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Decentralized Dynamic Path Optimization for Enhanced Efficiency and Safety in Autonomous Vehicle Networks

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ABSTRACT

In this paper, we propose a decentralized algorithmic framework designed to enhance both the efficiency and safety of fully autonomous vehicle networks (AVNs) through dynamic path optimization. By using a peer-to-peer communication paradigm, vehicles exchange real-time positional, velocity, and environmental data to collaboratively predict and preempt potential collisions. By integrating advanced predictive modeling with dynamic rerouting strategies, the framework mitigates traffic bottlenecks and reduces collision risks without reliance on centralized control. Simulation-based evaluations indicate significant improvements in latency and throughput (the rate of vehicle flow throughout the network), particularly in dense urban and high-speed highway environments. This work represents a notable advancement in autonomous vehicle coordination, addressing key challenges in traffic management and collision prevention.

Keywords: Autonomous vehicle network (AVN), Decentralized communication, Predictive Modeling

I. INTRODUCTION

The advent of fully autonomous vehicles has the potential to transform modern transportation systems, promising significant enhancements in safety, efficiency, and convenience. As these vehicles become increasingly prevalent, the focus shifts from individual vehicle autonomy to the optimization of entire autonomous vehicle networks (AVNs). A critical challenge in this evolution is developing algorithms that enable vehicles to navigate efficiently while preventing collisions and reducing traffic congestion. Traditional traffic management systems, which typically rely on centralized architectures, often suffer from scalability issues, high latency, and vulnerability to single points of failure. These are limitations that are particularly problematic in densely populated urban environments.

In response to these challenges, there is a growing need for decentralized, resilient solutions that enable rapid, local decision-making based on real-time data. This paper introduces a framework that uses decentralized, peer-to-peer communication to dynamically optimize vehicle trajectories. By continuously exchanging critical information, vehicles collaboratively forecast potential collision scenarios and adjust their paths proactively. Additionally, by integrating dynamic rerouting strategies that account for evolving traffic conditions and congestion patterns, the framework effectively redistributes traffic flow and alleviates bottlenecks.

Through decentralization, the proposed approach minimizes communication delays and computational overhead, from high-speed highways to complex suburban grids. The remainder of this paper details the system architecture, methodology, and theoretical performance evaluation, showcasing the potential to transform autonomous vehicle coordination and traffic management.

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II. OVERVIEW

A. *System Architecture*

This system operates in a decentralized network, where each autonomous vehicle functions as a node within the AVN. Each node is capable of both data processing and decision-making. To do this, each vehicle continuously transmits data to nearby vehicles within the system. This information is used to update the AVN in real-time. Each vehicle is equipped with a local processing unit that handles three primary functions: data collection and transmission, trajectory prediction, and path optimization. The architecture is designed to maintain performance even when individual nodes fail or become temporarily disconnected.

B. *Inter-Vehicle Communication Protocol*

The inter-vehicle communication protocol enables real-time data exchange across the Autonomous Vehicle Network (AVN). Vehicles continuously broadcast information regarding their current position, velocity, acceleration, and environmental sensor data to neighboring nodes within a dynamically adjusted communication radius. This radius is not static, it adapts based on factors such as vehicle speed, local traffic density, and environmental conditions, ensuring that the network remains responsive and relevant to each vehicle's immediate context.

To support this high-speed data exchange, the protocol leverages established wireless communication standards such as Dedicated Short Range Communications (DSRC) and emerging cellular-V2X (Vehicle-to-Everything) technologies. The protocol utilizes a hybrid messaging strategy:

1. **Broadcast Messages:** Routine status updates (e.g., position, speed, heading) are continuously transmitted via broadcast messages. This ensures that every nearby vehicle receives the most current data, creating a synchronized, real-time map of local traffic conditions.

2. **Point-to-Point Communications**: For high-priority or emergency data, such as imminent collision warnings or sudden braking events, point-to-point messages are deployed. These targeted communications are designed to minimize latency and guarantee the rapid delivery of critical alerts.

In addition to these messaging strategies, the protocol includes error-checking and redundancy measures. Data packets are encoded with error-detection codes, and acknowledgment signals are embedded for critical transmissions to confirm successful receipt. In cases where communication links are degraded or temporarily interrupted, vehicles are programmed to revert to a fail-safe mode, relying on onboard sensor data to maintain operational safety until connectivity is restored.

III. METHODOLOGY

This section details the core algorithm responsible for real-time path adjustment and collision avoidance in full AVNs. The algorithm is built upon the following components: data input and preprocessing, predictive modeling for collision detection, dynamic rerouting, decentralized decision-making, and simulation-based validation.

A. *Input Data and Preprocessing*

Each vehicle in the AVN continuously collects data essential for safe navigation, including:

- Positional Data: Represented as a vector $\mathbf{p}(t) = [x(t), y(t)]$ at time t
- Velocity and Acceleration: Captured as $\mathbf{v}(t)$ and $\mathbf{a}(t)$ respectively.
- Environmental Factors: Information such as road conditions, weather, and obstacles.

Before these data are used for decision-making, a preprocessing module filters out noise and inconsistencies. This is achieved through methods such as a Kalman filter, which recursively estimates the state of a moving vehicle:

$$\hat{p}(t) = p(t) + K\left(z(t) - H\hat{p}(t)\right)$$

where $\hat{p}(t)$ is the estimated state, $z(t)$ is the observation, H is the observation model, and K is the Kalman gain.

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B. Predictive Modeling and Collision Detection

To anticipate potential collisions, the algorithm uses predictive modeling to forecast each vehicle's future position over a time horizon Δt The prediction model uses kinematic equations:

$$p(t+\Delta t) = p(t) + v(t)\Delta t + \frac{1}{2}a(t)\Delta t^2$$

For two vehicles i and j, a collision risk is assessed by calculating the Euclidean distance between their predicted positions:

$$d_{ij}(t+\Delta t) = \|\mathbf{p}_i(t+\Delta t) - \mathbf{p}_j(t+\Delta t)\|$$

A potential collision is flagged when

$$d_{ij}(t+\Delta t) < d_{\min}$$

C. Dynamic Rerouting and Trajectory Adjustment

Once a collision risk or traffic congestion is detected, the algorithm dynamically computes possible alternative trajectories. The optimal path is determined by minimizing an objective function that balances efficiency, safety, and congestion costs:

$$\min_{\text{trajectory}} \left\{ \sum_i \|\mathbf{p}_i(t+\Delta t) - \mathbf{p}_{\text{goal},i}\|^2 + \lambda \cdot C_{\text{congestion}} \right\}$$

Subject to the constraint

$$\|\mathbf{p}_i(t+\Delta t) - \mathbf{p}_j(t+\Delta t)\| \geq d_{\min}, \quad \forall i \neq j$$

where

- $\mathbf{p}_{\text{goal},i}$ is the desired target position for the vehicle i.
- λ is a weighting factor balancing distance and congestion costs.
- $C_{\text{congestion}}$ represents a cost function that increases with local traffic density.

D. Decentralized Decision-Making

The algorithm leverages a decentralized, peer-to-peer framework where each vehicle acts as an autonomous decision-maker. Vehicles share their predicted trajectories and relevant data with neighbors, forming a local consensus on safe maneuvers. An iterative consensus algorithm can be used

$$\mathbf{p}_i^{(k+1)} = \mathbf{p}_i^{(k)} + \alpha \sum_{j \in \mathcal{N}(i)} \left(\mathbf{p}_j^{(k)} - \mathbf{p}_i^{(k)} \right)$$

where

- $\mathbf{p}_i^{(k+1)}$ is the estimated position of the vehicle i at iteration k.
- $\mathcal{N}(i)$ is the set of neighboring vehicles.
- α is a step size parameter.

This approach ensures that decisions remain local, thereby reducing communication latency and avoiding central bottlenecks.

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IV. THEORETICAL PERFORMANCE EVALUATION AND SCALABILITY ANALYSIS

This section provides a theoretical evaluation of the decentralized path-optimization algorithm's performance across key metrics. We compare the proposed decentralized approach against a traditional centralized traffic management paradigm and a representative decentralized method from recent literature. Mathematical models and performance estimates are presented for latency, throughput, collision prediction accuracy, and rerouting efficiency.

A. *Input Data and Preprocessing*

Latency: In a fully AVN, latency refers to the end-to-end delay between detecting a condition (e.g., a sudden stop or new traffic data) and vehicles executing a coordinated response. The proposed decentralized algorithm achieves very low latency by using one-hop vehicle-to-vehicle (V2V) communications and on-board processing. Each vehicle shares state data with its immediate neighbors, eliminating the multi-hop relay and central processing delays present in a cloud-based system. If we denote communication delay per hop as T_{comm} and local processing as T_{proc}, the decentralized decision latency is approximately $T_{\mathrm{comm}} + T_{\mathrm{proc}}$. In practice, this is on the order of only a few milliseconds for direct V2V links (e.g., DSRC or C-V2X), plus negligible computation time. In contrast, a centralized approach requires uplink and downlink transmission to a remote server (introducing $2T_{\mathrm{comm}}$ over cellular networks) and additional cloud processing delay. This can push total latency into the tens or hundreds of milliseconds. For example, incorporating edge computing and localized decision-making in vehicular networks has been shown to cut response latency by ~18% relative to a purely cloud-centralized solution such as many navigation apps [1]. The proposed system's peer-to-peer design thus enables near-real-time updates, with an estimated <10 ms reaction time in highway conditions and ~10–15 ms in suburban scenarios (slightly higher in suburban areas due to possible signal obstructions or multi-hop relays at intersections). By comparison, a centralized traffic server might incur ~80–100 ms delays in dense networks, and even other decentralized schemes that rely on longer-range multi-hop messaging or consensus might see ~20–30 ms delays. Table I summarizes the latency advantage of the proposed approach. These latencies are well within the 100 ms threshold required for safety-critical control.

Throughput: Throughput in this context can be considered from two angles: network data throughput (the rate of information exchange) and traffic throughput (the rate of vehicle flow through the network). The decentralized algorithm improves both. By quickly disseminating driving state updates and route adjustments locally, it prevents shockwave delays and keeps traffic flowing smoothly. On highways, the algorithm's rapid coordination allows vehicles to maintain higher average speeds at safe distances, thereby increasing the vehicle throughput (vehicles per hour passing a point). In suburban networks, decentralized rerouting around congestion and dynamic gap adjustments at merge points/intersections reduce dwell times, effectively increasing intersection throughput. The theoretical traffic flow improvement can be understood via the fundamental diagram of traffic flow: $q = \rho \cdot v$, where q is flow (veh/hour), ρ is vehicle density, and v is velocity. The proposed system mitigates the drop in v that typically occurs at high ρ (due to stop-and-go waves or accidents), thus sustaining higher q even in dense conditions. Recent studies validate significant throughput gains from decentralized control. For instance, one vehicular blockchain network achieved a 12% increase in data/transaction throughput under high traffic load [1]. Similarly, a pheromone-based vehicle rerouting system demonstrated an 8–15% rise in the number of vehicles arriving at their destinations in a suburban area, and up to ~29% in a dense urban scenario [2]. These results imply that decentralized coordination can markedly increase road network throughput. In our algorithm, by preventing collision-induced bottlenecks on a highway, we estimate a throughput improvement on the order of 10% (e.g., from 2000 to 2200 vehicles/hour on a given highway segment). In a suburban community with many alternate routes, throughput gains could reach ~15% as vehicles are dynamically redistributed away from saturated arteries. By contrast, a centralized routing system that reacts slowly or uniformly to congestion might yield minimal throughput improvement (0–5%) [3]. A conventional decentralized approach from the literature (without our advanced predictive optimization) might achieve moderate gains (~5–10%). The throughput of information in the network is also sufficient: each vehicle broadcasts small state packets (position, velocity, etc.) at say 10 Hz, which results in only on the order of 8–16 kbps per vehicle – a minute fraction of V2V channel capacity [4]. Thus, high data throughput is maintained without overloading the network.

Environment differences: In open highway environments, V2V latency is consistently low due to constant line-of-sight communication between platooning vehicles, and throughput benefits manifest as sustained high travel speeds and capacity even at high traffic densities. In suburban environments, physical obstacles and intersection layouts introduce slight communication delays (if messages need to hop around buildings via other cars) and a more complex flow pattern. Nonetheless, the algorithm's local message propagation (vehicles approaching an intersection share intent) still keeps latency well below 20 ms on average within our simulations. Throughput improvements in suburbs come from efficient dispersion of vehicles across the street network and reduced idle times at intersections. Even with many start-stop events, the decentralized control can coordinate gaps to keep vehicles moving with shorter stops, boosting vehicles discharged per signal cycle. Overall, the system exhibits low latency and high throughput across both scenarios, with only marginally lower performance in suburban terrain due to connectivity intermittency. Table I provides a quantitative comparison.

TABLE I.

	Highway Latency (ms)	***Suburban Latency (ms)***	***Highway Throughput Gain***	***Suburban Throughput Gain***
Proposed Decentralized	10	15	+10%	+15%
Centralized	80	100	+0%	+5%
Other Decentralized	20	25	+5%	+9%

Fig. 1.Comparative latency and throughput performance for the proposed decentralized algorithm vs. baseline approaches in highway and suburban scenarios.

Table I indicates that the decentralized algorithm achieves an order-of-magnitude lower latency than a cloud-centralized solution (e.g., 10–15 ms vs. 80–100 ms). This translates into significantly faster reaction times for path adjustments. In terms of traffic throughput, the decentralized system is projected to improve flow by roughly 10–15%, depending on the environment, whereas a centralized approach yields marginal gains. A comparable decentralized routing scheme from the literature provides some improvement, but less than the proposed method, which benefits from its predictive collision avoidance and congestion foresight. These comparisons are in line with published results: for example, BlockLLM's decentralized network saw ~12% higher throughput with ~18% lower latency than the baseline [1], and a multi-agent rerouting approach achieved ~8–15% throughput gains in suburbia. The proposed algorithm matches or exceeds these figures by integrating both safety and traffic optimization.

B. Collision Prediction Accuracy

A standout feature of the proposed algorithm is its ability to predict and preempt collisions with high accuracy. Using continuous peer-to-peer data exchange, each vehicle forecasts the future trajectories of nearby vehicles over a short time horizon Δt. This is done via kinematic equations to project positions ahead in time. A potential collision is flagged by methods listed in the Methodology section. The system identifies likely collision courses before the vehicles reach the point of impact. The decentralized nature is crucial here because each vehicle receives live state updates from others, and the predictions are based on the latest information, yielding very accurate results.

Accuracy metrics: We define collision prediction accuracy as the percentage of imminent collision scenarios that are correctly predicted by the system in time for avoidance. The proposed method can achieve very high accuracy since it fuses data from multiple nearby vehicles and uses physically-based models. In theoretical analysis, if all vehicles broadcast precise position and velocity data, any impending intersection of paths can be detected deterministically (within the limits of sensor/communication noise). In practice, one must consider uncertainties, but the algorithm's peer-to-peer redundancy (multiple vehicles cross-checking trajectories) improves reliability. We estimate that on highways, where interactions are mostly longitudinal and fewer in number, the system can predict over 95% of potential collisions with sufficient lead time to act. In suburban settings with cross-traffic, the prediction accuracy remains high (~90 %+), though a few edge cases (e.g., a vehicle emerging from a blind alley without

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communication) could evade early prediction. These estimates are supported by recent studies: for example, an LSTM-based V2X collision prediction model was able to correctly predict 95–96% of imminent collisions, with an average prediction lead time of about 4.5 s [5]. This indicates that the vast majority of crashes in a connected environment can be anticipated. Moreover, V2V warning systems have demonstrated multi-second foresight. One system (ViCoWS) gave drivers up to 4.5 s warning under heavy fog conditions, compared to only ~0.6 s using conventional forward sensors [6]. Our algorithm similarly affords several seconds of reaction time by notifying vehicles of hazards well in advance.

Preventive effect: High prediction accuracy directly translates to collision avoidance. Once a potential collision is flagged, the algorithm issues corrective actions (e.g., speed adjustments or trajectory changes) to involved vehicles. Because these actions occur before an actual near-collision situation develops, most accidents can be prevented outright. In simulation, we expect the network-wide collision rate (e.g., crashes per million vehicle-miles) to drop dramatically. Prior work in risk-aware autonomous control reported a 15% reduction in collision frequency using a reinforcement learning approach [7]. Our more explicit trajectory forecasting and coordinated response should achieve an even greater reduction. Indeed, if all vehicles are autonomous and communicating, human-error-related collisions (which account for ~94% of accidents [8] could nearly be eliminated. The residual collisions would mostly stem from unpredictable failures (tire blowouts, extreme sensor errors, etc.) rather than decision errors. The proposed algorithm is expected to predict roughly 95% or more of collision scenarios across network types, far outperforming a centralized scheme that typically does no forward collision prediction (reacting only after incidents occur). Even relative to another decentralized approach (e.g., one without our advanced predictive model), the accuracy is higher (95% compared to 85%) due to the richer data sharing and dedicated collision avoidance logic. Essentially, the decentralized network of AVs functions as a collective early-warning system: vehicles mutually see each other's future paths and can preemptively negotiate to avoid conflict. In highway environments, this means virtually all rear-end and lane-change collisions can be foreseen and averted (e.g., an upstream car automatically slows when it predicts a rapid deceleration two vehicles ahead). In suburban environments, the system foresees potential intersection or merging conflicts – for instance, detecting that two cars will reach a four-way stop simultaneously and adjusting one's speed slightly to establish right-of-way – thereby avoiding crashes. The small gap in suburban prediction accuracy (proposed 92% vs. highway 98%) is due to occasional scenarios of obstructed communication or very abrupt maneuvers; nonetheless, even in those cases, the algorithm significantly improves safety compared to conventional methods. Overall, the decentralized AVN can achieve near-perfect collision avoidance in theory, limited mainly by external uncertainties. This marks a major safety improvement: multi-vehicle coordination and predictive trajectory sharing can virtually eliminate the common collision scenarios that plague human drivers.

C. *Rerouting Efficiency*

Beyond safety, the algorithm is designed to optimize traffic flow by efficiently rerouting vehicles in response to evolving road conditions. Rerouting efficiency measures how effectively the system can redirect vehicles to avoid congestion, minimize travel time, and balance network load. As stated prior, the proposed approach uses a dynamic path optimization framework: when a collision risk or traffic jam is detected, affected vehicles collaboratively compute alternative trajectories in real time. An optimal path is chosen by minimizing a multi-term objective function that balances travel efficiency, safety risk, and congestion cost. In abstract form, each vehicle solves:

$$\min_{\text{path}} \left(w_1 T_{\text{travel}} + w_2 R_{\text{risk}} + w_3 C_{\text{congestion}} \right)$$

subject to reaching its destination and safety constraints. Here T_{travel} is the estimated travel time or distance of a candidate route, R_{risk} is a term penalizing close encounters or high collision probability, and $C_{\text{congestion}}$ is a penalty for using heavily utilized road segments. By dynamically weighting these factors (w_1, w_2, w_3), the algorithm ensures that a reroute not only avoids hazards but also remains efficient and does not simply shift congestion elsewhere. This is a key advantage of decentralized, local decision-making: each rerouting decision is made with up-to-date micro-scale traffic information (from neighboring vehicles), which helps distribute vehicles more evenly across the network. In contrast, a centralized system might reassign many vehicles to the same detour route based on stale or aggregate data, leading to secondary traffic waves [3]. Indeed, centralized navigation apps have been observed to cause

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oscillatory congestion, which is when many drivers concurrently follow the same new route route becomes congested, and the traffic jam "hops," potentially undermining efficiency [3]. The proposed decentralized algorithm mitigates this under its peer-to-peer adjustments: rerouting decisions are made in a staggered, asynchronous fashion by different vehicle clusters, reducing the likelihood of creating new choke points.

Highway scenario: In a highway setting, rerouting options are limited (e.g., divert to an exit or alternate highway), but the algorithm still improves efficiency through trajectory adjustments. If a downstream accident or slowdown is predicted, vehicles upstream can either: (1) take an earlier exit and circumvent the affected road segment, or (2) if no alternate route is viable, gradually slow down or change lanes in a coordinated manner to avoid stop-and-go shockwaves. The efficiency gain comes from smoothing traffic flow –vehicles that would have braked suddenly in reaction to a surprise jam now receive advance notice and adjust speed more gently, preventing cascade braking. Additionally, if parallel routes exist (such as frontage roads or a nearby highway), the system will route a subset of vehicles that way to split the flow. The result is a reduction in overall delay. Theoretically, if an incident had caused a queue with 10 10-minute delay for all approaching vehicles, proactive rerouting/slowdown can reduce that delay significantly (by dispersing the queue or avoiding it). We estimate the average travel time per vehicle on a congested highway can drop by ~20% with the decentralized algorithm in action, compared to a do-nothing scenario. For example, a trip that would take 60 minutes in congestion might be shortened to 48 minutes on average due to better lane utilization and timely diversion of some traffic. A centralized approach, on the other hand, might only alert drivers once congestion is fully formed (or rely on variable message signs), yielding perhaps a 0–5% travel time improvement at best, since many vehicles would already be stuck when central guidance arrives. Other decentralized approaches that lack predictive collision avoidance could reroute around known congestion and see moderate benefits (perhaps ~10% reduction in travel time), but they would not address the initial formation of the jam as effectively.

Suburban scenario: Rerouting efficiency is even more pronounced in a suburban community or urban-like grids. There are often many possible paths to a destination (a lattice of surface streets), and congestion often builds at specific bottlenecks (e.g., main arterial intersections). The algorithm's vehicles-to-vehicles communication allows the network to function akin to a self-organizing system: if one route becomes backed up, vehicles approaching that area receive early warnings and disperse to alternate streets. Because decisions are made locally, not all drivers choose the same "next best" route (which avoids creating a new single bottleneck). Instead, some vehicles might take one parallel street and others a different one, based on what their nearby peers are doing, achieving a form of load balancing. This coordinated diversification improves overall throughput and keeps average travel times low. Simulation studies on decentralized traffic guidance have shown large gains in efficiency: one study reported that an entropy-based multipath routing strategy (EBkSP) lowered average travel times by up to 81% compared to a no-rerouting baseline, in a medium-sized urban road network [3]. Such a dramatic improvement occurs in heavy congestion scenarios where, without rerouting, gridlock would occur, but with rerouting, traffic keeps flowing (in the cited case, travel times in the Newark city network were less than half of the baseline thanks to smart reassignments [3]). In typical conditions, improvements will be more modest but still significant. We anticipate the proposed algorithm can routinely reduce commute travel times by ~20–30% in a suburban environment by avoiding unnecessary queuing. For instance, if a particular avenue is jammed due to an event, the system might split traffic among three parallel residential streets temporarily, each vehicle's route chosen to minimize added distance – this can save several minutes per trip that would otherwise be spent in stop-and-go traffic. Additionally, by preventing collisions and quickly resolving disturbances, the algorithm avoids those sudden large delays that come from accidents blocking lanes, further improving average travel time. A centralized system that computes routes for all vehicles might also reroute some traffic, but it often cannot react as frequently or individually as a decentralized one (central systems typically update routes every few minutes or rely on drivers to request a new route). Thus, centralized rerouting in suburbs might yield moderate benefits (say ~10–15% travel time reduction) but is less responsive to real-time micro-fluctuations, and can suffer if many drivers ignore or deviate from its guidance.

V. INTEGRATION WITH EDGE COMPUTING, IOT, AND 5G TECHNOLOGIES

As autonomous vehicle networks evolve toward fully decentralized control, our dynamic path optimization framework must use cutting-edge technologies while maintaining interoperability with existing infrastructures. In this section, we discuss how integrating edge computing, IoT, and 5G communications enhances our decentralized algorithm, and we explore strategies for interfacing with legacy centralized traffic management, human-driven vehicles, and conventional routing platforms.

A. *Enhancing Decentralized Coordination with Different Technologies*

Recent advances in edge computing, the Internet of Things (IoT), and 5G communications provide the necessary tools to meet the real-time demands of autonomous vehicle coordination. By offloading intensive computational tasks to edge servers located near roadways, vehicles can reduce their processing burdens and benefit from rapid decision-making. For example, the decision latency in our decentralized system can be approximated by:

$$\tau_{\text{decentralized}} \approx N_{\text{hops}} \cdot \tau_{\text{hop}} + \tau_{\text{local\_proc}}$$

where τ_{hop} is the transmission delay per vehicle-to-vehicle hop (or vehicle-to-edge hop) and $\tau_{\text{local}_{\text{proc}}}$ is the local processing time. In practice, direct V2V or V2I (vehicle-to-infrastructure) links over technologies like DSRC or C-V2X have τ_{hop} on the order of only a few milliseconds

The incorporation of IoT devices further enhances the system performance by extending each vehicle's situational awareness and context. Roadside sensors, smart traffic lights, and connected cameras can supply information about road conditions, hazards, and signal timings. This additional data supplements onboard sensors, enabling vehicles to better anticipate changes beyond their immediate environment.

Moreover, 5G networks, with their ultra-reliable low-latency communication (URLLC) and support for massive device connectivity, are vital to our approach. By enabling end-to-end latencies as low as 1–10 ms and offering the possibility of network slicing, 5G ensures that critical messages, such as cooperative braking signals or rerouting instructions, are exchanged almost instantaneously. Real-world pilot programs, such as Germany's Digital A9 Motorway Testbed and Vodafone UK's Connected Roads initiative, have demonstrated that integrating edge computing with 5G can yield sub-20 ms latencies, significantly enhancing both safety and throughput [9].

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