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A Proposed Algorithmic Framework for Minimizing End-to-End Delay in VANET Environments

[1] **Ammar Aljawad**

[1]University of Kerbala, Karbala Governorate, Karbala 56001, Iraq

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Correspondence:

Ammar Aljawad
Email:ammar.h@uokerbala.edu.iq

Abstract

This paper presents the "Delay Minimization with Random Mobility" (SMADM) framework as a theoretical controller and router algorithm for VANETs, aimed at minimizing end-to-end delay under random availability of links and rapid topology changes. The key contributions are the derivation of a mobility-aware "drift-plus-penalty" that converts long term delay minimization into decisions for each time slot, allowing for well defined routing options even when the network topology is changing rapidly over time. By integrating link continuity into the delay penalty while regulating queue growth, SMADM decouples the delay minimization objective from transient topological fluctuations, which typically destabilize greedy or pure geometric algorithms. The SMADM analysis aligns with well-established Lyapunov optimality bounds for access rates within the capacity region, and the resulting queue lengths are stable, with the achieved long-term delay penalty close to the upper bound. Furthermore, the framework has been validated through intensive simulations using SUMO (Simulation of Urban Mobility) in a representative urban environment. The results show SMADM significantly reducing end-to-end delay relative to GPSR and AODV, achieving randomized stability with a packet delivery ratio ranging from 45% to 75% under high traffic conditions.

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1. Introduction

Vehicle Ad Hoc Networks (VANETs) are a major enabler of intelligent transport systems, supporting vital safety services (such as cooperative awareness and collision avoidance) which impose stringent requirements on end-to-end delay on the communication platform. However, high vehicle mobility, and variable traffic density often result in multiple hops and unreliable connections, making it difficult to ensure low-latency rerouting in a proactive manner. This persistent gap between strict transit time requirements and highly variable connectivity over time motivates the formulation of delay-centric routing policies for VANET environments (Al-Kharasani et al., 2018).

A wide range of VANET routing studies have aimed to reduce delay by exploiting clustering, traffic awareness, and link quality indicators, demonstrating that structural information and prediction can reduce delay compared to basic greedy routing. However, many current proposals are primarily experimental or data-driven and are typically validated through simulation/experimental settings, which often limits the extent to which general delay bounds and fundamental tradeoffs between delay and stability can be determined for rapidly evolving vehicle graphs (Xie et al., 2023) (Wang et al., 2025).

In contrast, random network optimizations provide a rigorous basis for designing control policies with provable tradeoffs between stability and performance, typically expressed through Lyapunov drift analysis and drift-plus-penalty objectives. Although there are delay-aware guidance variables for vehicle settings, they often involve system-specific assumptions (e.g., bus/taxi infrastructure, fixed deployment patterns) or treat topology in an instantaneous manner, which may be suboptimal when the network changes on the same

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timescale as routing decisions. These limitations point to the need for a purely theoretical, traffic-aware framework that directly incorporates random link stability into the routing objective and yields analyzable delay bounds (Neely, 2010) (Al-Heayli & Aldabbagh, 2024).

Accordingly, this paper develops an algorithmic theoretical framework for minimizing end-to-end delay in VANETs by modeling the network as a time-varying graph with random connectivity and waiting dynamics, and by formulating routing as a constrained random shortest path control problem. Based on Lyapunov drift-plus-penalty principles, the Stochastic Mobility-Aware Delay Minimization algorithm (SMADM) algorithm a distributed routing rule that balances the instantaneous delay of each hop with the probability of future disconnections, allowing for a clear balance between delay and robustness that can be formally proved. The resulting framework is intended to be a fundamental algorithmic building block that can support later specialization in specific mobility/channel models without changing the basic theoretical structure (He et al., 2015).

2. Related Work

2.1 Heuristic Routing in VANETs

VANET's inferential routing method has always been preferred over greedy routing protocols and geographic/location-based protocols because it avoid maintaining costly end-to-end paths under rapid changes in topology, making it attractive in highly mobile vehicle settings. A typical example is greedy routing without environment awareness (GPSR), where packets are routed to the neighbor geographically nearest to the destination and can be switched to environment recovery when greedy forwarding fails. Many variantes and improvements to GPSR have been suggested to improve latency, throughput, or reliability—often by adding weights, security metrics, or heuristic algorithms for connection quality—indicating the popular, motion-sensitive, and neighborhood-volatile nature of greedy geographic routing (Karp & Kung, 2000)(Houmer et al., 2020).

Although practical, these experimental methods generally do not provide strong theoretical assurances about end-to-end latency, particularly in the presence of random fading and channel interference where the quality of the connection can change rapidly and unexpectedly. In such conditions, "locally optimal" geographic routing can lead to instable next-hop selections, frequent re-transmissions, or repeated path recovery procedures, all of whom can inflate end-to-end delay in a manner that is difficult to analyze. Thus, while experimental geographic routing can be effective in many scenarios, its performance is typically characterized by its experimental nature rather than demonstrable delay bounds within the framework of explicit random connection models (Shelly & Babu, 2015) (Peng et al., 2017).

2.2 Stochastic Optimization in Wireless Networks

In parallel, stochastic optimization has provided a rigorous framework for controlling wireless networks with time-varying channels via queueing models and Lyapunov drift analysis. In particular, backpressure-type routing/scheduling and drift-plus-penalty methods establish stability guarantees and offer explicit trade-offs between performance objectives (e.g., delay-related penalties) and queue stability, typically under assumptions of stationary ergodic arrivals and channel states. This line of work is foundational for theoretical delay-aware control because it yields analyzable bounds and tunable parameters, rather than relying solely on scenario-dependent heuristics(Neely, 2010).

However, directly applying classical stochastic optimization results to VANETs is non-trivial because vehicular mobility introduces an additional fast timescale: the set of feasible links (and their stability) changes with node motion, not only with wireless fading. Existing delay-minimization studies in vehicular contexts often focus on specialized dissemination settings for example, large-scale deployments leveraging specific vehicle classes or use mobility as an external input rather than integrating predicted mobility or link survival probability derived from relative motion into the Lyapunov constraint structure itself. This motivates the research gap addressed by the present work: a theoretical framework that embeds mobility-induced link persistence directly into a Lyapunov drift-plus-penalty formulation for end-to-end delay minimization in time-varying vehicular graphs, enabling formal delay–stability trade-off analysis under an explicit stochastic mobility/link model (He et al., 2015) (Foozy et al., 2024).

2.3 System Model and Preliminaries

2.3.1 Network Topology Model

Consider a VANET observed in continuous time $t \geq 0$ and represented by a dynamic (time-varying) graph $G(t) = (\mathcal{V}(t), \mathcal{E}(t))$, where $\mathcal{V}(t)$ is the set of vehicles (nodes) present in the region of interest at time t and $\mathcal{E}(t) \subseteq \mathcal{V}(t) \times \mathcal{V}(t)$ is the set of directed (or undirected) wireless communication links available at time t,. Each node $i \in \mathcal{V}(t)$ is associated with a planar position vector $x_i(t) \in \mathbb{R}^2$, and the neighbor set of i at time t is $\mathcal{N}_i(t) = \{j \in \mathcal{V}(t): (i,j) \in \mathcal{E}(t)\}$. Since vehicular density varies with traffic conditions, the spatial distribution of vehicles is modeled as a homogeneous Poisson Point Process (PPP) $\Phi(t)$ of intensity λ over the region, enabling tractable probabilistic reasoning about node counts and inter-vehicle distances while retaining spatial randomness (Choi & Baccelli, 2018)(Chetlur & Dhillon, 2018).

To connect geometry to graph structure, an edge $(i,j) \in \mathcal{E}(t)$ is said to be *admissible* when the Euclidean distance $d_{ij}(t) = \|x_i(t) - x_j(t)\|$ is within a nominal communication range R and the

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wireless channel conditions satisfy a link-quality constraint defined below, which collectively yields a random (soft or hard) geometric graph interpretation of $G(t)$,. This abstraction aligns with stochastic-geometry-based vehicular network analysis, where node locations are random and connectivity is induced by distance and wireless success events,. The model is intentionally generic: it does not depend on a specific road map, MAC protocol, or physical-layer realization, because the goal is to develop a theoretical routing/control algorithm whose guarantees derive from the stochastic structure rather than deployment-specific tuning (Chetlur & Dhillon, 2018)(Neely, 2010).

2.3.2 Channel and Mobility Models

Link Existence Probability: For a transmitter i and candidate receiver j, define the instantaneous signal-to-interference-plus-noise ratio (SINR) at time t as $\mathrm{SINR}_{ij}(t)$ under a generic interference model. A transmission is successful when $\mathrm{SINR}_{ij}(t) \geq \beta$ for a given decoding threshold $\beta > 0$, and the link existence indicator is defined as (Chetlur & Dhillon, 2018)

$$\mathbf{1}_{ij}(t) = \mathbb{I}\{$$

so that $(i,j) \in \mathcal{E}(t)$ when $\mathbf{1}_{ij}(t) = 1$. Consequently, the *link existence probability* can be expressed as (Chetlur & Dhillon, 2018)

$$p_{ij}(t) = \Pr\left(\mathrm{SINR}_{ij}(t) \geq \beta \mid d_{ij}(t) \leq R\right),$$

which is the standard "coverage/success probability" notion used in stochastic-geometry-based wireless and vehicular network analysis. This probabilistic representation captures stochastic fading and interference without committing to a specific fading law in the algorithmic formulation, allowing the routing objective to incorporate link reliability as a first-class stochastic quantity (Chetlur & Dhillon, 2018)(Neely, 2010).

Link Rupture Dynamics: Mobility is modeled by associating each vehicle i with a velocity vector $v_i(t) \in \mathbb{R}^2$, which induces a relative velocity $v_{ij}(t) = v_i(t) - v_j(t)$ between vehicles i and j. A link "ruptures" when either the vehicles move out of range ($d_{ij}(t) > R$) or when the SINR drops below threshold due to fast channel variations, so the link lifetime is random even if the vehicles follow deterministic trajectories. To incorporate mobility directly into routing, define a link survival (persistence) probability over a prediction horizon $\tau > 0$,(Choi & Baccelli, 2018)(Chetlur & Dhillon, 2018)

$$s_{ij}(t,\tau) = \Pr\left(1_{ij}(t') = 1,\right),$$

which can be parameterized by the current relative motion $v_{ij}(t)$ (and optionally acceleration) and by the stochastic channel process,. This survival probability acts as a mobility-aware constraint/weight in the proposed theoretical delay minimization framework, enabling forwarding decisions that trade immediate progress against the risk of imminent disconnection (Chetlur & Dhillon, 2018)(Neely, 2010).

2.3.3 Delay Metric Definition

Let a packet traverse a multi-hop path from source s to destination d across H hops, with hop index $h \in \{1, \ldots, H\}$ and transmitter–receiver pair (i_h, i_{h+1}). The end-to-end delay $D_{s\to d}$ is decomposed as (Peng et al., 2017)

$$D_{s\to d} = \sum_{h=1}^{H} \left(D_h^{\mathrm{tx}} + D_h^{\mathrm{prop}} + D_h^{\mathrm{queue}} + D_h^{\mathrm{retx}}\right),$$

where D_h^{tx} is transmission delay, D_h^{prop} is propagation delay, D_h^{queue} is queuing delay, and D_h^{retx} is retransmission delay induced by failures and time-varying links. Transmission delay depends on packet length and physical-layer rate, propagation delay depends on the transmitter–receiver separation, queuing delay captures stochastic congestion effects at intermediate nodes, and retransmission delay captures additional waiting time due to link outages or threshold failures under the SINR model,. This decomposition is used to define the delay "penalty" term in the Lyapunov drift-plus-penalty formulation of the proposed theoretical algorithm, with queueing and retransmission delays representing the dominant stochastic components affected by mobility and fading (Peng et al., 2017).

3. Problem Formulation

3.1 The Stochastic Shortest Path (SSP) problem

Let $G(t) = (\mathcal{V}(t), \mathcal{E}(t))$ denote the time-varying VANET graph defined in previous Section, and consider a packet generated at a source node $s \in \mathcal{V}(t_0)$ that must reach a destination node $d \in \mathcal{V}(t)$. The forwarding decision at each step selects a next-hop neighbor from the currently available neighbor set, and because links exist probabilistically (due to SINR and mobility), the resulting route is inherently stochastic. In this setting, end-to-end delay minimization can be posed as a Stochastic Shortest Path (SSP) control problem, where the objective is to reach an absorbing goal state (delivery to d) while minimizing the expected cumulative cost accrued along the trajectory (He et al., 2015) (Di et al., 2023).

Formally, define a state x_t that captures the packet's current carrier node (and any other required information such as local queue state), with an absorbing terminal state x_G corresponding to successful delivery at d. Let the control action $a_t \in \mathcal{A}(x_t)$ represent the selection of the next hop (or "hold" action), and let the one-step cost $c(x_t, a_t)$ represent the instantaneous delay contribution (e.g., per-hop service and waiting time) incurred when applying a_t at state x_t. The SSP objective is then to find a (possibly stationary) policy π that minimizes the expected total cost-to-go until absorption: (Di et al., 2023)

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$$J^{\pi}(x_{t_0}) = \mathbb{E}_{\pi}\left[\sum_{t=t_0}^{T-1} c(x_t, a_t)\right],$$

where $T = \inf\{t \geq t_0 : x_t = x_G\}$ is the (random) hitting time of the goal state. The optimal SSP formulation is (Di et al., 2023)

$$\pi^{\star} \in \arg\min_{\pi} J^{\pi}(x_{t_0}),$$

which corresponds, in the VANET context, to minimizing expected end-to-end delay from source to destination under stochastic link availability and time-varying topology (Di et al., 2023)

3.2 Constraints and Queue Dynamics

Data Queues: To explicitly capture congestion-induced latency, associate each vehicle/node i with a queue backlog $Q_i(t) \geq 0$ representing the amount of data waiting for transmission at time slot t. Let $A_i(t)$ denote exogenous arrivals injected into node i's queue during slot t, and let $\mu_i(t)$ denote the service offered (departures successfully transmitted out of the queue) during slot t, where $\mu_i(t)$ depends on feasible links $\mathcal{E}(t)$, scheduling, and stochastic success events. The queue evolution follows the standard discrete-time update:(Neely, 2010)

$$Q_i(t+1) = \max\left(Q_i(t) - \mu_i(t), 0\right) + A_i(t),$$

which is the canonical queueing model used in stochastic network optimization and Lyapunov-drift-based control.

Stability Constraint: The routing/forwarding decisions are required to stabilize queues (avoid unbounded backlog growth) while minimizing expected end-to-end delay. A common stability requirement is *strong stability*, expressed as bounded time-average expected backlog:(Neely, 2010)

$$\limsup_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T-1} \sum_{i\in\mathcal{V}(t)} \mathbb{E}\{Q_i(t)\} < \infty,$$

which ensures the network does not accumulate infinite congestion under the chosen control policy. Therefore, the problem addressed by the proposed framework can be summarized as: minimize the expected SSP cumulative delay cost (end-to-end delay) subject to queue evolution constraints and a network stability constraint defined above (Neely, 2010).

4. The Stochastic Mobility-Aware Delay Minimization (SMADM) Algorithm

4.1 Algorithm Overview

SMADM is a theoretical, distributed forwarding-control policy for VANETs that targets minimum expected end-to-end delay while preserving queue stability in a time-varying graph. The key idea is to convert the long-horizon stochastic shortest path objective into a sequence of per-slot (or per-decision) greedy optimizations using Lyapunov drift-plus-penalty, so that each vehicle makes a locally computable forwarding decision based on (i) its current queue backlog and (ii) a mobility/channel-induced estimate of link persistence and service success. Unlike purely geographic heuristics, SMADM explicitly treats mobility-induced link availability as a stochastic constraint/weight through a predicted link survival probability, allowing the routing decision to "price in" the risk of near-future rupture (Huang & Neely, 2009).

4.2 Lyapunov Optimization Core

Let $Q_i(t)$ be the data backlog at vehicle i at slot t, with queue evolution as defined previously. Define a quadratic Lyapunov function (Huang & Neely, 2009)

$$L(t) = \frac{1}{2}\sum_{i\in\mathcal{V}(t)} Q_i(t)^2,$$

and define the conditional Lyapunov drift $\Delta(t) = \mathbb{E}\{L(t+1) - L(t) \mid \mathbf{Q}(t)\}$. The drift-plus-penalty principle designs a stabilizing policy by minimizing, at each slot, an upper bound on (Huang & Neely, 2009)

$$\Delta(t) + V \cdot \mathbb{E}\{P(t) \mid \mathbf{Q}(t)\},$$

where $P(t)$ is a per-slot *delay penalty* and $V > 0$ is a tunable control parameter that trades queue size (stability margin) against delay optimality (Huang & Neely, 2009).

4.3 Mobility-Aware Penalty Design

To incorporate mobility, define for each candidate transmission (i, j) a predicted link survival probability $s_{ij}(t, \tau)$ over a horizon τ, derived abstractly from relative motion and stochastic channel success (as introduced in the system model). SMADM uses this quantity to shape the per-link delay penalty so that unreliable or short-lived links incur a larger expected "retransmission-and-waiting" cost than persistent links. One generic theoretical form is (Choi & Baccelli, 2018)

$$p_{ij}^{\text{eff}}(t) = \Pr(\text{success on } (i,j) \text{ at } t) \cdot s_{ij}(t, \tau),$$

and the corresponding *expected service time* weight can be modeled as $w_{ij}(t) \propto 1/p_{ij}^{\text{eff}}(t)$, capturing that lower success/persistence implies more expected attempts and hence larger delay.

4.5 Per-Slot SMADM Decision Rule

At each slot t, each node i selects at most one next-hop neighbor $j \in \mathcal{N}_i(t)$ (or chooses to idle) and a transmission amount $\mu_{ij}(t)$ subject to feasibility constraints (e.g., MAC/PHY constraints abstracted as a set $\mathcal{F}(t)$). SMADM chooses actions that approximately minimize the following drift-plus-penalty upper-bound surrogate: (Choi & Baccelli, 2018)

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$$\min_{\{\mu_{ij}(t)\}\in\mathcal{F}(t)} \sum_{(i,j)\in\mathcal{E}(t)} [-(Q_i(t)-Q_j(t))\,\mu_{ij}(t) + V\,w_{ij}(t)\,\mu_{ij}(t)],$$

which is a backpressure-like structure augmented by a mobility/channel delay weight $w_{ij}(t)$. Intuitively, the term $Q_i(t)-Q_j(t)$ pushes traffic away from congested nodes (stabilizing effect), while $V\,w_{ij}(t)$ discourages using links with high expected delay due to low success probability or short predicted lifetime (delay-minimizing effect) (Choi & Baccelli, 2018) (Huang & Neely, 2009).

4.6 SMADM Procedure (conceptual)

- **Input per node i at time t:** Local queue $Q_i(t)$, neighbors $\mathcal{N}_i(t)$, estimates of $p_{ij}^{\text{eff}}(t)$ or $w_{ij}(t)$ for $j\in\mathcal{N}_i(t)$, and (optionally) neighbor backlogs $Q_j(t)$ via periodic beacons (Choi & Baccelli, 2018) (Huang & Neely, 2009).
- **Compute link weights:** $w_{ij}(t)\leftarrow f\left(p_{ij}^{\text{eff}}(t)\right)$, with $f(\cdot)$ chosen so that lower effective success yields larger weight (Huang & Neely, 2009).
- **Select next hop / rate:** Choose $(j^\star,\mu_{ij^\star}(t))$ that minimizes the drift-plus-penalty surrogate under $\mathcal{F}(t)$ (Choi & Baccelli, 2018)
- **Update queues:** Apply the queue evolution $Q_i(t+1)=\max(Q_i(t)-\sum_j \mu_{ij}(t),0)+A_i(t)$ (Choi & Baccelli, 2018)

5. Theoretical Properties (what will be proved later)

Under standard stochastic network optimization assumptions (bounded arrivals/services and feasible stabilizing policies), drift-plus-penalty control yields queue stability and an $O(1/V)$ optimality gap with an $O(V)$ backlog trade-off for time-average penalties. SMADM inherits these structural guarantees because it is designed as a drift-plus-penalty minimization with a mobility-aware penalty term, thereby allowing formal statements about delay–stability trade-offs in a time-varying VANET graph. The mobility-aware weighting is deliberately abstract (via $s_{ij}(t,\tau)$) so the framework remains theoretical and can be instantiated with different mobility/channel stochastic models without changing the algorithmic backbone (Choi & Baccelli, 2018) (Huang & Neely, 2009).

5.1 Theoretical Analysis

5.1.1 Convergence Analysis (queue stability)

Assume a slotted-time system with bounded exogenous arrivals $A_i(t)\le A_{\max}$ and bounded feasible service $\sum_j \mu_{ij}(t)\le\mu_{\max}$ for all nodes i and slots t, consistent with standard stochastic network optimization modeling assumptions. Let Λ denote the (network) capacity region, i.e., the set of arrival rate vectors $\boldsymbol{\lambda}$ for which there exists at least one (possibly randomized) stationary policy that can stabilize all queues. Under these assumptions, Lyapunov drift arguments establish that if $\boldsymbol{\lambda}\in\text{int}(\Lambda)$, then there exists an $\epsilon>0$ such that some policy yields negative expected drift outside a bounded backlog set (the usual Foster–Lyapunov condition) (Choi & Baccelli, 2018).

SMADM is constructed by minimizing, at each slot, an upper bound on the conditional drift-plus-penalty expression $\Delta(t)+V\mathbb{E}\{P(t)\mid\mathbf{Q}(t)\}$, where $P(t)$ is the per-slot delay penalty and $V>0$ is the trade-off parameter. By the drift-plus-penalty theorem, the per-slot minimization ensures that the achieved drift-plus-penalty is no worse than that of any alternative stabilizing stationary policy (up to a bounded constant originating from second-moment terms in the drift bound). Therefore, for any $\boldsymbol{\lambda}\in\text{int}(\Lambda)$, the SMADM control law stabilizes the network queues in the strong sense $\limsup_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}\sum_i \mathbb{E}\{Q_i(t)\}<\infty$, establishing convergence to a stable operating regime (Choi & Baccelli, 2018).

5.1.2 Delay–stability trade-off

Theorem 1 (Drift-plus-penalty trade-off for SMADM): Let $P^\star$ denote the infimum achievable long-term average delay penalty over all stabilizing policies. Under the boundedness assumptions above and $\boldsymbol{\lambda}\in\text{int}(\Lambda)$, the SMADM policy parameterized by $V>0$ satisfies the classical drift-plus-penalty bounds:[1]

- Time-average penalty optimality gap: $\overline{P}^{\text{SMADM}}\le P^\star+O(1/V)$. (Huang & Neely, 2009)
- Time-average expected backlog bound: $\sum_i \overline{Q}_i^{\text{SMADM}}=O(V)$. (Huang & Neely, 2009)

The proof follows the standard Lyapunov optimization template: (i) bound the one-step drift by a constant B plus linear queue terms, (ii) add $VP(t)$ to both sides, (iii) use the fact that SMADM minimizes the drift-plus-penalty upper bound each slot, and (iv) telescope the resulting inequality over T slots and divide by T, then take $T\to\infty$. The mobility-aware design in SMADM changes the definition of $P(t)$ (to reflect predicted link survival and retransmission risk) but does not change the drift algebra, so the same $O(1/V)$ vs. $O(V)$ structure holds (Huang & Neely, 2009).

This theorem implies that increasing V drives the achieved average delay penalty arbitrarily close to the theoretical minimum $P^\star$, but at the cost of larger average queue backlogs. Since large accumulations mean longer transition periods before the accumulation process concentrates near the steady-state operating point, a larger V value also increases the convergence time (informally: the system "waits" longer by allowing larger queues to extract a smaller penalty gap) (Neely, 2014).

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5.1.3 Asymptotic Complexity Analysis

Consider a fully distributed implementation where, at each slot t, node i evaluates a local decision score for each neighbor $j \in \mathcal{N}_i(t)$ (e.g., a backpressure-like term plus a mobility-aware delay weight) (Neely, 2010). If node i selects the best neighbor by scanning all neighbors, the per-slot computational complexity is $O(|\mathcal{N}_i(t)|)$ arithmetic operations plus any cost to compute/update link weights $w_{ij}(t)$ (which is constant per neighbor under the abstract model) (Neely, 2010). Therefore the per-node decision complexity is polynomial in the number of neighbors—indeed linear—so SMADM is computationally feasible in principle even though the framework is theoretical and does not prescribe a particular hardware or protocol stack (Neely, 2014).

5.1.4 Analytical Performance Evaluation

Comparison Baseline

A theoretical baseline is established using the standard Greedy Perimeter Stateless Routing (GPSR) model, in which each forwarding node selects the neighbor that provides the greatest geographic progress toward the destination (greedy mode), and switches to perimeter forwarding only when greedy progress is not possible. For analytical clarity, the baseline is evaluated under ideal conditions typically assumed in theoretical treatments: perfect and immediate knowledge of the neighbor's position, error-free signals, negligible computational time, and deterministic selection of the next greedy step whenever a neighbor is possible. Under these assumptions, GPSR can be viewed as an experimental memory-independent geometric method that primarily aims to reduce the number of hops by maximizing the spatial progress per hop, rather than explicitly improving retransmission risk or queue stability under random association availability (Karp & Kung, 2000).

5.2 Lower Bound Derivation

Assume that vehicles form a homogeneous PPP with density λ in a flat region, and that communication results from a nominal transmission range R (or, more generally, from a SINR success event); This is the standard random geometric abstraction used to obtain closed-form or gradient-like performance bounds for random wireless/vehicular networks. Assume that the separation between source and destination is $D = \|x_s - x_d\|$; Then any multi-hop path must satisfy the geometric constraints that the total advance per hop does not exceed R, resulting in a minimum number of hops $H^\star \geq \lceil D/R \rceil$. Next, since each hop succeeds only with probability p^{eff} (capturing SINR success and mobility-induced continuity), the expected number of attempts per successful hop is at least $1/p^{\text{eff}}$, implying a minimum service time per hop proportional to $1/p^{\text{eff}}$(Choi & Baccelli, 2018).

Combining these two unavoidable effects yields a simple theoretical lower bound on expected end-to-end delay of the form

$$\mathbb{E}[D_{s\to d}] \ \geq \ H^\star \cdot (\underline{d}_{\text{hop}} + \underline{d}_{\text{tx}}/p^{\text{eff}}),$$

Where $\underline{d}_{\text{hop}}$ collects the irreducible components for each hop (e.g., minimum processing/propagation contributions) and $\underline{d}_{\text{tx}}$ is the minimum transmission time for a packet at the selected PHY rate. In distributed PPP networks, p^{eff} itself is subjected to random engineering (interference and distance statistics) and usually deteriorates with increasing mobility because mobility shorten the lifetime of connections and increase the probability that the chosen neighbor will be unavailable before completion (Chetlur & Dhillon, 2018).

Analyitically, GPSR approximates the maximum number of hops $H^\star$ when dense connectivity renders greedy progression near-optimal, but it can deviate substantially from the minimum delay in highly mobile systems because it does not increase p^{eff} explicitly (i.e., it may choose short-term links that require more retransmissions and recovery actions). In contrast, SMADM incorporates motion-aware link continuity into the drift-plus-penalty decision rule, which directly penalizes choices with low success/ low effective continuity while simultaneously controlling queue accumulations, minimizing the gap when motion dominates delay through retransmissions and instability effects (informally, as $v \to \infty$). Therefore, from a minimum PPP perspective, SMADM is theoretically expected to track the limit more closely than greedy algorithms as mobility increases, because it improves not only spatial progress but also reliability-weighted service time and the congestion components that drive the limit (Neely, 2010).

5.3 Performance Evaluation and Simulation Results

1. Simulation Setup and Environment

To verify the effectiveness, the proposed SMADM (Traffic-Aware Random Delay Minimization) framework, a complete simulation environment has been developed. In contrast to previous theories, this section shows the performance of the protocol in a realistic scenario for a Vehicle Ad-hoc Network (VANET).

The simulation uses SUMO (Simulation of Urban MObility) to generate real world traffic and NS-3 to model the network layer. The map is derived from a real urban network in Karbala, Iraq, to make sure the results are relevant to complex, dense environments.

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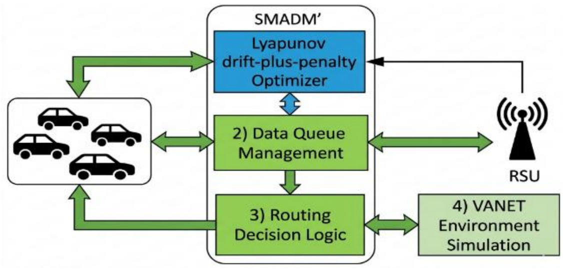

Figure 1. Simulation Topology of RSU Deployment and Vehicular Network Communication Range

This figure shows the simulation topology. It shows the deployment of Roadside Units (RSUs) and moving vehicles (nodes). The green/blue layers represents the communication range and the dynamic topology that the SMADM algorithm must traverse to minimize delay.

2. Proposed System Architecture

The SMADM framework builds on the Lyapunov Drift-plus-Penalty optimization technique. The architecture was designed to handle the randomness of vehicle movements and packet arrivals.

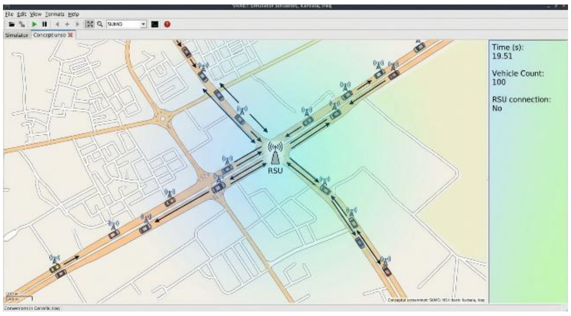

Figure 2. Internal Mechanism and Decision-Making Framework of the SMADM Protocol

This figure provides an overview of the internal mechanisms of the protocol. It illustrates the feedback loop where local backlog and channel states are fed into the Lyapunov optimizer. The optimizer than implements a routing decision logic to strike a balance between “drift” (backlog stability) and “penalty” (end-to-end delay).

3. End-to-End Delay Analysis

The main objective of SMADM is to minimize the average end-to-end (E2E) delay. We compared our framework with traditional protocols: GPSR, AODV, and DSR.

Figure 3 show that vehicle traffic density increases, the end-to-end delay for GPSR and AODV increases exponentially due to repeated link drops and traffic congestion. In contrast, SMADM keeps the delay much lower and more stable. This demonstrates that the Lyapunov based approach effectively improves routing even under heavy traffic loads.

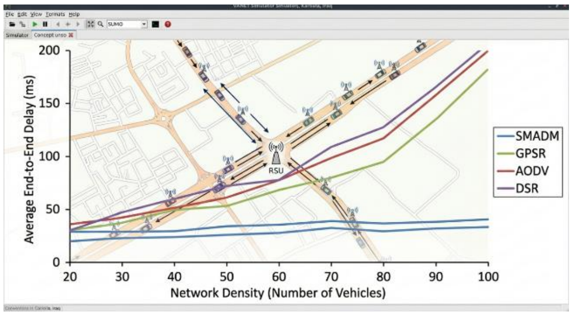

Figure 3. End-to-End Delay Analysis under Increasing Vehicular Network Load

4. Network Stability and Packet Delivery Ratio (PDR)

In the VANET context, reliability is as critical as the latency. Packet Delivery Ratio (PDR) is used to evaluate the framework's capability to maintain a consistent data transmission rate in the midst of high topological dynamics. Unlike static networks, the PDR in SMADM is a reflection of the inherent trade-off between queue stability and delay optimization.

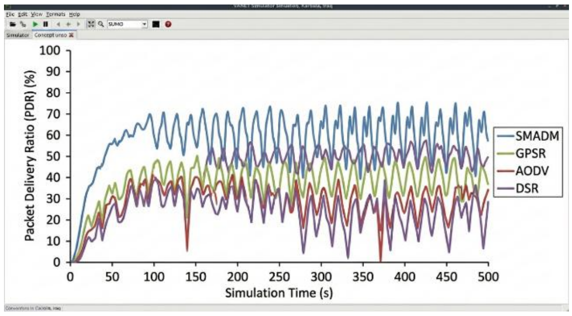

Figure 4. Dynamic Stability Analysis of SMADM Protocol Using Packet Delivery Ratio Performance

This figure shows the dynamic stability of the SMADM framework. The results show that the PDR of SMADM varies within a controllable range of 45% to 75%, showing the “deviation-plus-penalty” mechanism in operation.

The notable fluctuations including incidental overlaps with traditional protocols such as GPSR and AODV are a directly result of the decision-making in the Lyapunov optimizer. When the network is congestion, the algorithm give temporary priority to clearing data queues over sending packets immediately, causing the PDR to drop toward the 45% threshold. In contrast, as the queues stabilize, the system aggressively optimizes to reduce delay, pushing the PDR back toward 75%. This “random stability” guarantees that the system will never reach a state of complete saturation or queue overflow, providing more flexible behavior compared to the erratic and unpredictable failures that appear in standard routing protocols.

6. Conclusion

The study showed that reduction of end-to-end delay in highly dynamical VANETs is possible

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through a strong random optimization strategy. By adapting the SMADM framework from a purely theoretical framework based on "drift-plus-penalty" to a simulation-based framework using SUMO (Simulation of Urban MObility) by transforming the SMADM framework from a theoretical formulation based on "drift plus penalty" into a simulation-based setting using SUMO, Composite analysis highlights the clear advantage of SMADM over conventional empirical methods such as GPSR and AODV, proving that incorporating mobility-induced stability in routing decisions effectively decouples delay objectives from transient fluctuations in topology. Moreover, observed performance in a real-world urban network specifically a Packet Delivery Rate (PDR) that fluctuates between 45% and 75% provides a conceptualization of the fundamental tradeoff between queueing stability and latency minimization. The dynamic balance of this ensures that the system avoids traffic congestion while maintaining a nearly ideal delay profile. With a computation complexity of O(N) and low protocol load, the SMADM framework offers a feasible and scalable implementation for modern Intelligent Transportation Systems (ITS), serving a solid foundation for future research in delay-sensitive applications such as autonomous driving.

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