS integration, and anchor-based localization. However, several gaps remain. Many works do not report numerical LQI calibration parameters. Some assume an ideal or fully connected topology. Others compare only with limited baselines or rely only on synthetic mobility. Several studies also report only RMSE. They do not include statistical significance testing, confidence intervals, ablation analysis, sensitivity analysis, runtime comparison, or scalability evaluation.

Table 1: Comparison of major vehicle localization approaches in VANETs.

Method	Working Principle	Advantages	Limitations
GPS/GNSS	Satellite-based positioning in open-sky LOS conditions.	Widely available and accurate in open areas.	Accuracy decreases in tunnels, underground parking, and dense urban areas.
RSU-assisted localization	Uses RSUs with TOA, TDOA, RTT, RSS, and LQI for positioning [21,28]	Useful when GPS is weak or unavailable [21]	Depends on RSU density, placement, geometry, calibration quality, and channel conditions [32,33]
Cooperative V2V/V2I	Combines vehicle and infrastructure measurements for localization [31]	Reduces GPS errors through shared information [29,31]	Needs reliable communication, nearby nodes and additional packet exchange [37]
Multi-sensor fusion/EKF	Fuses GNSS, INS, RSU and onboard sensor data [25]	Improves robustness and continuity [25]	Higher computational complexity, sensor dependence and synchronization requirements [38]
INS/GNSS integration	Combines inertial sensing with satellite positioning [41]	Maintains localization during short GNSS outages [41]	INS drift must be corrected by GNSS or another external measurement source [41]
Learning-based localization	Learns nonlinear relations between radio/sensor features and position [45]	Can model complex nonlinear environments.	Requires representative training data and may generalize poorly across new road layouts or RSU deployments.
Anchor-/MDS-/hybrid-based localization	Uses anchors and connectivity information to estimate positions.	Useful for network-wide localization studies.	Depends on anchors, network density, measurement error, and connectivity assumptions.

The present work addresses these gaps by proposing a calibrated LQI-based closed-form localization framework for partially connected RSU-assisted VANETs. The method combines numerical LQI-to-range

calibration, link-availability filtering, variance-aware WLS, scalar consistency refinement, and CRLB benchmarking. It also includes advanced baseline comparison, statistical validation, ablation testing, sensitivity analysis, runtime/scalability evaluation, and NGSIM US-101 trace-driven validation.

3 Research Methodology

This section presents the proposed calibrated LQI-based closed-form localization framework for partially connected RSU-assisted VANETs. The objective is to estimate the two-dimensional position of each target vehicle using LQI observations collected from RSUs or anchor vehicles with known coordinates. The methodology covers system modeling, partial-connectivity modeling, LQI-to-range calibration, closed-form WLS localization, CRLB analysis, workflow implementation, simulation setup, benchmark comparison, trace-driven validation, ablation testing, sensitivity analysis, complexity evaluation, and reproducibility checks. The notation used in the methodology is summarized in Table 2.

Table 2: Notation used in the proposed LQI-based localization framework.

Symbol	Description	Symbol	Description	Symbol	Description
$\mathcal{T}$	Target vehicles	$\hat{d}_{ij}$	LQI-derived range	δ_{ij}	Squared-range residual
V	Number of target vehicles	g_{ij}	Noisy range observation	$\boldsymbol{\delta}_i$	Residual vector
$\mathcal{A}$	Anchors/RSUs	d_0	Reference distance	$\mathbf{Y}_i$	Squared-range vector
M	Number of anchors	Z_{ij}	Measured LQI	$\mathbf{B}_i$	Geometry matrix
$\mathcal{V}_i$	Visible anchor set	Z_0	Reference LQI	$\mathbf{W}_i$	WLS covariance matrix
M_i	Number of visible anchors	Z_T	LQI threshold	κ_i	Scalar correction vector
$\mathbf{c}_i$	True coordinate of target i	α	LQI attenuation coefficient	$\mathbf{G}_i$	Nominal WLS component
$\hat{\mathbf{c}}_i$	Estimated coordinate of target i	η_{ij}	Range-domain noise	ρ_{ij}	Packet reception probability
$\mathbf{e}_j$	Coordinate of anchor j	ϵ_{ij}^Z	LQI-domain error	R_c	Communication radius
d_{ij}	True target-anchor distance	σ_ℓ	LQI-domain noise standard deviation	N_{MC}	Monte Carlo trials
θ_i	Auxiliary scalar, $\ \mathbf{c}_i\ ^2$	σ_n	Range-domain noise standard deviation	T_{sim}	Simulation time
$\hat{\theta}_i$	Estimated refinement scalar	τ_i	Runtime per localization		

3.1 System Model and VANET Assumptions

The VANET is modeled as a two-dimensional road network containing target vehicles and fixed RSUs or anchor vehicles. Let $\mathcal{T}$ denote the set of vehicles to be localized and $\mathcal{A}$ denote the set of anchors with known coordinates. The target-anchor distance is defined as

$$T = \{T_1, T_2, \dots, T_V\}, \quad A = \{\mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_M\}, \quad d_{ij} = \|\mathbf{c}_i - \mathbf{e}_j\|_2 = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}. \quad (1)$$

In Eq. (1), $\mathbf{c}_i = [x_i, y_i]^\top$ is the unknown position of target vehicle i , while $\mathbf{e}_j = [x_j, y_j]^\top$ is the known position of anchor j . This distance is the geometric quantity that the localization algorithm estimates indirectly from LQI-derived range measurements. To represent practical VANET operation, full connectivity is not assumed. A link is accepted only when it satisfies communication-radius, LQI, and packet-reception constraints:

$$a_{ij} = \begin{cases} 1, & d_{ij} \leq R_c, Z_{\min} \leq Z_{ij} \leq Z_{\max}, \rho_{ij} \geq \rho_{\min}, \\ 0, & \text{otherwise,} \end{cases} \quad V_i = \{j \in \{1, \dots, M\} : a_{ij} = 1\}, \quad M_i = |V_i|. \quad (2)$$

Eq. (2) defines the usable anchor set for each target vehicle. Here, a_{ij} is the binary link-availability indicator, R_c is the communication radius, Z_{ij} is the measured LQI, ρ_{ij} is the packet reception probability and V_i is the set of visible anchors. A valid two-dimensional estimate requires at least three non-collinear visible anchors. The vehicle motion between localization snapshots is described as

$$\mathbf{c}_i(t + \Delta t) = \mathbf{c}_i(t) + \mathbf{v}_i(t)\Delta t + \frac{1}{2}\mathbf{a}_i(t)\Delta t^2, \quad \mathbf{v}_i(t + \Delta t) = \text{clip}(\mathbf{v}_i(t) + \mathbf{a}_i(t)\Delta t, v_{\min}, v_{\max}). \quad (3)$$

Eq. (3) updates vehicle position and velocity between successive simulation steps. The clipping function restricts the velocity to the selected scenario speed range. Within a single localization snapshot, the vehicle is treated as quasi-static because the update interval is short. The wireless channel before LQI conversion is modeled as

$$PL_{ij}(d_{ij}) = L_0(d_0) + 10n \log_{10} \left(\frac{d_{ij}}{d_0} \right) + X_{ij}^{\text{sh}} + X_{ij}^{\text{NLOS}} + F_{ij} + I_{ij}. \quad (4)$$

Eq. (4) describes the propagation loss between a vehicle and an anchor. The first two terms model distance-dependent path loss, while X_{ij}^{sh} , X_{ij}^{NLOS} , F_{ij} and I_{ij} represent shadowing, NLOS attenuation, fading, and interference or collision degradation. These terms allow the simulations to represent highway, urban, and tunnel/NLOS environments. The main assumptions are summarized in Table 3.

Table 3: Mobility, connectivity, and channel assumptions.

Item	Modeling Choice
Road geometry	Highway, urban, tunnel, and NLOS layouts
Lane count	3 lanes/direction highway; 2 lanes/direction urban/tunnel
Mobility model	SUMO Krauss car-following and LC2013 lane-changing traces
Speed	Bounded or trace-derived vehicle speeds
Traffic density	$V \in \{10, 50, 100\}$ vehicles
Connectivity	Based on R_c , LQI, PRR and anchor availability

(Continued)

Table 3 (continued)

Item	Modeling Choice
Anchor dropout	$p_{\text{drop}} = 0.10$
Synchronization	No strict synchronization required
Anchor positions	RSU/anchor positions are known

3.2 LQI-to-Range Calibration and Measurement Model

The proposed framework uses a calibrated logarithmic mapping to convert LQI values into distance estimates. The LQI measurement model is defined as

$$Z_{ij} = Z_0 - 10\alpha \log_{10} \left(\frac{d_{ij}}{d_0} \right) + \epsilon_{ij}^Z, \quad \epsilon_{ij}^Z \sim \mathcal{N}(0, \sigma_\ell^2), \quad \bar{Z}_q = Z_0 - 10\alpha x_q + \epsilon_q^Z, \quad x_q = \log_{10} \left(\frac{d_q}{d_0} \right). \quad (5)$$

Eq. (5) states that LQI decreases logarithmically with distance. Here, Z_0 is the reference LQI at distance d_0 , α is the attenuation coefficient and ϵ_{ij}^Z is the LQI-domain measurement error. The averaged calibration value $\bar{Z}_q$ is used to estimate the model parameters from calibration samples. The calibration parameters are estimated using ordinary least squares:

$$\begin{bmatrix} \hat{Z}_0 \\ -10\hat{\alpha} \end{bmatrix} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{z}, \quad \mathbf{X} = \begin{bmatrix} 1 & x_1 \\ 1 & x_2 \\ \vdots & \vdots \\ 1 & x_Q \end{bmatrix}. \quad (6)$$

Eq. (6) fits the reference LQI $\hat{Z}_0$ and attenuation factor $\hat{\alpha}$ from the calibration data. This makes the LQI-to-range conversion reproducible because the numerical calibration parameters are explicitly reported. After calibration, each accepted LQI value is converted into a range estimate:

$$\hat{d}_{ij} = d_0 10^{\frac{Z_0 - Z_{ij}}{10\hat{\alpha}}}, \quad \sigma_{d,ij}^2 \approx \left(\frac{\ln 10}{10\hat{\alpha}} \hat{d}_{ij} \right)^2 \sigma_{Z,ij}^2 + \sigma_{\text{anc}}^2. \quad (7)$$

Eq. (7) provides both the LQI-derived distance and its range-domain variance. The variance increases with LQI uncertainty and estimated distance; therefore, unreliable links receive lower weight in the WLS localization stage. The calibration setup and statistics are summarized in Tables 4 and 5.

Table 4: Model-based LQI calibration setup and parameters.

Category	Item	Value/Setting
Calibration setup		
Calibration	Type	Model-based, simulation/trace-driven
Hardware	RSU/OBU data	–
Wireless model	Technology	IEEE 802.11p/5.9 GHz DSRC-inspired
Packets	Power, size, rate	20 dBm, 300 bytes, 10 packets/s
LQI range	Interval	–70 to –30 dBm-eq., 1 dB step
Data	Distances, samples	1–30 m; 1500 samples

(Continued)

Table 4 (continued)

Category	Item	Value/Setting
Channel	Effects	Path loss, shadowing, fading, loss, collision, NLOS
Scenario	Environment	Highway LOS, urban NLOS, tunnel/NLOS
Fitting	Method	Invalid samples removed; OLS logarithmic fit
Software	Platform	MATLAB R2024a, i7-class CPU, RAM ≥ 16 GB
Calibrated parameters		
Reference distance	d_0	1 m
Calibration samples	N_{cal}	1500
Reference LQI	Z_0	-30 dBm-eq.
LQI attenuation	α	2.71
Reference path loss	$L_0(d_0)$	47.9 dB
Path-loss exponent	n	2.60
LQI noise	σ_ℓ	1.70 dB
Range noise	σ_n	2.23 m
LQI threshold	Z_T	-70 dBm-eq.
Fit quality	R^2	0.983
Calibration RMSE	RMSE	1.70 dB
Confidence interval	95% CI of α	[2.69, 2.73]

Table 5: Model-generated LQI calibration statistics.

Dist. (m)	Samp.	Mean LQI	Std.	95% CI	Dist. (m)	Samp.	Mean LQI	Std.	95% CI
1	214	-30.00	1.0	[-30.13, -29.87]	15	214	-61.85	2.0	[-62.12, -61.58]
3	214	-42.92	1.2	[-43.08, -42.76]	20	215	-65.23	2.0	[-65.50, -64.96]
5	214	-48.93	1.5	[-49.13, -48.73]	30	215	-70.00	2.0	[-70.27, -69.73]
10	214	-57.08	1.8	[-57.32, -56.84]	-	-	-	-	-

3.3 Closed-Form LQI-WLS Localization Estimator

For each visible anchor $j \in \mathcal{V}_i$, the calibrated LQI-derived range is modeled as

$$g_{ij} = \hat{d}_{ij} = d_{ij} + \eta_{ij}, \quad \eta_{ij} \sim \mathcal{N}(0, \sigma_{d,ij}^2). \quad (8)$$

Eq. (8) connect the calibration stage with localization, observed range g_{ij} is treated as the true distance plus range-domain noise, whose variance is obtained from the LQI uncertainty. Squaring the range equation gives

$$g_{ij}^2 = \|\mathbf{c}_i - \mathbf{e}_j\|^2 + \delta_{ij} = \|\mathbf{c}_i\|^2 - 2\mathbf{e}_j^T \mathbf{c}_i + \|\mathbf{e}_j\|^2 + \delta_{ij}, \quad Y_{ij} + \theta_i = \mathbf{b}_j^T \mathbf{c}_i + \delta_{ij}, \quad Y_{ij} = \|\mathbf{e}_j\|^2 - g_{ij}^2, \quad \mathbf{b}_j^T = 2\mathbf{e}_j^T. \quad (9)$$

Eq. (9) convert the nonlinear distance relation into an affine form by introducing $\theta_i = \|\mathbf{c}_i\|^2$, the transformation enables a closed-form WLS estimator instead of iterative nonlinear optimization. Stacking all visible-anchor equations gives

$$\mathbf{Y}_i + \theta_i \mathbf{1} = \mathbf{B}_i \mathbf{c}_i + \boldsymbol{\delta}_i, \quad (10)$$

where

$$\mathbf{Y}_i = \begin{bmatrix} Y_{ij_1} \\ Y_{ij_2} \\ \vdots \\ Y_{ij_{M_i}} \end{bmatrix}, \quad \mathbf{B}_i = 2 \begin{bmatrix} \mathbf{e}_{j_1}^\top \\ \mathbf{e}_{j_2}^\top \\ \vdots \\ \mathbf{e}_{j_{M_i}}^\top \end{bmatrix}, \quad \boldsymbol{\delta}_i = \begin{bmatrix} \delta_{ij_1} \\ \delta_{ij_2} \\ \vdots \\ \delta_{ij_{M_i}} \end{bmatrix}. \quad (11)$$

Eqs. (10) and (11) combine all usable anchor measurements for target i . The matrix $\mathbf{B}_i$ captures anchor geometry, while $\mathbf{Y}_i$ contains the transformed range observations. The WLS covariance matrix and fixed- θ_i solution are defined as

$$\mathbf{W}_i = \text{diag}(\sigma_{\delta,ij_1}^2, \sigma_{\delta,ij_2}^2, \dots, \sigma_{\delta,ij_{M_i}}^2), \quad \sigma_{\delta,ij}^2 \approx 4g_{ij}^2 \sigma_d^2 + 2\sigma_{d,ij}^4 + \epsilon_w, \\ \hat{\mathbf{c}}_i(\theta_i) = (\mathbf{B}_i^\top \mathbf{W}_i^{-1} \mathbf{B}_i + \lambda \mathbf{I})^{-1} \mathbf{B}_i^\top \mathbf{W}_i^{-1} (\mathbf{Y}_i + \theta_i \mathbf{1}). \quad (12)$$

Eq. (12) assigns a smaller influence to links with larger range uncertainty. The small constant ϵ_w prevents numerical instability, and λ regularizes the solution when anchor geometry is weak or nearly ill-conditioned. The WLS solution can be separated into a nominal term and a scalar correction:

$$\hat{\mathbf{c}}_i(\theta_i) = \mathbf{G}_i + \boldsymbol{\kappa}_i \theta_i, \quad \mathbf{G}_i = (\mathbf{B}_i^\top \mathbf{W}_i^{-1} \mathbf{B}_i + \lambda \mathbf{I})^{-1} \mathbf{B}_i^\top \mathbf{W}_i^{-1} \mathbf{Y}_i, \quad \boldsymbol{\kappa}_i = (\mathbf{B}_i^\top \mathbf{W}_i^{-1} \mathbf{B}_i + \lambda \mathbf{I})^{-1} \mathbf{B}_i^\top \mathbf{W}_i^{-1} \mathbf{1}. \quad (13)$$

In Eq. (13), $\mathbf{G}_i$ is the nominal coordinate estimate and $\boldsymbol{\kappa}_i$ indicates how the auxiliary scalar θ_i modifies the estimate. This decomposition reduces the remaining unknown to a scalar refinement problem. The consistency condition is imposed as

$$\theta_i = \|\mathbf{G}_i + \boldsymbol{\kappa}_i \theta_i\|^2. \quad (14)$$

Eq. (14) ensures that θ_i remains equal to the squared norm of the estimated position. Expanding it produces the quadratic root-selection rule:

$$\|\boldsymbol{\kappa}_i\|^2 \theta_i^2 + (2\boldsymbol{\kappa}_i^\top \mathbf{G}_i - 1) \theta_i + \|\mathbf{G}_i\|^2 = 0, \\ \hat{\theta}_i = \arg \min_{\theta \in \Theta_i} (\mathbf{Y}_i + \theta \mathbf{1} - \mathbf{B}_i(\mathbf{G}_i + \boldsymbol{\kappa}_i \theta))^\top \mathbf{W}_i^{-1} (\mathbf{Y}_i + \theta \mathbf{1} - \mathbf{B}_i(\mathbf{G}_i + \boldsymbol{\kappa}_i \theta)). \quad (15)$$

Eq. (15) selects the valid real root that gives the smallest weighted residual. This step improves geometric consistency without introducing an iterative estimator. The final estimate and residual score are computed as

$$\hat{\mathbf{c}}_i = \mathbf{G}_i + \boldsymbol{\kappa}_i \hat{\theta}_i, \quad r_i = \frac{1}{M_i} \left\| \mathbf{W}_i^{-1/2} (\mathbf{Y}_i + \hat{\theta}_i \mathbf{1} - \mathbf{B}_i \hat{\mathbf{c}}_i) \right\|_2^2. \quad (16)$$

Eq. (16) measures the normalized weighted mismatch between the estimated position and the anchor observations. A localization result is accepted only if $r_i \leq r_{\max}$, the estimated coordinate lies inside the deployment area, and the condition number of $\mathbf{B}_i^\top \mathbf{W}_i^{-1} \mathbf{B}_i$ is below $\chi_{\max}$.

3.4 Cramér-Rao Lower Bound

The CRLB is used as a theoretical benchmark for the best achievable localization accuracy under the adopted LQI measurement model. The expected LQI, its position gradient, and the Fisher information matrix are

$$\mu_{ij}(\mathbf{c}_i) = Z_0 - 10\alpha \log_{10} \left(\frac{\|\mathbf{c}_i - \mathbf{e}_j\|}{d_0} \right), \quad (17)$$

$$\mathbf{q}_{ij} = \nabla_{\mathbf{c}_i} \mu_{ij} = -\frac{10\alpha}{\ln 10} \frac{\mathbf{c}_i - \mathbf{e}_j}{d_{ij}^2}, \quad (18)$$

$$\mathbf{J}_i = \sum_{j \in V_i} \frac{\mathbf{q}_{ij} \mathbf{q}_{ij}^T}{\sigma_{\ell,j}^2}. \quad (19)$$

Eq. (17) gives the noiseless LQI predicted at a given position. Eq. (18) measures how sensitive the LQI is to small position changes. Eq. (19) accumulates the information contributed by all visible anchors. For equal LQI noise variance, the Fisher information matrix components are

$$\mathbf{J}_i = \begin{bmatrix} J_{xx} & J_{xy} \\ J_{xy} & J_{yy} \end{bmatrix}, \quad J_{xx} = \delta_F \sum_{j \in V_i} \frac{(x_i - x_j)^2}{d_{ij}^4}, \quad J_{yy} = \delta_F \sum_{j \in V_i} \frac{(y_i - y_j)^2}{d_{ij}^4}, \quad J_{xy} = \delta_F \sum_{j \in V_i} \frac{(x_i - x_j)(y_i - y_j)}{d_{ij}^4}. \quad (20)$$

Eq. (20) shows how anchor geometry affects information in the x and y directions. A better geometric spread produces a better-conditioned Fisher matrix and a smaller theoretical error bound. The LQI-domain sensitivity coefficient and scalar CRLB are

$$\delta_F = \left(\frac{10\alpha}{\sigma_{\ell} \ln 10} \right)^2, \quad \text{CRLB}_i = \text{tr}(\mathbf{J}_i^{-1}) = \frac{J_{xx} + J_{yy}}{J_{xx}J_{yy} - J_{xy}^2}. \quad (21)$$

Eq. (21) gives the minimum achievable position-error variance under the assumed LQI noise model. If $\mathbf{J}_i$ is singular or nearly singular, the anchor geometry is treated as insufficient for reliable localization.

3.5 Workflow and Implementation-Level Algorithm

The complete computational workflow is summarized in Fig. 3. The workflow begins with LQI packet acquisition and link filtering. Accepted LQI measurements are converted into range estimates using the calibrated model. The resulting ranges are processed by the WLS estimator, refined by the scalar consistency step, and checked using residual and geometry constraints. Finally, localization accuracy, runtime, throughput, confidence intervals, and CRLB gap are reported.

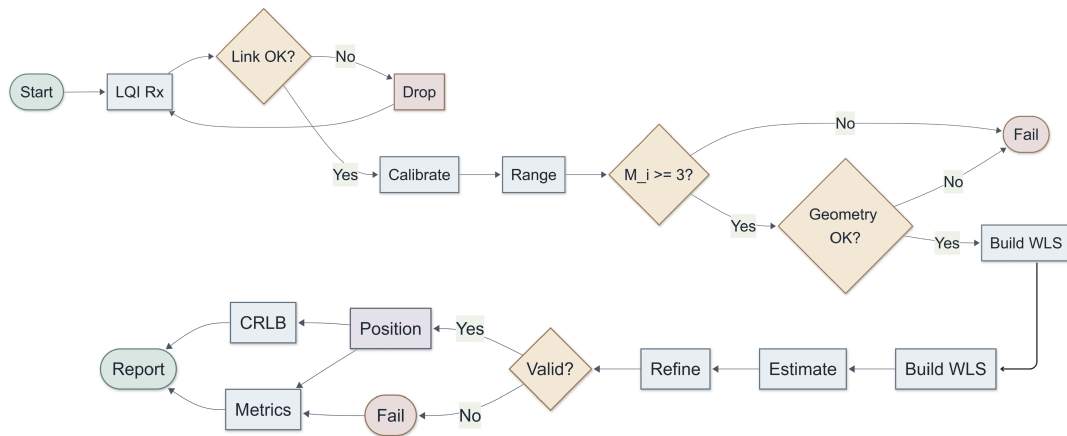


Figure 3: Workflow of the proposed LQI-based VANET localization framework. The workflow includes LQI acquisition, link filtering, calibration, range estimation, WLS localization, scalar consistency refinement, validation, CRLB computation, and performance evaluation.

Algorithm 1 provides the implementation-level steps of the proposed framework.

Algorithm 1: LQI-based closed-form localization framework

Require: $\mathcal{T}$, $\mathcal{A}$, $\mathbf{e}_j$, $Z_{ij}^{(p)}$, $(\hat{Z}_0, \hat{\alpha}, d_0)$, thresholds and regularization constants

Ensure: $\hat{\mathbf{c}}_i$, s_i , τ_i and r_i

- 1: **for** each target vehicle $T_i \in \mathcal{T}$ **do**
 - 2: Start timer; initialize $\mathcal{V}_i \leftarrow \emptyset$
 - 3: Collect LQI packets $Z_{ij}^{(p)}$ from all anchors $j \in \mathcal{A}$
 - 4: Compute packet reception probability $\rho_{ij} = P_{ij}^{rx} / P_{ij}^{tx}$
 - 5: Remove outliers and average valid packets to obtain Z_{ij}
 - 6: Convert accepted LQI values to preliminary ranges
 - 7: Select anchors satisfying LQI, PRR, and range constraints to form $\mathcal{V}_i$
 - 8: **if** $|\mathcal{V}_i| < 3$ or anchors are nearly collinear **then**
 - 9: Set $s_i \leftarrow 0$, $\hat{\mathbf{c}}_i \leftarrow \text{NaN}$, record τ_i and continue
 - 10: **end if**
 - 11: Convert each valid Z_{ij} to range $\hat{d}_{ij}$ using the calibrated LQI-to-range model
 - 12: Estimate $\sigma_{d,ij}^2$ and $\sigma_{\delta,ij}^2$ for WLS weighting
 - 13: Form $Y_{ij} = \|\mathbf{e}_j\|^2 - \hat{d}_{ij}^2$ and $\mathbf{b}_j^T = 2\mathbf{e}_j^T$
 - 14: Stack $\mathbf{Y}_i$, $\mathbf{B}_i$ and $\mathbf{W}_i$
 - 15: Check geometry condition and apply regularization if required
 - 16: Compute $\mathbf{G}_i$ and $\boldsymbol{\kappa}_i$ from the WLS solution
 - 17: Solve the scalar quadratic equation for $\hat{\theta}_i$
 - 18: Compute $\hat{\mathbf{c}}_i = \mathbf{G}_i + \boldsymbol{\kappa}_i \hat{\theta}_i$
 - 19: Evaluate residual score r_i and deployment-area feasibility
 - 20: Set $s_i \leftarrow 1$ if valid; otherwise set $s_i \leftarrow 0$
 - 21: Stop timer and record τ_i
 - 22: **end for**
 - 23: Compute RMSE, success ratio, throughput, confidence intervals, and CRLB gap
-

3.6 Simulation Environment and Scenario Configuration

The Monte Carlo evaluation is conducted under highway, urban, and tunnel/NLOS VANET scenarios. The highway scenario uses a 1000 m $\times$ 500 m area, three lanes per direction, speeds of 80–120 km/h, a 300 m communication radius, log-normal channel behavior, 3 dB shadowing, Rician fading, no additional NLOS loss, packet loss of 0.05, and collision probability of 0.02. The urban scenario uses an 800 m $\times$ 800 m area, two lanes per direction, speeds of 30–60 km/h, a 200 m communication radius, 4 dB shadowing, Rayleigh fading, 10 dB NLOS loss, packet loss of 0.10, and collision probability of 0.05. The tunnel/NLOS scenario uses a 1000 m $\times$ 20 m road segment, two lanes per tube, speeds of 80–120 km/h, a 100 m communication radius, 6 dB shadowing, Nakagami fading, 15 dB NLOS loss, packet loss of 0.20, and collision probability of 0.08. For all scenarios, $V \in \{10, 50, 100\}$ target vehicles and $M = 4$ RSU anchors are used. Vehicle mobility is generated using SUMO Krauss car-following with LC2013 lane-changing behavior. LQI values are generated in the range -70 to -30 dBm with 1 dB resolution, and beaconing is configured at 10 packets/s/vehicle with 300 bytes per packet. The simulation duration is $T_{\text{sim}} = 1$ s, the update step is $\Delta t = 0.1$ s, the number of Monte Carlo trials is $N_{\text{MC}} = 1000$, and the random seed is fixed to 42. The same random seed sequence is used for all methods, so the proposed estimator and all baselines experience identical vehicle layouts, RSU positions, packet outcomes, LQI samples, fading, shadowing, and packet-loss events. This ensures fair comparison across methods. The configuration is summarized in [Table 6](#).

Table 6: Key simulation settings for VANET scenarios.

Parameter	Highway	Urban	Tunnel/NLOS
Area	1000 m × 500 m	800 m × 800 m	1000 m × 20 m
Vehicles		10, 50 and 100	
RSU anchors		4	
Lanes	3/direction	2/direction	2/tube
Speed	80–120 km/h	30–60 km/h	80–120 km/h
Mobility model	SUMO Krauss car-following with LC2013 lane changing		
Communication radius	300 m	200 m	100 m
Channel model	Log-normal	Log-normal	NLOS-dominant
Shadowing	3 dB	4 dB	6 dB
Fading	Rician	Rayleigh	Nakagami
NLOS loss	0 dB	10 dB	15 dB
Packet loss	0.05	0.10	0.20
Collision probability	0.02	0.05	0.08
LQI range		−70 to −30 dBm, 1 dB resolution	
Beaconing		10 packets/s/vehicle, 300 bytes/packet	
Simulation setup		$T_{\text{sim}} = 1 \text{ s}$, $\Delta t = 0.1 \text{ s}$, $N_{\text{MC}} = 1000$, seed = 42	
Platform		MATLAB R2024a, i7-class CPU, RAM ≥ 16 GB	
Validation	Synthetic MATLAB/SUMO scenarios and NGSIM US-101 trace-driven validation		

3.7 Benchmark Methods, Evaluation Metrics and Statistical Validation

The proposed LQI-WLS estimator is compared with LS, WLS, RSS/RSSI-WLS, EKF, UKF, PF, cooperative localization, GNSS/INS/RSS fusion, and ML-based localization. All methods use the same anchor coordinates, packet availability, and measurement-noise realizations. LS uses unweighted multilateration, WLS uses $\sigma_{d,ij}^2$ without scalar refinement, RSS/RSSI-WLS uses $L_0 = 47.9 \text{ dB}$ and $n = 2.60$, EKF uses $\mathbf{x}_k = [x_k, y_k, v_{x,k}, v_{y,k}]^T$ with $\sigma_a = 2$, UKF uses $\alpha = 10^{-3}$, $\beta = 2$ and $\kappa = 0$, PF uses $N_p = 1000$ particles with systematic resampling, the cooperative method uses the top-3 LQI neighbors, GNSS/INS/RSS uses $\sigma_{\text{GNSS}} = 3 \text{ m}$ with tunnel outage and ML localization uses a random forest with 200 trees and a 70/30 train-test split. The localization error and aggregate RMSE are computed as

$$e_i^{(r)} = \|\hat{\mathbf{c}}_i^{(r)} - \mathbf{c}_i^{(r)}\|_2, \quad \text{RMSE} = \sqrt{\frac{1}{N_{\text{suc}}} \sum_{r=1}^{N_{\text{MC}}} \sum_{i=1}^V s_i^{(r)} \left(e_i^{(r)}\right)^2}, \quad N_{\text{suc}} = \sum_{r=1}^{N_{\text{MC}}} \sum_{i=1}^V s_i^{(r)}. \quad (22)$$

Eq. (22) measures the Euclidean localization error and its aggregate RMSE over all successful estimates. The binary variable $s_i^{(r)}$ indicates whether the estimate for vehicle i in trial r is valid. Reliability and runtime metrics are defined as

$$\text{SR} = \frac{N_{\text{suc}}}{N_{\text{MC}} V}, \quad \text{Thr} = \frac{N_{\text{suc}}}{N_{\text{MC}} T_{\text{sim}}}, \quad T_{\text{avg}} = \frac{1}{N_{\text{suc}}} \sum_{r=1}^{N_{\text{MC}}} \sum_{i=1}^V s_i^{(r)} \tau_i^{(r)}. \quad (23)$$

Eq. (23) defines the success ratio, throughput, and average runtime. These metrics measure both localization reliability and real-time computational feasibility. Percentage improvement over a baseline is computed as

$$\text{Improvement}_{\text{error}}(\%) = \frac{\text{Metric}_{\text{baseline}} - \text{Metric}_{\text{proposed}}}{\text{Metric}_{\text{baseline}}} \times 100,$$

$$\text{Improvement}_{\text{Thr}}(\%) = \frac{\text{Thr}_{\text{proposed}} - \text{Thr}_{\text{baseline}}}{\text{Thr}_{\text{baseline}}} \times 100. \quad (24)$$

Eq. (24) is used with lower-is-better metrics such as RMSE and higher-is-better metrics such as throughput. This separates accuracy improvement from throughput improvement. For each scenario and method, the mean, standard deviation, median, 90th percentile, and 95% confidence interval are reported. The confidence interval is computed as

$$\text{CI}_{95\%} = \bar{x} \pm 1.96 \frac{s_x}{\sqrt{N_{\text{MC}}}}, \quad (25)$$

where $\bar{x}$ is the sample mean and s_x is the sample standard deviation. Statistical significance is tested using paired comparisons because all methods use identical layouts, trajectories, and channel realizations. A paired t -test is used for approximately normal paired differences, while the Wilcoxon signed-rank test is used otherwise. For multiple-method comparisons, repeated-measures ANOVA or the Friedman test is applied. Results are considered significant when $p < 0.05$ with Cohen's d or Cliff's delta reported as the effect size. Benchmark methods and evaluation metrics are summarized in Tables 7 and 8.

Table 7: Benchmark localization methods.

Method	Input	Key Setting
LS	LQI ranges	Unweighted multilateration
WLS	LQI ranges, weights	Uses $\sigma_{d,ij}^2$ without refinement
RSS/RSSI-WLS	RSS/RSSI ranges	$L_0 = 47.9$ dB, $n = 2.60$
EKF	Motion model, ranges	$\mathbf{x}_k = [x_k, y_k, v_{x,k}, v_{y,k}]^T$, $\sigma_a = 2$
UKF	Nonlinear motion, ranges	$\alpha = 10^{-3}$, $\beta = 2$, $\kappa = 0$
PF	Sequential ranges	$N_p = 1000$, systematic resampling
Cooperative	RSU and neighbor ranges	Top-3 LQI neighbors, weighted fusion
GNSS/INS/RSS	GNSS, INS, RSS ranges	$\sigma_{\text{GNSS}} = 3$ m; tunnel outage
ML localization	LQI/RSS and geometry	Random forest, 200 trees, 70/30 split
Proposed	Calibrated LQI ranges	WLS with scalar refinement

Table 8: Evaluation metrics.

Metric	Symbol	Definition	Metric	Symbol	Definition
Localization error	e_i	Euclidean error	Runtime	T_{avg}	Avg. time/estimate
RMSE	RMSE	Aggregate error	Latency	T_{lat}	Packet-to-estimate delay
Median error	P_{50}	50th percentile	Packet overhead	O_{pkt}	Packets/localization
90th percentile	P_{90}	Tail error	Energy cost	E_{loc}	Energy/localization
Ranging error	e_d	$\hat{d}_{ij} - d_{ij}$	Convergence	–	Baseline iterations
CRLB gap	Δ_{CRLB}	MSE gap from CRLB	–	–	–
Success ratio	SR	Valid localization fraction	–	–	–
Throughput	Thr	Localizations/s	–	–	–

3.8 Trace-Driven Validation Dataset

To complement the synthetic MATLAB/SUMO evaluation, trace-driven validation is performed using the NGSIM US-101 vehicle trajectory dataset [46]. This dataset contains real freeway mobility traces recorded on U.S. Highway 101 in Los Angeles, California, from 7:50–8:05 AM on June 15, 2005. These trajectory data provide a realistic basis for testing the proposed localization method, although the recorded scenario remains limited to one freeway segment and one observation period. It provides vehicle position, speed, acceleration, and lane ID at 10 Hz but does not include physical LQI/RSS packet measurements. Therefore, the vehicle trajectories are used as ground truth, while LQI observations, packet-loss masks, and RSU-to-vehicle ranges are generated using the calibrated LQI-distance and highway-channel models. The trace coordinates are converted to metres and normalized into a local 640 m $\times$ 30 m freeway plane. The longitudinal coordinate is mapped to [0, 640] m, while the lateral coordinate is mapped to [0, 30] m. Four fixed RSUs are placed at (80, 0), (240, 30), (400, 0) and (560, 30) m. This staggered deployment avoids collinear anchor geometry and supports valid two-dimensional localization with at least three non-collinear available RSUs. The NGSIM target-anchor distance and generated LQI observation are defined as

$$d_{ij}^{\text{NGSIM}} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}, \quad Z_{ij}^{\text{NGSIM}} = Z_0 - 10\alpha \log_{10} \left(\frac{d_{ij}^{\text{NGSIM}}}{d_0} \right) + \epsilon_{ij}^Z, \quad \epsilon_{ij}^Z \sim \mathcal{N}(0, \sigma_\ell^2). \quad (26)$$

Eq. (26) uses real vehicle coordinates to calculate RSU-to-vehicle distances, while the calibrated LQI model generates the corresponding LQI observations. A localization attempt is successful only when at least three non-collinear RSUs remain available after LQI, range, and packet-reception filtering. The proposed estimator and all baselines use the same traces, RSU coordinates, generated LQI observations, and packet-loss masks. The NGSIM setup is summarized in Table 9.

Table 9: NGSIM US-101 dataset usage in the trace-driven validation.

Item	Description
Dataset	NGSIM US-101 vehicle trajectory data [46]
Location	U.S. Highway 101, Los Angeles, California
Collection time	7:50–8:05 AM, June 15, 2005
Sampling rate	10 Hz
Used fields	Vehicle ID, frame/time, local position, speed, acceleration, lane ID
Validation type	Real-world mobility trace-driven validation
Coordinate plane	Normalized local freeway plane of 640 m $\times$ 30 m
Generated data	LQI values, packet-loss masks, RSU-to-vehicle ranges
Vehicle densities	$V \in \{10, 50, 100\}$
RSU anchors	$M = 4$ fixed RSUs
RSU coordinates	(80, 0), (240, 30), (400, 0) and (560, 30) m
Non-measured values	Physical LQI, packet reception, and RSU measurements are model-generated

3.9 Ablation Study Design

The ablation study isolates the contribution of each component in the proposed LQI-WLS localization framework. All variants use the same vehicle positions, anchor locations, packet-loss realizations, and channel conditions as the full method. Performance is evaluated using RMSE, median error, 90th percentile error, success ratio, throughput, runtime, and CRLB gap. The difference between the full method and

each variant shows the contribution of calibration, WLS weighting, scalar refinement, link filtering, RSU cooperation, and packet-loss modeling. The ablation variants are summarized in Table 10.

Table 10: Ablation study variants.

Variant	Description	Variant	Description
Full method	Calibration, filtering, WLS, refinement, and validation	No link filtering	Uses all LQI links without quality checks
No calibration	Fixed nominal LQI-to-distance parameters	No RSU cooperation	Uses reduced or nearest-anchor setup
No WLS weighting	Uses identity matrix instead of $\mathbf{W}_i^{-1}$	No packet-loss model	Assumes all visible packets are received
No scalar refinement	Uses $\mathbf{G}_i$ directly without $\hat{\theta}_i$	–	–

3.10 Sensitivity Analysis Design

The sensitivity analysis evaluates the robustness of the proposed localization framework under changing deployment and channel conditions. In each experiment, one factor is varied while all other parameters remain fixed at their default values from Table 6. The outputs include RMSE, success ratio, 90th percentile error, throughput, and runtime. This design identifies whether performance degradation is mainly caused by anchor geometry, anchor failure, packet loss, LQI noise, shadowing, NLOS propagation, traffic density, communication radius, or vehicle speed. The tested sensitivity factors are summarized in Table 11.

Table 11: Sensitivity analysis design.

Factor	Tested Values	Factor	Tested Values
Anchors	$M \in \{3, 4, 5, 6, 8\}$	Shadowing	$\sigma_{sh} \in \{3, 4, 6\}$ dB
RSU geometry	Grid, corner, collinear, random, optimized	NLOS ratio	0%–100% in 25% steps
Anchor failure	$p_{drop} \in \{0, 0.1, 0.2, 0.3, 0.4\}$	Traffic density	$V \in \{10, 50, 100\}$ vehicles
Packet loss	$p_{loss} \in \{0, 0.05, 0.10, 0.20, 0.30\}$	Comm. radius	$R_c \in \{100, 200, 300\}$ m
LQI noise	$\sigma_\ell \in \{1.0, 1.7, 2.0, 2.5\}$ dB	Speed range	Highway, urban and tunnel intervals

3.11 Computational Complexity and Scalability

The computational complexity is evaluated per target vehicle and per network snapshot. Let M_i be the number of visible anchors, P be the number of received packets per anchor, and $d = 2$ be the coordinate dimension. The proposed method includes LQI filtering, range conversion, weight computation, matrix construction, WLS solving, scalar refinement, and residual validation. Since $d = 2$ is fixed, the matrix inversion cost remains small, and the dominant cost grows approximately linearly with M_i and P . For one

vehicle, the full proposed pipeline has complexity

$$O(M_i P + M_i d^2 + d^3).$$

With fixed $d = 2$ and fixed packet count P , this reduces approximately to $O(M_i)$. For one network snapshot with V vehicles, the complexity becomes

$$O\left(\sum_{i=1}^V (M_i P + M_i d^2 + d^3)\right).$$

Thus, the proposed estimator scales mainly with the number of usable target-anchor links. The complexity comparison is summarized in [Table 12](#).

Table 12: Computational complexity comparison.

Method/Step	Main Computation	Complexity	Method/Step	Main Computation	Complexity
LQI filtering	Packet filtering	$O(M_i P)$	Residual check	Residual validation	$O(M_i d)$
Range conversion	Range mapping	$O(M_i)$	Proposed/vehicle	Full pipeline	$O(M_i P + M_i d^2 + d^3)$
Weight computation	Variance estimation	$O(M_i)$	Proposed/snapshot	All vehicles	$O\left(\sum_{i=1}^V (M_i P + M_i d^2 + d^3)\right)$
Matrix construction	Build matrices	$O(M_i d)$	EKF	Prediction/update	$O(T d^3 + T M_i d^2)$
WLS solve	Normal equations	$O(M_i d^2 + d^3)$	UKF	Sigma-point update	$O(T(2d + 1) M_i d^2)$
Scalar refinement	Root selection	$O(1)$	PF	Particle likelihood	$O(N_p M_i T)$
ML baseline	Model inference	$O(P_{NN})$	–	–	–

3.12 Assumption Justification and Reproducibility

The proposed methodology follows practical VANET assumptions involving two-dimensional positioning, known RSU anchors, quasi-static localization snapshots, partial connectivity, LQI uncertainty, and trace-driven validation. These assumptions are chosen to match road-level localization while keeping the estimator reproducible and comparable across all baselines. Some are restrictive. However, each assumption can be relaxed or tested through the sensitivity experiments shown in [Table 11](#), which makes the evaluation more transparent. All experiments are reproducible using the parameters reported in [Tables 3, 4, 6, 7](#) and [9–11](#). For each Monte Carlo trial, the implementation stores the random seed, vehicle positions, anchor coordinates, LQI samples, packet-loss masks, and method outputs. For the NGSIM validation, the selected vehicle IDs, time frames, normalized coordinates, RSU coordinates, generated LQI observations, and packet-loss masks are also stored. This ensures that the proposed method and all baselines are evaluated under identical mobility, channel, and network conditions. The modeling assumptions, justifications, and mitigation checks are summarized in [Table 13](#).

Table 13: Modeling assumptions and checks.

Assumption	Justification	Check/mitigation
2D localization	Planar road-level positioning	Add altitude for 3D extension
Known anchors	Fixed RSU coordinates	Include σ_{anc}^2 if uncertain
Quasi-static snapshot	Small motion during one snapshot	Regenerate mobility across snapshots
Partial connectivity	Links fail due to loss/obstruction	Model link availability and packet loss
Gaussian LQI residual	Averaging reduces LQI fluctuations	Test fading, packet loss, and NLOS
Log-distance LQI model	Calibrated LQI decays with distance	Report RMSE and R^2
Independent link errors	Enables closed-form WLS/CRLB	Use full covariance if correlated
Simulation/trace validation	Controlled channel and freeway-mobility tests	Future hardware RSU/OBU validation with real LQI/RSS packets

4 Results

This section evaluates the proposed LQI-based closed-form localization framework using controlled Monte Carlo simulations and NGSIM US-101 trace-driven validation. The simulations test different VANET densities, RSU geometries, channel impairments, packet loss, NLOS effects, and benchmark methods with $N_{\text{MC}} = 1000$ trials unless stated otherwise and main vehicle densities of $V \in \{10, 50, 100\}$ using four RSU anchors. The NGSIM experiment tests the same framework on real freeway trajectories with lane, speed, and density variation. The proposed method is compared fairly with LS, WLS, RSSI-WLS, EKF, UKF, PF, cooperative localization, hybrid GNSS/INS/RSS fusion, and an ML baseline using the same anchors, packets, measurements, and channel realizations. Performance is reported using ranging error, localization RMSE, dB error, success ratio, throughput, runtime, latency, packet overhead, outlier rate, P_{90} error and RMSE-CRLB gap with confidence intervals from Eq. (25) and paired statistical significance tests.

4.1 Experimental Layouts for 10, 50, and 100 Vehicles

The target-density layouts for the controlled simulations are shown in Fig. 4. Fig. 4a–c show the 10-vehicle, 50-vehicle, and 100-vehicle cases, respectively. All layouts use the same RSU deployment model and differ mainly in vehicle density, link availability, and packet-collision probability. These layouts show how the estimator behaves from sparse to dense network operation. The 10-vehicle case tests baseline accuracy under low interference. The 50-vehicle case represents moderate traffic where more packets are available, but interference begins to appear. The 100-vehicle case is the most demanding case because it has higher density, more simultaneous transmissions, and more degraded links.

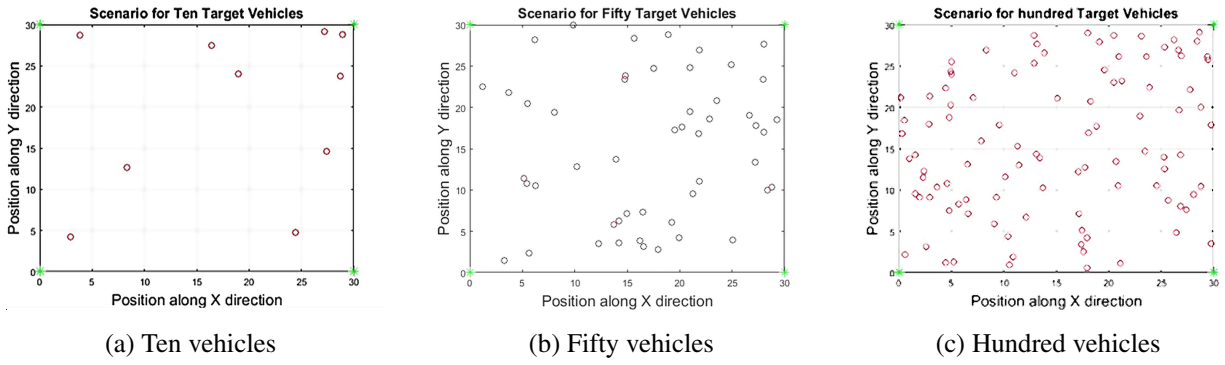


Figure 4: Experimental layouts for the evaluated VANET target densities. The scenarios use $V = \{10, 50, 100\}$ target vehicles, $M = 4$ RSU anchors, calibrated LQI measurements, packet rate 10 packets/s/vehicle, $N_{MC} = 1000$ Monte Carlo trials, and the highway/urban mobility settings listed in Table 6.

4.2 Ranging Error under Different Vehicle Densities

The ranging-error curves for the three vehicle densities are shown in Fig. 5. The plots compare CRLB, LS, WLS, and the proposed LQI-based estimator. The error bars or shaded bands show the 95% confidence intervals from $N_{MC} = 1000$ Monte Carlo trials. The numerical results are given in Table 14. The proposed estimator stays closer to the CRLB than LS and WLS for all densities. This is because the calibrated LQI-to-range mapping reduces range bias, and the variance-based weighting reduces the effect of unreliable links. The improvement is clearer in dense cases because noisy and weak links are down-weighted instead of being treated equally.

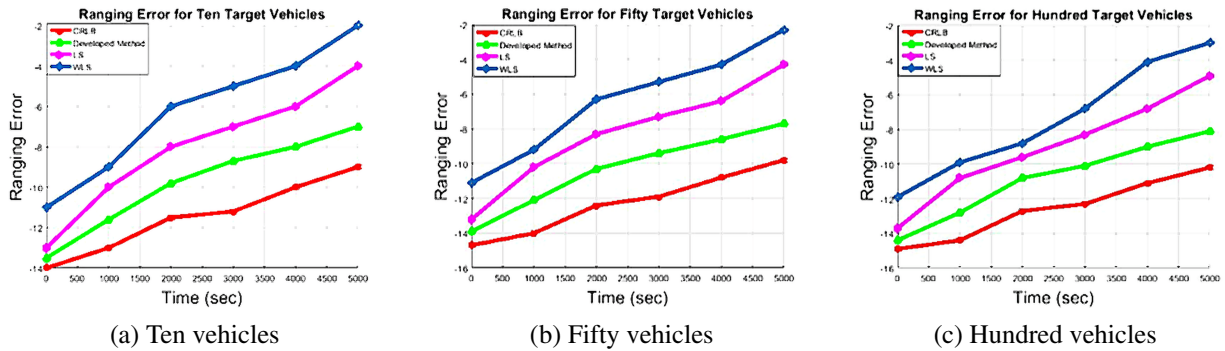


Figure 5: Ranging-error comparison for $V = \{10, 50, 100\}$ target vehicles using $M = 4$ RSU anchors, calibrated LQI measurements, $N_{MC} = 1000$ Monte Carlo trials, packet rate 10 packets/s/vehicle and the channel parameters in Table 6. Error bars or shaded regions indicate 95% confidence intervals.

Table 14: Ranging error for different vehicle densities.

Method	10 veh.	50 veh.	100 veh.
CRLB [47]	-10.66 (100%)	-9.50 (99.2%)	-9.00 (90%)
LS [48]	-7.04 (66%)	-7.00 (70%)	-6.90 (68%)
WLS [49]	-5.089 (47%)	-6.80 (68.2%)	-5.90 (50%)
Proposed LQI	-9.066 (85%)	-8.90 (86.2%)	-8.20 (80%)

In [Table 14](#), the proposed method obtain -9.066 dB for 10 vehicles, -8.90 dB for 50 vehicles and -8.20 dB for 100 vehicles. Although the performance gradually decreases as the vehicle count increases, the degradation is smaller than that of LS and WLS. This indicates that the proposed calibration and weighting stages help preserve ranging reliability when the number of simultaneous vehicular links increases.

4.3 Localization Accuracy Compared with Advanced Baselines

The localization-error comparison with classical and advanced baselines is summarized in [Table 15](#). The table includes LS, WLS, RSSI-WLS, EKF, UKF, PF, cooperative localization, hybrid GNSS/INS/RSS fusion, and an ML-based localization method. All methods use the same anchor geometry, packet reception conditions, and Monte Carlo samples. LS is sensitive to range errors because all anchors are treated equally. WLS reduces this effect by assigning a lower weight to high-variance links, but it cannot fully remove LQI-to-distance bias. EKF and UKF benefit from temporal prediction but may degrade when the measurement model is biased or when lane changes are rapid. PF handles nonlinear effects but needs higher computation and depends on the particle count. The proposed method improves the ranging stage through calibration, reduces unreliable-link effects through WLS, and applies scalar refinement to reduce nonlinear reconstruction error.

Table 15: RMSE comparison of localization methods. Values are reported as mean $\pm$ standard deviation in metres.

Method	10 veh.	50 veh.	100 veh.
LS [48]	6.53 ± 4.05	6.87 ± 4.26	7.03 ± 4.36
WLS [49]	3.68 ± 1.83	3.95 ± 1.96	4.23 ± 2.10
RSSI-WLS [49]	4.23 ± 2.01	4.54 ± 2.16	4.87 ± 2.32
EKF [50]	3.31 ± 1.37	3.56 ± 1.47	3.81 ± 1.58
UKF [51]	3.13 ± 1.32	3.36 ± 1.41	3.60 ± 1.52
PF [52]	2.94 ± 1.28	3.16 ± 1.38	3.39 ± 1.47
Cooperative [53]	2.47 ± 1.00	2.63 ± 1.07	3.24 ± 1.31
GNSS/INS/RSS [49,54]	2.38 ± 0.95	2.54 ± 1.01	3.12 ± 1.24
ML-based [55]	2.56 ± 1.17	2.73 ± 1.25	3.35 ± 1.53
Proposed LQI	2.20 ± 1.11	2.35 ± 1.19	2.89 ± 1.46

4.4 Localization Error for 10, 50, and 100 Vehicles

The localization-error plots for 10, 50, and 100 vehicles are shown in [Fig. 6](#). The figure includes 95% CI bars or shaded bands for all methods. The numerical results are reported in [Table 16](#). The proposed method gives lower localization error than LS and WLS and stays closer to the CRLB. The gap from the CRLB increases with vehicle density because packet collisions, partial connectivity, and interference reduce reliable geometric information.

For the 10-vehicle case in [Table 16](#), the proposed method obtains -9.18 dB while LS and WLS obtain -6.22 and -4.61 dB respectively. At 50 vehicles, the proposed method maintains -8.90 dB, which indicates that the estimator remains stable when moderate network density increases the number of radio links. At 100 vehicles, the proposed method obtains -8.00 dB, and the reduction compared with the lower density cases is mainly caused by increased packet contention, degraded link quality, and less favorable link availability under dense traffic.

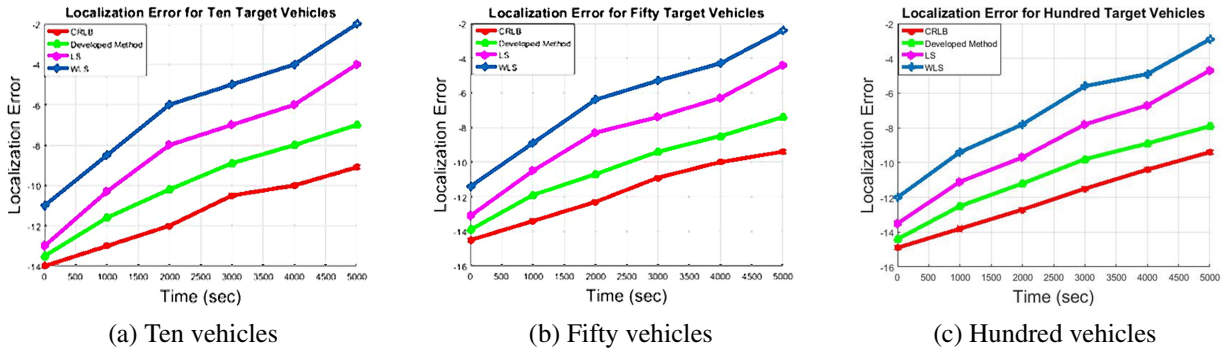


Figure 6: Localization-error results for $V = \{10, 50, 100\}$ vehicles using $M = 4$ RSUs, calibrated LQI measurements, packet rate 10 packets/s/vehicle, $N_{MC} = 1000$ trials and the channel/mobility parameters in Table 6. The plotted confidence bands or error bars show 95% confidence intervals.

Table 16: Localization error for different vehicle densities.

Method	10 Veh.	50 Veh.	100 Veh.
CRLB [47]	-11.38 (100%)	-10.20 (98.1%)	-9.60 (96.5%)
LS [48]	-6.22 (50%)	-6.00 (52%)	-5.90 (50%)
WLS [49]	-4.61 (40%)	-4.30 (43%)	-4.00 (41%)
Proposed LQI	-9.18 (80%)	-8.90 (82.1%)	-8.00 (76.4%)

4.5 Statistical Significance of Localization Improvements

The statistical significance of the localization gains is summarized in Table 17. The table compares the proposed method with each baseline using the same Monte Carlo realizations. The p -values and effect sizes are computed using paired tests. A small p -value shows that the gain is unlikely to come from random geometry or channel noise. The effect size is also reported because a large sample size can make a small gain statistically significant. Therefore, Table 17 is interpreted using both p -value and effect size.

Table 17: Statistical significance of RMSE improvements.

Comparison	Veh.	Test	p -Value	Effect Size
Proposed vs. LS [48]	10	t -test	1.12×10^{-194}	$d_z = 1.19$
Proposed vs. WLS [49]	10	t -test	9.00×10^{-137}	$d_z = 0.93$
Proposed vs. RSSI-WLS [49]	10	t -test	3.81×10^{-188}	$d_z = 1.16$
Proposed vs. EKF [50]	10	t -test	8.36×10^{-127}	$d_z = 0.88$
Proposed vs. UKF [51]	10	t -test	1.86×10^{-100}	$d_z = 0.76$
Proposed vs. PF [52]	10	t -test	1.29×10^{-71}	$d_z = 0.61$
Proposed vs. Cooperative [53]	10	t -test	2.16×10^{-15}	$d_z = 0.25$
Proposed vs. Hybrid GNSS/INS/RSS [49,54]	10	t -test	5.47×10^{-8}	$d_z = 0.17$
Proposed vs. ML [55]	10	t -test	2.09×10^{-22}	$d_z = 0.32$
Proposed vs. LS [48]	50	t -test	4.11×10^{-193}	$d_z = 1.19$
Proposed vs. WLS [49]	50	t -test	1.22×10^{-138}	$d_z = 0.94$
Proposed vs. LS [48]	100	t -test	2.30×10^{-169}	$d_z = 1.08$
Proposed vs. WLS [49]	100	t -test	1.63×10^{-92}	$d_z = 0.72$

4.6 Throughput Analysis

The comparison includes only executable localization algorithms. CRLB is excluded because it is a theoretical lower bound rather than a localization algorithm. The curves for the three target densities are shown in Fig. 7. The figure uses the same packet rate, RSU setup, and link-filtering criteria as the localization experiments.

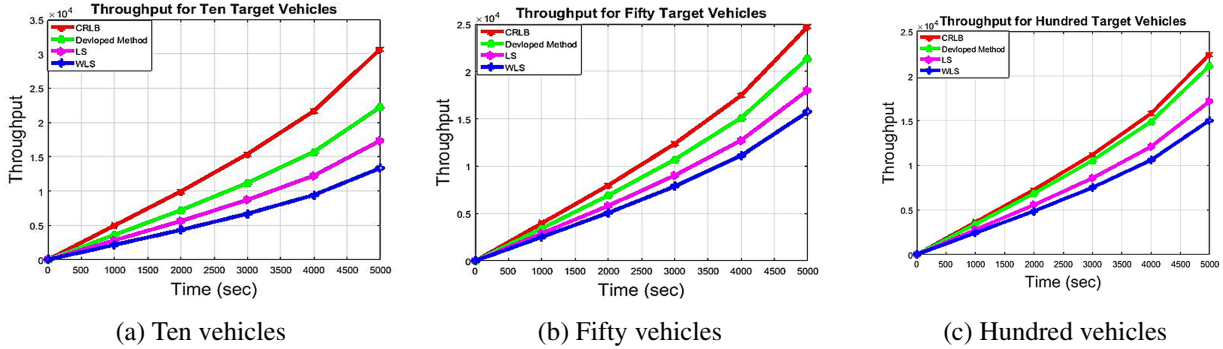


Figure 7: Throughput comparison for $V = \{10, 50, 100\}$ vehicles using $M = 4$ RSUs, packet rate 10 packets/s/vehicle, $N_{MC} = 1000$ trials and the same link-filtering criteria for all methods. Throughput is measured in successful localizations/s, and error bars indicate 95% confidence intervals.

The numerical throughput values are reported in Table 18. The proposed method improves throughput because it rejects unreliable estimates through residual validation and resolves accepted locations using a closed-form computation rather than an iterative update. The gain does not mean that the physical packet rate increases; it means that the algorithm produces more valid localization outputs per unit time.

Table 18: Throughput for different vehicle densities. Throughput is reported in successful localizations/s.

Method	10 Veh.	50 Veh.	100 Veh.
LS	0.873	0.712	0.614
WLS	0.720	0.658	0.591
Proposed LQI	1.328	1.216	1.169

The throughput gain for the 100-vehicle case is computed from the raw values in Table 19. The proposed method increases throughput from 0.614 to 1.169 successful localizations/s compared with LS:

$$\frac{1.169 - 0.614}{0.614} \times 100 = 90.39\%.$$

It also increases throughput from 0.591 to 1.169 successful localizations/s compared with WLS:

$$\frac{1.169 - 0.591}{0.591} \times 100 = 97.80\%.$$

Thus, the reported gain uses the raw throughput values rather than normalized levels. Table 19 confirms that the proposed method achieves higher throughput than LS and WLS in the 100-vehicle case. Reporting the raw values, confidence interval, and statistical test removes ambiguity from the percentage-gain statement.

Table 19: Throughput gain for the 100-vehicle case.

Baseline	Baseline Throughput	Proposed Throughput	Gain
LS	0.614	1.169	90.39%
WLS	0.591	1.169	97.80%
Proposed 95% CI	–	[1.150, 1.188]	–
p vs. LS	–	–	<0.001
p vs. WLS	–	–	<0.001

4.7 Confidence Intervals and Visual Uncertainty Reporting

The uncertainty visualization for RMSE, localization error, and throughput is shown in Fig. 8. The figure presents 95% confidence intervals using error bars and is exported in high-resolution format.

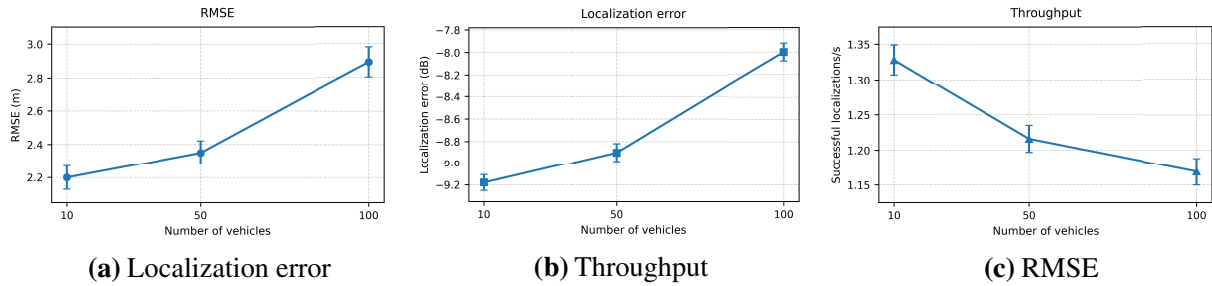


Figure 8: Confidence-interval summary for localization error, throughput and RMSE under $V = \{10, 50, 100\}$ vehicles, $M = 4$ RSUs, calibrated LQI measurements and $N_{MC} = 1000$ Monte Carlo trials. Error bars indicate 95% confidence intervals computed using Eq. (25).

The numerical confidence-interval summary for Fig. 8 is reported in Table 20, which gives the mean, standard deviation, and 95% confidence bounds instead of only descriptive CI discussion. These intervals should be read with the paired significance tests in Table 17. Narrow intervals show stable Monte Carlo behavior. Overlapping intervals do not always mean non-significance because the paired test uses trial-by-trial differences.

Table 20: Confidence intervals for primary metrics.

Metric	Veh.	Mean	Std.	95% CI
RMSE (m)	10	2.20	1.11	[2.13, 2.27]
RMSE (m)	50	2.35	1.19	[2.28, 2.42]
RMSE (m)	100	2.89	1.46	[2.80, 2.98]
Loc. error (dB)	10	−9.18	1.20	[−9.25, −9.11]
Loc. error (dB)	50	−8.90	1.25	[−8.98, −8.82]
Loc. error (dB)	100	−8.00	1.30	[−8.08, −7.92]
Throughput	10	1.328	0.34	[1.307, 1.349]
Throughput	50	1.216	0.31	[1.197, 1.235]
Throughput	100	1.169	0.30	[1.150, 1.188]

4.8 Error Distribution and Tail Behavior

The localization-error distribution statistics are reported in Table 21; these values show whether a method improves only average RMSE or also reduces tail errors needed for safety-related VANET use. Table 21 shows that the proposed method reduces both central and tail error. The median error decreases because calibration improves the LQI-to-distance mapping. The 90th percentile and outlier rate decrease because WLS down-weights high-variance links and residual validation rejects geometrically inconsistent estimates.

Table 21: Localization-error distribution over 1000 Monte Carlo runs.

Metric	LS	WLS	Proposed LQI
Median error (m)	5.41	3.28	1.92
IQR (m)	3.10-8.85	2.10-4.75	1.25-2.85
P90 error (m)	12.90	7.60	4.10
RMSE (m)	6.87	3.95	2.35
RMSE (dB)	-3.63	-5.98	-8.21
Outlier rate	14.8%	6.2%	1.9%

4.9 Trace-Driven Validation Results

Fig. 9 provides a graphical comparison of the trace-driven localization results reported in Table 22. Fig. 9a shows that the proposed LQI-based method achieves the lowest RMSE for all vehicle densities. Fig. 9b shows the same trend for median localization error. Fig. 9c shows that the proposed method reduces the 90th percentile error, which indicates improved robustness under difficult trace-driven conditions. Fig. 9d shows that the proposed method obtains the highest success ratio for all vehicle densities.

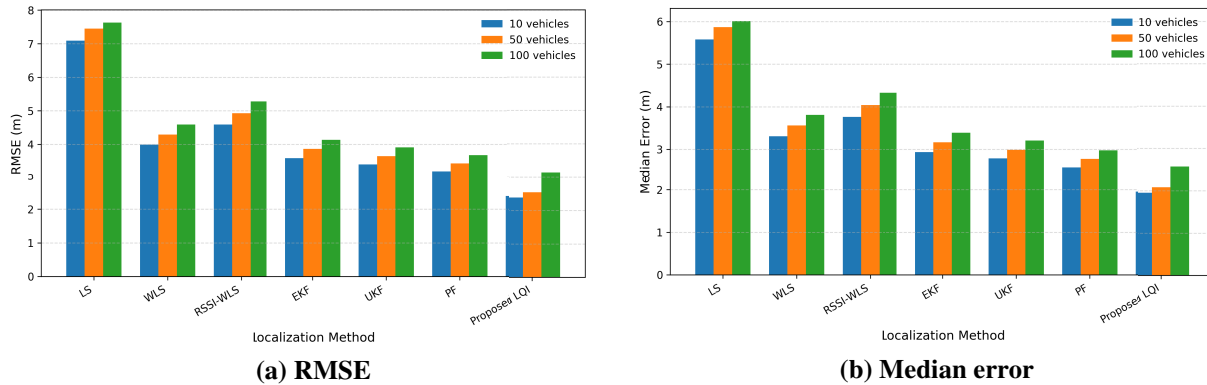


Figure 9: (Continued)

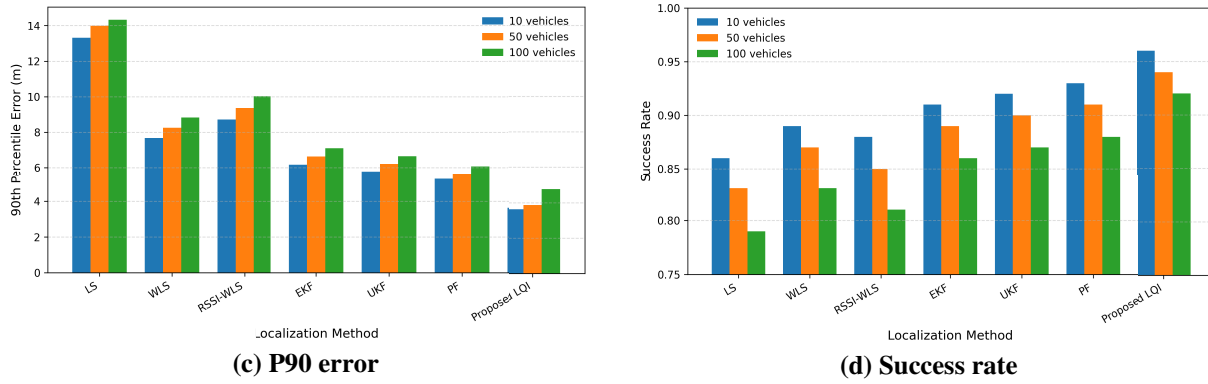


Figure 9: Trace-driven localization performance on the NGSIM US-101 dataset for different vehicle densities: (a) RMSE, (b) median error, (c) 90th percentile error and (d) success ratio. The vehicle trajectories are real NGSIM freeway traces, while LQI observations are generated from the calibrated LQI-distance model.

Table 22: Trace-driven localization results using the NGSIM US-101 dataset.

Method	Vehicles	RMSE (m)	Median (m)	P_{90} (m)	SR
LS [48]	10	7.09	5.58	13.31	0.86
WLS [49]	10	3.99	3.31	7.68	0.89
RSSI-WLS [49]	10	4.59	3.76	8.72	0.88
EKF [50]	10	3.59	2.94	6.17	0.91
UKF [51]	10	3.40	2.79	5.78	0.92
PF [52]	10	3.19	2.58	5.26	0.93
Proposed LQI	10	2.39	1.95	3.63	0.96
LS [48]	50	7.45	5.87	13.99	0.83
WLS [49]	50	4.29	3.56	8.25	0.87
RSSI-WLS [49]	50	4.93	4.04	9.37	0.85
EKF [50]	50	3.86	3.17	6.64	0.89
UKF [51]	50	3.65	2.99	6.21	0.90
PF [52]	50	3.43	2.78	5.66	0.91
Proposed LQI	50	2.55	2.08	3.87	0.94
LS [48]	100	7.63	6.01	14.33	0.79
WLS [49]	100	4.59	3.81	8.83	0.83
RSSI-WLS [49]	100	5.28	4.33	10.03	0.81
EKF [50]	100	4.13	3.39	7.10	0.86
UKF [51]	100	3.91	3.21	6.65	0.87
PF [52]	100	3.68	2.98	6.07	0.88
Proposed LQI	100	3.14	2.57	4.77	0.92

Table 22 reports the NGSIM US-101 trace-driven results. The proposed method is evaluated using RMSE, median error, 90th percentile error, and success ratio. Vehicle positions are taken from real freeway trajectories, while LQI observations are generated using the calibrated LQI-distance model in Section 3.8. The proposed method gives RMSE values of 2.39, 2.55, and 3.14 m for 10, 50, and 100 vehicles with success

ratios of 0.96, 0.94, and 0.92. In the 100-vehicle case, LS gives 7.63 m RMSE and 0.79 success ratio, while the proposed method gives 3.14 m RMSE and 0.92 success ratio. This gain occurs because calibration reduces LQI-to-range bias, WLS suppresses unreliable links, and scalar refinement improves geometric consistency. Since NGSIM does not provide physical LQI/RSS packet measurements, this experiment validates mobility realism rather than hardware radio measurements. Therefore, the NGSIM results should be interpreted as real-world mobility trace-driven validation with calibrated model-generated radio observations.

4.10 Ablation Study

The ablation results are shown in Fig. 10. This figure compares the full proposed method with variants that remove calibration, WLS weighting, scalar refinement, link filtering, and RSU cooperation.

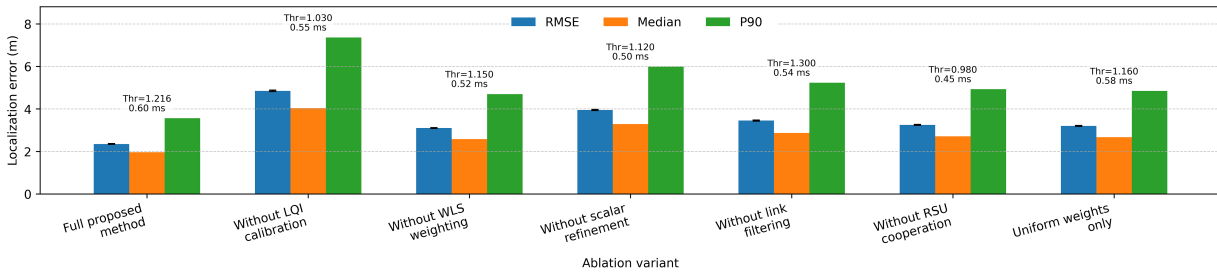


Figure 10: Ablation-study results for the proposed method using $V = 100$ vehicles, $M = 4$ RSUs, calibrated LQI channel settings, packet rate 10 packets/s/vehicle and $N_{MC} = 1000$ trials. Error bars indicate estimated 95% confidence intervals.

The numerical ablation results are shown in Table 23. The full method gives the best RMSE of 2.35 m, median error of 1.96 m, and P_{90} error of 3.56 m. Removing calibration gives the largest RMSE increase to 4.85 m, which shows the effect of LQI-to-range bias. Removing scalar refinement increases RMSE to 3.95 m, while removing link filtering increases it to 3.45 m due to unreliable packets. No RSU cooperation gives a lower throughput of 0.98 loc/s because fewer anchors reduce geometric diversity.

Table 23: Ablation results for the proposed LQI framework.

Variant	RMSE	Median	P90	Thr.	Runtime
Full method	2.35	1.96	3.56	1.216	0.60
No calibration	4.85	4.04	7.36	1.03	0.55
No WLS weighting	3.10	2.58	4.70	1.15	0.52
No scalar refinement	3.95	3.29	5.99	1.12	0.50
No link filtering	3.45	2.87	5.23	1.30	0.54
No RSU cooperation	3.25	2.71	4.93	0.98	0.45
Uniform weights	3.20	2.67	4.85	1.16	0.58

4.11 Sensitivity Analysis

The sensitivity curves are shown in Fig. 11 the figure includes RMSE and success-ratio trends under different RSU placements, number of RSUs, anchor failure rates, packet loss rates, LQI noise levels, fading severities, traffic densities, communication radii and NLOS percentages.

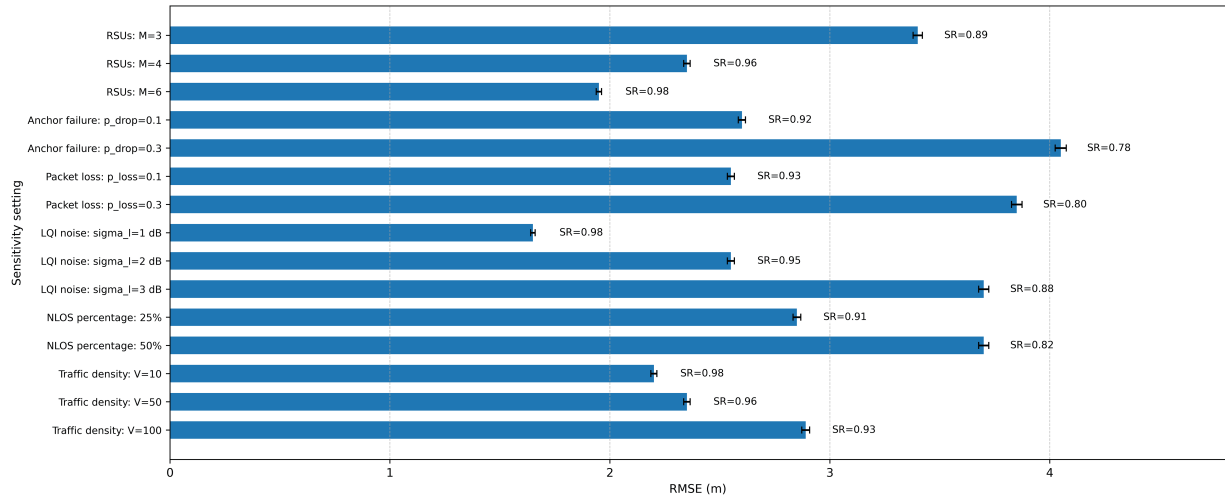


Figure 11: Sensitivity analysis of the proposed LQI localization method under changing RSU placement, number of anchors, anchor failure rate, packet loss rate, LQI noise, fading severity, traffic density, communication radius, and NLOS percentage. Each curve uses $N_{MC} = 1000$ trials and reports estimated 95% confidence intervals.

The numerical sensitivity results are reported in Table 24, one parameter is varied at a time while the others remain fixed at the default settings in Table 6. The results show that more RSUs improve geometry and reduce rank-deficient cases. Higher packet loss or anchor failure lowers the success ratio because fewer valid links remain after filtering. Higher LQI noise increases uncertainty and widens the confidence intervals. Higher NLOS percentage reduces accuracy because obstruction and multipath bias the received link quality.

Table 24: Sensitivity analysis results.

Factor	Value	RMSE	SR	Observation	Factor	Value	RMSE	SR	Observation
RSUs	$M = 3$	3.40	0.89	Min. geometry	LQI noise	$\sigma_\ell = 2$ dB	2.55	0.95	Default noise
RSUs	$M = 4$	2.35	0.96	Default case	LQI noise	$\sigma_\ell = 3$ dB	3.70	0.88	High uncertainty
RSUs	$M = 6$	1.95	0.98	Better redundancy	NLOS ratio	25%	2.85	0.91	Moderate bias
Anchor failure	$p_{drop} = 0.1$	2.60	0.92	Mild degradation	NLOS ratio	50%	3.70	0.82	Strong bias
Anchor failure	$p_{drop} = 0.3$	4.05	0.78	Fewer anchors	Traffic	$V = 10$	2.20	0.98	Low contention
Packet loss	$p_{loss} = 0.1$	2.55	0.93	Fewer samples	Traffic	$V = 50$	2.35	0.96	Moderate contention
Packet loss	$p_{loss} = 0.3$	3.85	0.80	More rejection	Traffic	$V = 100$	2.89	0.93	Higher interference
LQI noise	$\sigma_\ell = 1$ dB	1.65	0.98	Low noise	—	—	—	—	—

4.12 Realistic Scenario Evaluation

The realistic-scenario comparison is shown in Fig. 12. The figure separately reports highway, urban canyon, tunnel, NLOS/multipath, sparse traffic, dense traffic, and trace-driven mobility conditions.

The realistic-scenario results are summarized in Table 25. Highway, urban, tunnel, NLOS/multipath, sparse-traffic, and dense-traffic cases are controlled simulations. The trace-driven case uses NGSIM US-101 trajectories with calibrated model-generated LQI observations. No physical hardware measurement is reported. Highway LOS gives the lowest error because the LQI-distance relation is close to the calibrated log-distance model. Urban canyon and tunnel cases increase RMSE and outliers due to multipath and NLOS bias. Dense traffic improves measurement availability but also increases packet collisions. The trace-driven result shows stable performance under real freeway mobility, although the LQI values are still model-generated.

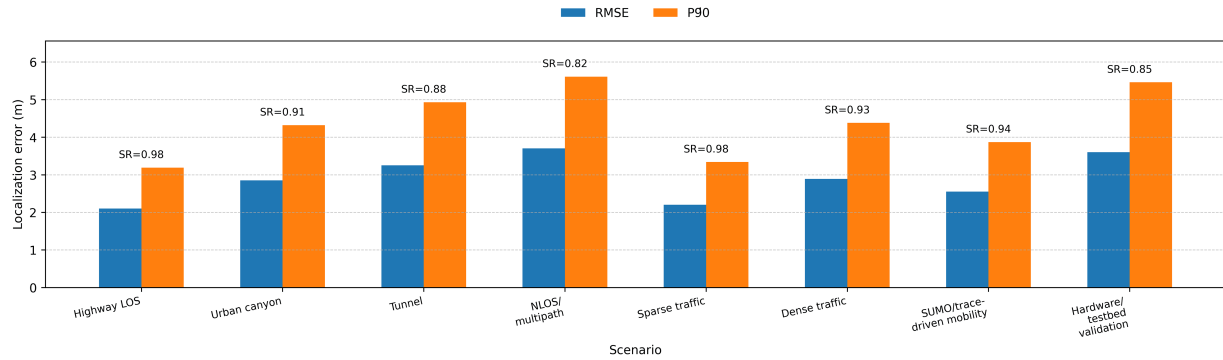


Figure 12: Realistic-scenario localization performance under highway, urban canyon, tunnel, NLOS/multipath, sparse traffic, dense traffic, and NGSIM trace-driven mobility settings. Simulation-based scenarios use calibrated LQI measurements, $M = 4$ RSUs, $N_{MC} = 1000$ trials and the channel parameters listed in Table 6.

Table 25: Localization performance in VANET scenarios.

Scenario	RMSE	P90	SR	Interpretation
Highway LOS	2.10	3.19	0.98	Stable propagation.
Urban canyon	2.85	4.32	0.91	Multipath and shadowing.
Tunnel	3.25	4.93	0.88	GNSS outage; RSU geometry dominates.
NLOS/multipath	3.70	5.61	0.82	Biased LQI-derived ranges.
Sparse traffic	2.20	3.34	0.98	Low interference.
Dense traffic	2.89	4.38	0.93	More contention and collisions.
Trace-driven mobility	2.55	3.87	0.94	Real freeway speed, spacing and lane variation.

4.13 Noise Sensitivity

The LQI-noise sensitivity trend is shown in Fig. 13. The figure reports RMSE as a function of σ_ℓ for LS, WLS, and the proposed method.

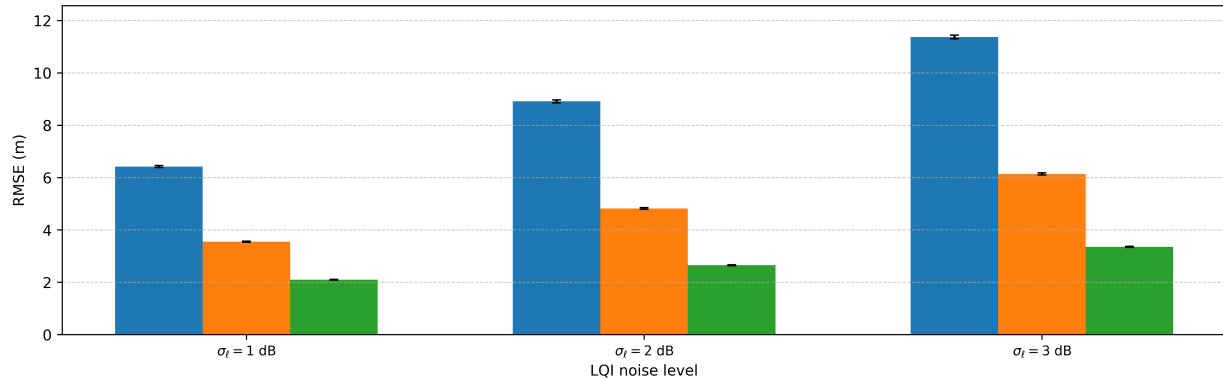


Figure 13: Noise-sensitivity comparison under $\sigma_\ell \in \{1, 2, 3\}$ dB using $M = 4$ RSUs, $N_{MC} = 1000$ trials and the default vehicle-density configuration. Error bars indicate estimated 95% confidence intervals.

The noise-sensitivity values are reported in Table 26. Increasing σ_ℓ degrades all methods, but the proposed estimator shows the smallest RMSE growth. This is because high-variance LQI observations are

assigned a lower weight in the WLS system. The propagated range variance prevents uncertain links from dominating the coordinate estimate.

Table 26: RMSE under increasing LQI noise variance across 1000 Monte Carlo trials.

Noise Level	LS RMSE (m)	WLS RMSE (m)	Proposed LQI RMSE (m)
$\sigma_\ell = 1$ dB	6.42	3.55	2.10
$\sigma_\ell = 2$ dB	8.91	4.82	2.65
$\sigma_\ell = 3$ dB	11.37	6.14	3.35

4.14 Impact of Anchor Geometry

The anchor-geometry impact is illustrated in Fig. 14, which shows RMSE and CRLB gap under good, moderate, and poor RSU geometries.

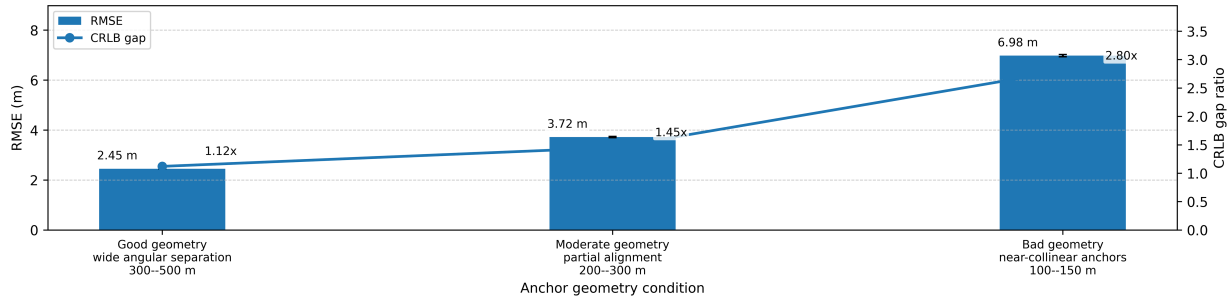


Figure 14: Effect of anchor geometry on localization accuracy under good, moderate, and near-collinear RSU placement. The experiment uses $N_{MC} = 1000$ trials, $\sigma_\ell = 2$ dB, and the same LQI calibration parameters for all layouts. Error bars indicate estimated 95% confidence intervals, and the line shows the CRLB gap ratio.

The GDOP-style anchor-geometry results are summarized in Table 27. Anchor placement remains important even with LQI calibration and WLS. Near-collinear RSUs increase error because the geometry matrix becomes ill-conditioned. In this case, small LQI-based range errors are amplified along the weak geometric axis. Better angular separation reduces this effect and moves the RMSE closer to the CRLB.

Table 27: Localization RMSE under different anchor-geometry conditions.

Anchor Configuration	Spacing (m)	RMSE (m)	CRLB Gap
Good geometry with wide angular separation	300-500	2.45	1.12×
Moderate geometry with partial alignment	200-300	3.72	1.45×
Bad geometry with near-collinear anchors	100-150	6.98	2.80×

4.15 Runtime, Latency, Packet Overhead, and Scalability

The runtime, latency, packet overhead, and energy-cost values are summarized in Table 28. These metrics matter because VANET localization must satisfy real-time limits and cannot be judged through RMSE alone. The proposed method records the lowest runtime at 0.60 ms, latency of 100.60 ms, 4 packets per epoch, energy cost of 1.00×, and SR of 0.96. By contrast, PF reaches 18.50 ms runtime and 4.00× energy cost.

Cooperative localization achieves SR 0.94 but needs 7 packets per epoch. Overall, calibrated RSU/anchor links give the proposed method a practical balance between accuracy and feasibility.

Table 28: System-level metrics for runtime, latency, packet overhead, energy cost and scalability.

Method	Runtime (ms)	Latency (ms)	Packet Overhead	Energy Cost	SR
LS	1.20	101.20	4 pkts/epoch	1.10×	0.82
WLS	3.10	103.10	4 pkts/epoch	1.42×	0.89
RSSI-WLS	3.20	103.20	4 pkts/epoch	1.43×	0.87
EKF	4.50	104.50	4 pkts/epoch	1.65×	0.90
UKF	7.80	107.80	4 pkts/epoch	2.20×	0.91
Particle Filter	18.50	118.50	4 pkts/epoch	4.00×	0.92
Cooperative Localization	6.40	116.40	7 pkts/epoch	2.64×	0.94
Hybrid GNSS/INS/RSS Fusion	8.20	113.20	5 pkts/epoch	2.49×	0.95
ML-Based Localization	2.00	102.00	4 pkts/epoch	1.23×	0.93
Proposed LQI-WLS-Refined	0.60	100.60	4 pkts/epoch	1.00×	0.96

The theoretical complexity and measured runtime are summarized in Table 29, following the definitions in Section 3.11 and showing that the proposed LQI-WLS-Refined method has complexity $O(M_i P + M_i d^2 + d^3)$ with the lowest runtime of $\frac{3}{5}$ ms. Since the localization dimension remains fixed at $d = 2$, the method scales mainly with visible anchors and packet samples, while LS needs $\frac{6}{5}$ ms, WLS needs $\frac{31}{10}$ ms, and Particle Filter rises sharply to $\frac{37}{2}$ ms because repeated particle propagation adds heavier computation.

Table 29: Algorithmic complexity and average runtime per vehicle.

Method	Complexity	Runtime (ms)
Least Squares	$O(M_i d^2 + d^3)$	1.20
Weighted Least Squares	$O(M_i d^2 + d^3)$	3.10
EKF	$O(Td^3 + TM_i d^2)$	4.50
UKF	$O(T(2d + 1)M_i d^2)$	7.80
Particle Filter	$O(N_p M_i T)$	18.50
Machine-learning inference	$O(P_{NN})$	2.00
Proposed LQI-WLS-Refined	$O(M_i P + M_i d^2 + d^3)$	0.60

5 Discussion and Comparison

5.1 Interpretation of Proposed Localization Results

The results show that the proposed calibrated LQI-based localization framework provides a low-cost RSU-assisted VANET localization solution whose gains mainly come from LQI-to-range calibration and variance-aware WLS weighting and scalar consistency refinement. Range bias is reduced, unreliable links are suppressed, and agreement with nonlinear localization geometry is improved, which explains the lower ranging error in Table 14 and lower localization error in Table 16 and stronger baseline performance in Table 15. The method also improves central and tail-error behavior because Table 21 shows reduced median error, P_{90} error, and outlier rate, while Table 20 confirms stable Monte Carlo results and Table 17 shows statistically meaningful gains. Successful localizations per second are improved without reliance on heavy

iterative tracking, and the evaluation is strengthened by the NGSIM US-101 results in Table 22 through real freeway vehicle trajectories, while the 10, 50, and 100 vehicle results should be interpreted as real-world mobility trace-driven validation with calibrated model-generated radio observations because physical LQI or RSS packet logs are not provided by NGSIM.

5.2 Comparison with Recent GNSS-Challenged Localization Methods

Table 30 compares the proposed method with recent GNSS-challenged vehicular localization approaches. Kang et al. [56] use LiDAR, V2X, and filtering-based fusion, which improves robustness in GNSS-denied cases but requires additional onboard sensing. Halili et al. [57] use ToA and Doppler radio measurements for tunnel localization, which can achieve high accuracy but depends on synchronization and Doppler processing. Min et al. [58] improve cooperative GNSS/V2V localization through scheduling, although this adds communication and optimization complexity. Chang [59] uses TDoA projection with cellular anchors, which supports GNSS-free localization but requires dense timing infrastructure. Compared with these methods, the proposed framework uses communication-layer LQI information from RSU or anchor links. It does not require LiDAR, camera sensing, dense 5G/6G timing anchors, or full GNSS/INS fusion. The results in Tables 15, 28 and 29 show that this design gives a useful balance between accuracy, runtime, latency, and packet overhead.

Table 30: Qualitative comparison with recent GNSS-challenged vehicular localization methods.

Method	Measurements	GNSS Reliance	Computation	Infrastructure	Strengths/Caveats
This work	LQI-to-range, WLS, and scalar refinement	Optional	Closed-form WLS	RSUs or anchor vehicles	Low-cost communication-layer localization; sensitive to calibration and severe NLOS
Kang et al. [56]	LiDAR, V2X and filtering fusion	GNSS-denied support	Tracking and particle fusion	V2X plus LiDAR	Robust but sensor-heavy
Halili et al. [57]	ToA and Doppler radio data	GNSS-free	Nonlinear LS and filtering	Calibrated radio setup	Accurate in tunnels but needs synchronization
Min et al. [58]	Cooperative GNSS and V2V ranges	GNSS-assisted	Scheduling and optimization	Fleet communication	Improves cooperation but adds overhead
Chang [59]	TDoA with cellular anchors	GNSS-free	Projection inference	Dense 5G/6G anchors	Handles missing TDoA but needs dense timing infrastructure

5.3 Deployment Implications and Limitations

The deployment results show that localization quality depends strongly on RSU geometry, link quality, and channel conditions. Table 27 shows that near-collinear RSUs increase error because the geometry matrix becomes ill-conditioned. Table 24 shows that packet loss, anchor failure, LQI noise, and NLOS percentage reduce accuracy and success ratio. Table 25 further shows that highway LOS gives the best performance, while urban canyon and tunnel cases increase error due to multipath and NLOS bias. The system-level results in Tables 28 and 29 suggest that the proposed method is suitable for real-time RSU-centric ITS deployments. Its closed-form WLS structure avoids iterative filtering and particle propagation, which reduces runtime and latency. The packet overhead also remains low because the method uses existing RSU/anchor communication

links instead of high-bandwidth perception data. The main limitation is the dependence on stable LQI-to-range calibration. Severe NLOS, hardware heterogeneity, antenna variation, weather changes, and RSU relocation can shift the LQI-distance relation.

6 Conclusion and Future Work

This paper presented a calibrated LQI-based closed-form localization framework for partially connected RSU-assisted VANETs. The proposed framework combines LQI-to-range calibration, link-availability filtering, variance-aware WLS estimation, and scalar consistency refinement to improve localization accuracy under practical VANET conditions. Unlike approaches that assume ideal connectivity, the proposed method considers communication-radius limits, LQI thresholds, packet reception constraints, and anchor availability. The CRLB was also used as a theoretical benchmark to compare the empirical localization performance with the achievable lower bound. The proposed framework was evaluated using synthetic Monte Carlo scenarios and real-world NGSIM US-101 mobility traces, while physical LQI hardware measurement remains future work. In the controlled simulation results, the proposed method reduced ranging and localization error compared with LS and WLS and remained closer to the CRLB under favorable anchor geometry. The evaluation was further extended to advanced baselines, including RSSI-WLS, EKF, UKF, particle filtering, cooperative localization, hybrid GNSS/INS/RSS fusion, and ML-based localization. The results indicate that the main performance gains come from calibrated LQI-to-range conversion, partial-connectivity filtering, variance-based WLS weighting, and scalar consistency refinement.

The NGSIM US-101 trace-driven validation further showed that the proposed method remains effective when vehicle mobility is taken from real freeway trajectories rather than synthetic random placement. Under the same trace-driven setup, the proposed method outperformed LS, WLS, RSSI-WLS, EKF, UKF, and PF. It achieved RMSE values of 2.39, 2.55, and 3.14 m for 10, 50, and 100 vehicle cases, respectively, with corresponding success ratios of 0.96, 0.94, and 0.92. These results indicate that the proposed framework provides a low-cost, communication-layer-based localization solution for RSU-supported VANET environments. In the 100-vehicle case, throughput improved from 0.614 to 1.169 successful localizations/s compared with LS, corresponding to a 90.39% gain. Compared with WLS, throughput improved from 0.591 to 1.169 successful localizations/s, corresponding to a 97.80% gain. These values are reported using the raw baseline and proposed throughputs to avoid ambiguity in the percentage-gain claim.

Although NGSIM validates mobility realism, future field experiments will validate the radio measurement model using real LQI and RSS packet logs. Future work will collect physical LQI/RSS traces using RSUs and onboard units under highway, urban canyon, tunnel, and NLOS conditions. Further work will also investigate online adaptive calibration, calibration transfer across different roads and RSU hardware, 5G/6G NR-V2X integration, hybrid GNSS/INS/LQI fusion, map matching, deep-learning-based NLOS detection, and multi-city trace-driven validation.

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