Cyber-Physical Interference Modeling for Predictable Reliability of Inter-Vehicle Communications

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Abstract—Predictable inter-vehicle communication reliability is a basis for the paradigm shift from the traditional single-vehicle-oriented safety and efficiency control to networked vehicle control. The lack of predictable interference control in existing mechanisms of inter-vehicle communications, however, makes them incapable of ensuring predictable communication reliability. For predictable interference control, we propose the Cyber-Physical Scheduling (CPS) framework that leverages the PRK interference model and addresses the challenges of vehicle mobility to PRK-based scheduling. In particular, CPS leverages physical locations of vehicles to define the gPRK interference model, a geometric approximation of the PRK model, for effective interference relation estimation, and CPS leverages cyber-physical structures of vehicle traffic flows (particularly, spatiotemporal interference correlation as well as macro- and micro-scopic vehicle dynamics) for effective use of the gPRK model. Through experimental analysis with high-fidelity ns-3 and SUMO simulation, we observe that CPS enables predictable reliability while achieving high throughput and low delay in communication. To the best of our knowledge, CPS is the first field-deployable method that ensures predictable interference control and thus reliability in inter-vehicle communications.

I. INTRODUCTION

Transcending the traditional paradigm of single-vehicle-oriented safety and efficiency control, next-generation vehicles are expected to cooperate with one another and with transportation infrastructures to ensure safety, maximize fuel economy, and minimize emission as well as congestion [7]. One basis for this vision of networked vehicle control (e.g., active safety and fuel economy control [7]) is wireless communication between close-by vehicles. Critical to the optimality and safety of networked vehicle control, inter-vehicle communication is required to be predictably reliable according to the requirement of vehicle control [27]. Given the different impact that communication reliability, delay, and throughput have on networked vehicle control [27], [26] and the inherent tradeoff between communication reliability, delay, and throughput [21], [28], the optimal operation of networked vehicle systems also requires controlling the tradeoffs between communication reliability, delay, and throughput, for which controlling communication reliability in a predictable manner is a basis [19], [28].

Despite extensive research in inter-vehicle wireless networking and pilot field-deployments of IEEE 802.11p-based networks, there still lack solutions for ensuring predictable inter-vehicle communication reliability. Inheriting the basic design principles of WiFi such as CSMA-based channel access control, for instance, existing 802.11p-based solutions may not even be able to ensure a communication reliability of 30% [29]. One major reason for the unpredictability and low reliability in existing inter-vehicle wireless networking solutions is the lack of predictable interference control. Thus scheduling data transmissions to control interference in a predictable manner is a basic element of inter-vehicle networking.

Given the pervasiveness of vehicles, networks of vehicles tend to be of large scale even though most networked vehicle control only involve communications between close-by vehicles [7]. In the meantime, vehicle mobility introduces dynamics in network topology which, together with uncertainties in wireless communication, introduces complex dynamics and uncertainties in inter-vehicle communication. For agile adaptation to uncertainties and for avoiding information inconsistency in centralized scheduling in large-scale V2V networks, distributed scheduling becomes desirable for interference control in inter-vehicle communications. Because wireless signals propagate far away in space and signals from different vehicles add to one another, however, inter-vehicle interference relations tend to be non-local and combinatorial, and predictable interference control tends to require coordination between transmitters far away from one another, which is challenging in highly-dynamic, large-scale V2V networks.

For predictable interference control in distributed scheduling, Zhang et. al [28] have identified the physical-ratio-K (PRK) interference model that transforms non-local interference control problems into local control problems which only require explicit coordination between close-by transmitters in scheduling. Based on the PRK model, Zhang et. al [29] have also proposed the PRK-based scheduling protocol PRKS which ensures predictable communication reliability in networks of no or low node mobility. Not targeting V2V networks, however, PRKS does not address the challenges of vehicle mobility to PRK-based scheduling, and it is not applicable to inter-vehicle communications. In V2V networks, vehicle mobility makes network topology and inter-vehicle channel properties highly dynamic, which in turn makes interference relations between vehicles highly dynamic, especially for vehicles on different roads or in opposite driving directions of a same road. The highly dynamic nature of inter-vehicle interference relations challenges the precise identification of interference relations in terms of both interference relation estimation and the signaling of interference relations. Thus the open question is whether it is feasible and how to apply PRK-based scheduling in V2V networks so that the interference between concurrently transmitting vehicles is controlled in a predictable manner to ensure the required inter-vehicle communication reliability.

In this paper, we give a constructive, positive answer to the question by developing the Cyber-Physical Scheduling (CPS)
framework that leverages cyber-physical structures of V2V networks to address the challenges of vehicle mobility, and we make the following contributions:

- For effective control signaling of fast-varying interference relations and by leveraging the physical locations of vehicles, we propose a geometric approximation of the PRK interference model, denoted as the gPRK model. The gPRK model enables vehicles to learn their mutual interference relations in the presence of vehicle mobility and without requiring significant control signaling bandwidth.

- For accurate identification of interference relations in the presence of vehicle mobility, we propose to leverage cyber-physical structures of vehicle traffic flows (particularly, spatiotemporal interference correlation as well as macro- and micro-scopic vehicle dynamics) for agile instantiation and effective use of the gPRK model in scheduling.

- We propose the distributed Cyber-Physical Scheduling (CPS) framework that integrates the above interference modeling mechanisms in scheduling inter-vehicle communications. We implement CPS in ns-3 [1], and we experimentally analyze CPS through integrated, high-fidelity simulation of wireless networks and vehicle dynamics using ns-3 and SUMO [10] respectively. We validate that CPS ensures predictable reliability while achieving high throughput and low delay in inter-vehicle communication, thus providing a wireless networking foundation for networked vehicle control.

Note that, even though concepts such as vehicle location, vehicle mobility, and wireless channel correlation have been used in various forms in existing protocols, CPS is the first approach that is able to effectively leverage vehicle location information, spatiotemporal interference correlation, vehicle dynamics, and the gPRK model to ensure predictable interference control and thus predictable reliability in inter-vehicle communication, which is non-trivial and is also a critical enabler of the vision of networked vehicle control.

The rest of the paper is organized as follows. In Section II we present the system model and problem specification, and we review the PRK interference model [28] and PRKS scheduling protocol [29]. We give an overview of the CPS framework in Section III and then we present our approaches to addressing vehicle mobility in Sections IV. We experimentally analyze CPS in Section V and we discuss related work in Section VI. We make concluding remarks in Section VII.

II. Preliminaries

System model & problem specification. In inter-vehicle wireless communication networks, referred to as V2V networks hereafter, a fundamental communication primitive is single-hop broadcast via which a vehicle shares its states (e.g., location and speed) with close-by vehicles within a certain distance (e.g., 150 meters) [7]. Given the significance of single-hop broadcast (e.g., for real-time networked vehicle control [7]) and for conciseness of presentation, our discussion in this paper focuses on single-hop broadcast, but the proposed methodology for scheduling inter-vehicle broadcasts applies to the scheduling of inter-vehicle single-hop unicast. Even though we only consider single-hop broadcasts by individual vehicles, we do consider real-world settings where the individual vehicles are widely distributed in space and may well be beyond the broadcast range of many other vehicles.

With the above V2V network setup, we study the online slot-scheduling problem [3] where, given a set of vehicles on the road at any time instant, a maximal subset of the vehicles need to be scheduled in a distributed manner to transmit concurrently while ensuring that the mean packet delivery reliability (PDR) from every transmitting vehicle S to each of its broadcast receivers R is no less than an application-required PDR $T_{S,R}$. Note that a vehicle R is a broadcast receiver of a transmitting vehicle S if the Euclidean distance between S and R, denoted by $D(S,R)$, is no more than the communication range of S, denoted by $D_S$. Focusing on predictable co-channel interference control in broadcast scheduling, we assume that all vehicles share a single communication channel and that the broadcast transmission power is fixed for each vehicle even though different vehicles may use different transmission powers; multi-channel scheduling and broadcast power control are relegated as future research.

PRK interference model & PRKS. Despite decades of research in interference-oriented channel access scheduling, most existing literature are either based on the protocol interference model or the physical interference model, neither of which is a good foundation for distributed interference control in the presence of uncertainties [28], [29]. The protocol model is local and suitable for distributed protocol design, but it is inaccurate and does not ensure reliable data delivery [17]. The physical model has high-fidelity, but it is non-local and combinatorial and thus not suitable for distributed protocol design in dynamic, uncertain network settings [28], [29]. To bridge the gap between the existing interference models and the design of distributed, field-deployable scheduling protocols with predictable communication reliability, Zhang et. al [28] have identified the physical-ratio-K (PRK) interference model that integrates the protocol model’s locality with the physical model’s high-fidelity. In the PRK model, a node C’ is regarded as not interfering and thus can transmit concurrently with the transmission from another node S to its receiver R if and only if $P(C’,R) > \frac{K_{S,R}T_{S,R}}{P(S,R)}$, where $P(C’,R)$ and $P(S,R)$ is the average strength of signals reaching R from C’ and S respectively, $K_{S,R,T_{S,R}}$ is the minimum real number chosen such that, in the presence of cumulative interference from all concurrent transmitters, the probability for R to successfully receive packets from S is no less than the minimum link reliability $T_{S,R}$ required by applications.

For predictable interference control, the parameter $K_{S,R,T_{S,R}}$ of the PRK model needs to be instantiated for every link $(S,R)$ according to in-situ, potentially unpredictable network and environmental conditions (e.g., data traffic load and wireless signal power attenuation). To
In this end, Zhang et al. [29] have formulated the PRK model instantiation problem as a regulation control problem where the “plant” is the link $\langle S, R \rangle$, the “reference input” is the required link reliability $T_{S,R}$, the “output” is the actual link reliability $Y_{S,R}$ from $S$ to $R$, the “control input” is the PRK model parameter $K_{S,R,T_S,R}$, and the objective of the regulation control is to adjust the control input so that the plant output is no less than the reference input. Then control theory can be used to derive the controller for instantiating the PRK model parameter [29]. For every link $\langle S, R \rangle$, using its instantiated PRK model parameter $K_{S,R,T_S,R}$ and the local signal maps that contain average signal power between $S, R$, and every other close-by node $C$ that may interfere with the transmission from $S$ to $R$, link $\langle S, R \rangle$ and every close-by node $C$ become aware of their mutual interference relations. With precise awareness of mutual interference relations with close-by nodes/links, nodes schedule data transmissions in a TDMA fashion using the distributed optimal-node-activation-multiple-access (ONAMA) algorithm [15], and the resulting PRK-based scheduling protocol is denoted as PRKS [29]. Through extensive measurement study in the high-fidelity Indriya [4] and NetEye [8] wireless network testbeds, Zhang et al. [29] observe that PRKS enables predictable interference control while achieving high channel spatial reuse. Accordingly, PRKS enables predictable link reliability, high network throughput, and low communication delay [29].

III. OVERVIEW OF CPS

A major challenge in applying PRK-based scheduling to V2V networks is vehicle mobility. Vehicle mobility makes inter-vehicle wireless channels highly dynamic, thus, as we will analyze in Section IV-A, it would be too costly or even infeasible for vehicles to maintain accurate signal maps that store reception power of data signals between close-by vehicles, thus making the PRK interference model and the PRKS scheduling protocol not applicable to V2V networks. To address this challenge, we observe that the physical vehicle locations are readily available in V2V networks through GPS and/or other mechanisms such as simultaneous-localization-and-mapping (SLAM). Accordingly, we propose the gPRK interference model as a geometric approximation of the PRK model, so that the gPRK model enables lightweight approaches for vehicles to detect their mutual interference relations using vehicle locations instead of signal maps. Vehicle mobility also makes vehicle locations and thus inter-vehicle interference relations highly dynamic. For enabling vehicles to accurately track their mutual interference relations, we propose to leverage spatiotemporal interference correlation and macroscopic vehicle dynamics to quickly instantiate the gPRK model parameters of newly-established and transient links, and to leverage well-understood microscopic vehicle dynamics to track vehicle locations.

Using the above methods of leveraging cyber-physical structures of V2V networks (particularly, spatiotemporal interference correlation, correlated ER adaptation, physical vehicle location, as well as macro- and micro-sopic vehicle dynamics) to address vehicle mobility, vehicles can identify their mutual interference relations in an agile, distributed manner. Based on the mutual interference relations among vehicles, inter-vehicle communications can be scheduled in a TDMA manner similar to that in PRKS [29]. To realize the above methods, we propose the Cyber-Physical Scheduling (CPS) framework for inter-vehicle communications as shown in Figure 1. In this framework, time is divided into time slots, and, as in PRKS [29], the transmissions of control signaling packets (e.g., those containing gPRK model parameters, vehicle locations, and/or sender ERs) and data packets are separated in frequency or in time so that there is no interference between control packet transmission and data packet transmission. Through the exchange of control signaling packets, close-by vehicles discover one another and initialize the gPRK model parameters for the corresponding links. Based on feedback on the status (i.e., success or failure) of data packet transmissions, in-situ communication reliabilities are estimated and then gPRK model parameters are adapted on the fly. Together with estimated locations of close-by vehicles, the in-situ gPRK model parameters enable vehicles to detect their mutual interference relations. Based on in-situ interference relations, a maximal set of mutually non-interfering vehicles are scheduled to transmit their data packets at each time slot according to the distributed TDMA algorithm ONAMA [15].

From each vehicle’s perspective, immediately after it starts, it quickly discovers close-by vehicles, initializes related gPRK model parameters, and detects mutual interference relations with close-by vehicles; then, in parallel with data transmissions and using feedback on data transmission status (i.e., success or failure), the vehicle adapts its gPRK model parameters, and, with adaptive estimation of the locations of close-by vehicles, the vehicle adapts data transmission schedules according to in-situ interference relations with close-by vehicles. Figure 1 shows the timescales of different protocol actions in CPS. When a vehicle starts, it quickly performs neighbor-discovery at every time slot for a short period (e.g., 2 seconds), and then it maintains neighborhood information at a frequency of regular control packet transmissions (e.g., every 100 time slots). Given a vehicle and a link from a sending vehicle,
the gPRK model parameter is updated each time a new communication reliability estimation becomes available (e.g., every 1,000 time slots). Each vehicle updates its estimation of the locations of close-by vehicles and its interference relations with close-by vehicles every time slot, which enables the ONAMA-based scheduling of non-interfering concurrent transmitters at each time slot. In our implementation, we have set the duration of each time slot to be 2.5 milliseconds so that a data packet up to 1,500 bytes can be delivered in a time slot when the radio transmission rate is 6Mbps (i.e., the lowest transmission rate of the current 802.11p standard) and when operations other than the actual data transmission (e.g., composing the data packet) may take up to 0.5 millisecond in a time slot; accordingly, inter-vehicle interference relations and gPRK model parameters are updated every 2.5 milliseconds and about every 2.5 seconds respectively.

With the above overview of the CPS framework, next we elaborate on our approaches to addressing vehicle mobility in Section IV. For conciseness of presentation, our discussion will focus on a sender \( S \) and its receiver set \( R = \{ R : R \neq S \land D(S, R) < D_S \} \) unless mentioned otherwise.

### IV. Addressing Vehicle Mobility

#### A. Geometric Approximation of PRK Model

**Challenge of using PRK model in V2V networks.** As discussed in Section II, the definition of the PRK interference model is based on signal power between close-by nodes. To use the PRK model in data transmission scheduling, nodes need to maintain local signal maps so that interfering nodes and links can be aware of their mutual interference relations. For networks of no or low node mobility which Zhang et al. [29] have considered, the average signal power between nodes does not change at timescales such as seconds, minutes, or even hours. Accordingly, the frequency of signal map update and thus the overhead of signal map maintenance tends to be low for networks of no or low mobility [29]. For V2V networks, however, vehicle mobility makes average signal power between close-by vehicles fast-varying in nature, for instance, at the timescales of seconds or less. If we were to apply the PRK interference model to V2V networks, the local signal maps between close-by vehicles would need to be updated frequently. In particular, every vehicle \( R \) needs to frequently estimate the in-situ signal power from every other potentially interfering vehicle \( C \) to itself; after each estimation, \( R \) needs to share the newly estimated signal power \( P(C, R) \) with every other potentially interfering vehicle through control signalling packet exchange [29], which would introduce significant messaging overhead. As we derive in [14], for a typical network setting, Figure 2 shows the significant overhead of signal map maintenance in V2V networks. Considering that the current physical layer of the V2V communication standard IEEE 802.11p can only support a transmission rate of 6Mbps - 27Mbps, that the total bandwidth available to a set of mutually interfering vehicles is no more than the transmission rate, and that \( N \) (i.e., the number of interfering vehicles for a vehicle) may well be in the range of hundreds (e.g., in urban settings),

\[
D(C', R) > D(S, R)K_{S,R,T_{S,R}},
\]

where \( D(C', R) \) and \( D(S, R) \) is the geometric distance between \( C' \) and \( R \) and that between \( S \) and \( R \) respectively, \( K_{S,R,T_{S,R}} \) is the minimum real number chosen such that, in the presence of cumulative interference from all concurrent transmitters, the probability for \( R \) to successfully receive packets from \( S \) is no less than the minimum link reliability \( T_{S,R} \) required by applications. As shown in Figure 2, the gPRK model, denoted as the gPRK interference model. In the gPRK model, interference relations among vehicles are defined based on inter-vehicle distance instead of inter-vehicle signal power, and a vehicle \( C' \) is regarded as not interfering and thus can transmit concurrently with the transmission from another vehicle \( S \) to its receiver \( R \) if and only if

Figure 2 shows that the signal map maintenance overhead accounts for a significant portion or even exceed the total communication bandwidth of V2V networks. This implies that it is too costly or even infeasible to maintain accurate signal maps for PRK-based scheduling in V2V networks. Therefore, it is difficult, if not impossible, to directly apply the PRK interference model to data transmission scheduling in V2V networks.

**gPRK interference model.** In V2V network systems, vehicle locations are important factors for networked vehicle control, and thus they are readily available through GPS and/or other mechanisms such as simultaneous-localization-and-mapping (SLAM). Using vehicle locations, it is easy for vehicles to know the distances among themselves. To avoid the significant overhead (and sometimes infeasibility) of maintaining accurate signal maps in V2V networks and considering the fact that, on average, close-by vehicles tend to introduce higher interference signal power to one another than farther away vehicles, we propose to leverage the availability of vehicle location information to define a geometric approximation of the PRK interference model, denoted as the gPRK interference model. In the gPRK model, interference relations among vehicles are defined based on inter-vehicle distance instead of inter-vehicle signal power, and a vehicle \( C' \) is regarded as not interfering and thus can transmit concurrently with the transmission from another vehicle \( S \) to its receiver \( R \) if and only if

\[
D(C', R) > D(S, R)K_{S,R,T_{S,R}},
\]

where \( D(C', R) \) and \( D(S, R) \) is the geometric distance between \( C' \) and \( R \) and that between \( S \) and \( R \) respectively, \( K_{S,R,T_{S,R}} \) is the minimum real number chosen such that, in the presence of cumulative interference from all concurrent transmitters, the probability for \( R \) to successfully receive packets from \( S \) is no less than the minimum link reliability \( T_{S,R} \) required by applications. As shown in Figure 3, the gPRK model defines, for each link \( (S, R) \), an exclusion region (ER) \( E_{S,R,T_{S,R}} \) around the receiver \( R \) such that a node \( C \) is in the region (i.e., \( C \in E_{S,R,T_{S,R}} \)) if and only if \( D(C, R) \leq D(S, R)K_{S,R,T_{S,R}} \).
Similar to the PRK model, the gPRK model is local since only local, pairwise interference relations are defined between close-by vehicles. Similar to the PRK model and unlike the protocol interference model which is not adaptive to network and environmental conditions and thus unable to ensure predictable interference control, the gPRK model is suitable for reliable inter-vehicle communication since it ensures the application-required link reliability by adapting parameter \( K \) according to in-situ network and environmental conditions and by considering wireless communication properties such as cumulative interference. Unlike the PRK model where the ER around a link may be of an irregular shape due to anisotropic wireless signal propagation, the ER around a link in the gPRK model is of the regular shape of a disk. As we elaborate in detail in [14], this difference between the gPRK model and PRK models becomes insignificant for inter-vehicle broadcast for the following reasons: firstly, the exclusion region of a broadcast is the union of the exclusion regions of all the links from the broadcast sender to the individual receivers, as we will discuss in detail shortly; secondly, a vehicle in the PRK-based (or gPRK-based) exclusion region of a link \( S,R \) may still be in the gPRK-based (or PRK-based) exclusion region of another link \( l_j \) (\( j \neq i \)) and thus in the gPRK-based (or PRK-based) exclusion region of the broadcast.

With the gPRK model, a vehicle only needs to share its location with potentially interfering vehicles in order for an interfering vehicle to detect their mutual interference relation using the gPRK model parameter \( K \), and a vehicle does not need to share with other vehicles the signal power from every other potentially interfering vehicle to itself. As we show in [14], this enables orders of magnitude reduction in control signaling overhead, which in turn makes it feasible and efficient to use the gPRK model in real-world V2V networks.

### gPRK Model Adaptation

Similar to the PRK model, the parameter \( K_{S,R,T,S,R} \) of the gPRK model needs to be instantiated for every link \( \langle S,R \rangle \) according to in-situ network and environmental conditions such as vehicle spatial distribution and wireless signal power attenuation. To this end, we use the control-theoretic approach of Zhang et al. [29] that, upon a feedback on the link reliability of \( \langle S,R \rangle \) at a time instant \( t \), denoted by \( Y_{S,R}(t) \), computes the change of cumulative interference power at the receiver \( R \), denoted by \( \Delta I_R(t) \), that the change of \( K_{S,R,T,S,R} \) at time \( t \) needs to introduce to make \( Y_{S,R}(t+1) = T_{S,R} \) at the next time instant \( t+1 \). In particular, letting \( y(t) = cy(t-1) + (1-c)Y_{S,R}(t) \) (\( 0 \leq c < 1 \)), \( \Delta I_R(t) \) is computed as follows:

\[
\Delta I_R(t) = \frac{(1+c)y(t) - cy(t-1) - T_{S,R}}{(1-c)a(t)} - \mu_U(t),
\]

where \( a(t) = \frac{T_{S,R} - Y_{S,R}(t)}{f^{-1}(Y_{S,R}) - f^{-1}(Y_{S,R}(t))} \). \( f(.) \) is the radio model function that defines the relation between link reliability \( Y_{S,R}(t) \) and the signal-to-interference-plus-noise-ratio (SINR) at the receiver \( R \) at time \( t \), and \( \mu_U(t) \) denotes the mean change of the cumulative interference power that vehicles not in \( E_{S,R,T,S,R}(t) \cup E_{S,R,T,S,R}(t+1) \) introduce to the receiver \( R \) from time \( t \) to \( t+1 \).

Since the receiver \( R \) can locally measure or estimate \( y(t), y(t-1), a(t) \), and \( \mu_U(t) \) [29], \( R \) can locally compute \( \Delta I_R(t) \). After computing \( \Delta I_R(t) \) at time \( t \), \( R \) needs to compute \( K_{S,R,T,S,R}(t+1) \) so that the expected link reliability is no less than \( T_{S,R} \) when the PRK model parameter is \( K_{S,R,T,S,R}(t+1) \) and, when the PRK model parameter is \( \min\{K_{S,R,T,S,R}(t), K_{S,R,T,S,R}(t+1)\} \), the expected interference introduced to \( R \) by the nodes in either \( E_{S,R,T,S,R}(t) \) or \( E_{S,R,T,S,R}(t+1) \) but not in both is as close to \( |\Delta I_R(t)| \) as possible to ensure as high channel spatial reuse as possible.

To realize the above design, we define, for each node \( C \) that may be included in the exclusion region of \( R \) during network operation, the expected interference \( I(C,R,t) \) that \( C \) introduces to \( R \) when \( C \) is not in the exclusion region of \( R \). Then \( I(C,R,t) = \beta_C(t)P(C,R,t) \), where \( \beta_C(t) \) is the probability for \( C \) to transmit data packets at time \( t \); \( P(C,R,t) \) is the power strength of the data signals reaching \( R \) from \( C \), and \( R \) can estimate \( P(C,R,t) \) and \( \beta_C(t) \) by passively monitoring the control signaling packets transmitted by \( C \) without introducing additional control signal packets [29]. Considering the discrete nature of node distribution in space and the requirement on satisfying the minimum link reliability \( T_{S,R} \), we propose the following rules for computing \( K_{S,R,T,S,R}(t+1) \):

- **Rule-ER0**: If \( \Delta I_R(t) = 0 \), let \( K_{S,R,T,S,R}(t+1) = K_{S,R,T,S,R}(t) \).
- **Rule-ER1**: If \( \Delta I_R(t) < 0 \) (i.e., need to expand the exclusion region), let \( E_{S,R,T,S,R}(t+1) = E_{S,R,T,S,R}(t) \cup E_{S,R,T,S,R}(t+1) \), then keep adding nodes not already in \( E_{S,R,T,S,R}(t+1) \) in the non-decreasing order of their distance to \( R \); into \( E_{S,R,T,S,R}(t+1) \) until the node \( B \) such that adding \( B \) into \( E_{S,R,T,S,R}(t+1) \) makes \( \sum_{C \in E_{S,R,T,S,R}(t+1) \setminus E_{S,R,T,S,R}(t)} I(C,R,t) \geq |\Delta I_R(t)| \) for the first time. Then let \( K_{S,R,T,S,R}(t+1) = \frac{D(B,R,t)}{D(S,R,t)} \), where \( D(B,R,t) \) and \( D(S,R,t) \) denote the distance from \( B \) to \( S \) to \( R \) at time \( t \) respectively.
- **Rule-ER2**: If \( \Delta I_R(t) > 0 \) (i.e., need to shrink the exclusion region), let \( E_{S,R,T,S,R}(t+1) = E_{S,R,T,S,R}(t) \setminus E_{S,R,T,S,R}(t+1) \), then keep removing nodes out of \( E_{S,R,T,S,R}(t+1) \), then in the non-increasing order of their distance to \( R \), until the node \( B \) such that removing any more node after removing \( B \) makes \( \sum_{C \in E_{S,R,T,S,R}(t) \setminus E_{S,R,T,S,R}(t+1)} I(C,R,t) > |\Delta I_R(t)| \) for the first time. Then let \( K_{S,R,T,S,R}(t+1) = \frac{D(B,R,t)}{D(S,R,t)} \).

For convenience, we call the above rules the **gPRK-model-adaptation rules.** (An example of gPRK model adaptation

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1 In protocol implementation, the actual time interval between time instants \( t \) and \( t+1 \) is the time interval for \( R \) to compute its \((t+1)\)-th sample of communication reliability along \( \langle S,R \rangle \).

2 Due to the discrete nature of node distribution, the resulting link reliability may be slightly higher than the required reliability \( T_{S,R} \) instead of being exactly \( T_{S,R} \).
Due to vehicle Agile model instantiation for new links. Reliable broadcast is a well-known challenge because, even though acknowledgments from receivers are required for many reliability-enhancement mechanisms such as ACK/negative-ACK-based retransmission of lost packets and RTS/CTS-based collision avoidance in medium access control, it is difficult for a sender to reliably and efficiently get an acknowledgment from every receiver, especially when the number of receivers is large in V2V networks (e.g., up to hundreds).

To address the challenge, we observe that, to ensure a minimum broadcast reliability $T_S$ for a sender $S$, we need to make sure that the communication reliability along the link from $S$ to every one of its receiver $R_i \in \mathcal{R}$ is at least $T_S$. This fact enables us to define, for a broadcast sender $S$, a receiver exclusion region (ER) $\mathcal{E}_{S,R_i,T_S}$ for every receiver $R_i \in \mathcal{R}$ based on the gPRK model. Accordingly, we define the sender ER for $S$, denoted by $\mathcal{E}_{S,T_S}$, as the union of its corresponding receiver ERs; that is, $\mathcal{E}_{S,T_S} = \bigcup_{R_i \in \mathcal{R}} \mathcal{E}_{S,R_i,T_S}$. Based on the definition of the sender ER, the broadcast reliability of $T_S$ is ensured as long as no node in $\mathcal{E}_{S,T_S}$ transmits concurrently with sender $S$.

### B. gPRK Modeling with Vehicle Mobility

Vehicle mobility makes network topology and interference relations highly dynamic (especially for vehicles on different roads or in opposite driving directions of a same road), and this challenges the instantiation and use of the gPRK model in V2V networks. In what follows, we elaborate on our design that addresses the challenges by effectively leveraging cyber-physical structures of V2V networks, particularly, the spatiotemporal interference correlation as well as macro- and micro-scorpio vehicle dynamics.

#### Agile model instantiation for new links.

Due to vehicle mobility and starting of vehicles, new links may form when vehicles come within one another’s communication ranges. The need for reliable inter-vehicle communication makes it desirable for the gPRK model parameters of the newly-formed links to quickly converge to their safe-state where application-required link reliabilities are ensured. To this end, it is desirable to initialize the gPRK model parameters of newly formed links close to where their safe-state may be, and we propose to leverage spatial interference correlation to accomplish this. More specifically, in large-scale wireless networks such as V2V networks, close-by links whose senders and receivers are close to one another respectively tend to experience similar interference power and similar set of close-by strong interferers, especially if the radii of their receiver-side exclusion regions (ERs) are similar. For the network setting of Section [IV] for instance, Figure [4] shows the empirical cumulative distribution function (CDF) of the correlation coefficient between the receiver-side interference power of any two links for which the inter-sender distance, the inter-receiver distance, and the difference in the radii of receiver-side ERs are no more than 30 meters. We see that the correlation coefficient tends to be large. This spatial interference correlation enables us to develop mechanisms for accurate gPRK model initialization as below.

When a new link from $S_i$ to $R_i$, denoted by $\langle S_i, R_i \rangle$, is formed at time $t$, $R_i$ first checks whether there exists another sender vehicle $S_j (j \neq i)$ for which the gPRK model parameter $K_{S_j,R_i,T_{S_j,R_i}}(t)$ has converged to a safe state for link $\langle S_j, R_i \rangle$ (i.e., the communication reliability from $S_j$ to $R_i$ has met the requirement $T_{S_j,R_i}$). For convenience, we call the link $\langle S_j, R_i \rangle$ a self-reference link for $\langle S_i, R_i \rangle$. Let $\mathbb{S} = \{ S_j : \langle S_j, R_i \rangle \}$ be a self-reference link for $\langle S_i, R_i \rangle$, and let $S^*$ be the vehicle that is closest to $S_i$ out of all the vehicles in $\mathbb{S}$. $R_i$ then uses $(S^*, R_i)$ to initialize the gPRK model of $\langle S_i, R_i \rangle$ as follows: $R_i$ first sets the gPRK model parameter of $\langle S_i, R_i \rangle$ such that the ER of $\langle S_i, R_i \rangle$ is the same as that of $(S^*, R_i)$, and, based on the assumption that $R_i$ experiences similar interference power when senders $S^*$ and $S_i$ transmit to $R_i$ with the same ER around $R_i$ (i.e., $D(S^*, R_i)K_{S^*,R_i,T_{S^*,R_i}} = D(S_i, R_i)K_{S_i,R_i,T_{S_i,R_i}}$), $R_i$ then uses the gPRK-model-adaptation rules to adjust the model parameter of $\langle S_i, R_i \rangle$ to accommodate the differences between $\langle S_i, R_i \rangle$ and $(S^*, R_i)$. More specifically, $R_i$ first sets $K_{S_i,R_i,T_{S_i,R_i}}(t) = D(S^*, R_i)K_{S^*,R_i,T_{S^*,R_i}}(t)$, where $D(V_j, V_i)$ denotes the geometric distance between two vehicles $V_j$ and $V_i$ at time $t$; then $R_i$ computes $\Delta I_{R_i}(t) = P(S_i, R_i, t) - P(S^*, R_i, t) + P(S^*, R_i, t)\left(\frac{1}{T_{S_i,R_i}} - \frac{1}{T_{S^*,R_i}}\right)$, where $P(V_j, V_i)$ denotes the signal power from vehicle $V_j$ to $V_i$ at time $t$, the term $P(S_i, R_i, t) - P(S^*, R_i, t)$ accounts for the difference in tolerable interference due to different signal power from $S^*$ and $S_i$, and the term $P(S_i, R_i, t)\left(\frac{1}{T_{S_i,R_i}} - \frac{1}{T_{S^*,R_i}}\right)$ accounts for the change in tolerable interference when the communication reliability requirement by $\langle S_i, R_i \rangle$ changes from $T_{S^*,R_i}$ to $T_{S_i,R_i}$; finally $R_i$ applies the gPRK-model-adaptation rules (as discussed in Section [V-A]) to adjust the value of $K_{S_i,R_i,T_{S_i,R_i}}(t)$, and the final value of $K_{S_i,R_i,T_{S_i,R_i}}(t)$ is set as the initial gPRK model parameter for the newly formed link $\langle S_i, R_i \rangle$.

If there exists no self-reference link for $\langle S_i, R_i \rangle$ when it newly forms (e.g., when vehicle $R_i$ just got started), $R_i$ tries to identify a neighbor-reference link $\langle S_j, R_i \rangle (j \neq i)$ such that the gPRK model parameter $K_{S_j,R_i,T_{S_j,R_i}}(t)$ has converged to a safe state, and $D(S_j, S_i, t)$ as well as $D(R_j, R_i, t)$ are less than a threshold $D_0$, where
$D_0$ is chosen such that links $\langle S_j, R_i \rangle$ and $\langle S_i, R_i \rangle$ experience similar interference power when the radii of their ERs are the same (i.e., $D(S_j, R_j)K_{S_j, R_j, T_{S_j, R_j}} = D(S_i, R_i)K_{S_i, R_i, T_{S_i, R_i}}$). Let $\mathcal{L} = \{ \langle S_j, R_j \rangle : \langle S_j, R_i \rangle$ is a neighbor-reference link for $\langle S_i, R_i \rangle \}$, define the distance between two links $\langle S_j, R_j \rangle$ and $\langle S_i, R_i \rangle$ at time $t$ as $\max\{D(S_j, S_i, t), D(R_j, R_i, t)\}$, and let $\{S^*, R^*\}$ be the link closest to $\langle S_i, R_i \rangle$ among all the links in $\mathcal{L}$. $R_i$ then uses $\{S^*, R^*\}$ to initialize the gPRK model for $\langle S_i, R_i \rangle$ as in the case of estimation via self-reference links as discussed above.

Leveraging the spatial correlation between $\langle S_i, R_i \rangle$ and its self-reference and neighbor-reference links, the above gPRK model initialization mechanism enables good approximation of the safe-state gPRK model parameter of $\langle S_i, R_i \rangle$ in normal and heavy vehicle traffic settings where there are usually enough number of surrounding vehicles/links around $\langle S_i, R_i \rangle$. In the case of very light vehicle traffic settings (e.g., at 3 a.m.), there may exist no self-reference link nor neighbor-reference link for a newly formed link $\langle S_i, R_i \rangle$. In this case, vehicles are sparsely distributed, cumulative interference from far-away vehicles tends to be small, and the exclusion region (ER) tends to be smaller than in the case of normal and heavy vehicle traffic settings. Accordingly, $R_i$ can approximate its safe-state gPRK model parameter by only considering pairwise interference among close-by vehicles. More precisely, $R_i$ sets the initial value of the gPRK model parameter such that the initial ER around itself includes every vehicle whose transmission alone, concurrent with the transmission from $S_i$ to $R_i$, can make the communication reliability drop below $T_{S_i, R_i}$.

**Agile model instantiation for transient links.** For an established link $\langle S_i, R_i \rangle$ where $S_i$ and $R_i$ are on different roads or in opposite driving directions of the same road, the link may be transient since the relative position between $S_i$ and $R_i$ and thus the link properties between them may change significantly during an update interval of the gPRK model parameter (e.g., every 2.5 seconds). In this case, the gPRK-model-adaptation rules of Section V-A won’t be agile enough to track the gPRK model parameter of $\langle S_i, R_i \rangle$. Thus we propose to treat the transient link between $S_i$ and $R_i$ as a “new” link from one time slot to the next and use the gPRK model initialization approach presented above to instantiate the gPRK model parameter of $\langle S_i, R_i \rangle$. In normal and heavy vehicle traffic settings, vehicles of the same traffic flow (i.e., vehicle traffic along the same direction of a road segment) tend to form clusters depending on their speed, with the vehicles in the same cluster having approximately equal speed and relatively stable spatial distribution, and this clustering behavior applies to both free-flow and congested traffic and for both highways and urban roads. With spatiotemporal constraints on vehicle movement along a traffic flow, vehicle cluster membership tends to last at timescales from seconds to minutes or even longer. The relative stability of intra-cluster vehicle spatial distribution and cluster membership make the gPRK-model-adaptation rules applicable to the links between vehicles of the same cluster, and these stable links can serve as the self-reference and neighbor-reference links for other transient links, thus enabling online, adaptive instantiation of the gPRK model parameters of transient links. In the case of very light vehicle traffic where there may exist no self-reference nor neighbor-reference link for a transient link $\langle S_i, R_i \rangle$, the gPRK model parameter of $\langle S_i, R_i \rangle$ may be instantiated by considering pairwise interference as discussed earlier.

Another type of transient link $\langle S_i, R_i \rangle$ exists when $R_i$ repeatedly moves in and out of the communication range of $S_i$. In this case, if the interval between $R_i$ moving out of and then back into the communication range of $S_i$ is small (e.g., less than 2 seconds), then $\langle S_i, R_i \rangle$ can retain its last gPRK model parameter considering the temporal correlation of interference at the receiver $R_i$ (as we elaborate in more detail in [14]); if the interval is large, $\langle S_i, R_i \rangle$ can be treated as a new link, and its gPRK model parameter can be initialized using the gPRK model initialization method discussed earlier.

**Effective use of gPRK model.** In order for vehicles to use the gPRK model to detect their mutual interference relations in a distributed manner, close-by, potentially interfering vehicles need to be aware of one another’s locations. A vehicle can update and share its location with close-by vehicles by broadcasting its location periodically. In the presence of high vehicle mobility, however, the relative positions of two vehicles may change in an non-negligible manner during the broadcast intervals. For instance, even if the location information is updated every half a second, the distance between two vehicles driving at a speed of 80km/h (i.e., 50mph) along the opposite directions of a road may change 22.22 meters during the update interval. In order for vehicles to have accurate information about one another’s locations during update intervals and with limited location update frequencies, we propose to have vehicles estimate one another’s locations during update intervals. For accurate estimation of vehicle locations, it is important to have a good model for vehicle location dynamics.

Fortunately, vehicle dynamics have been studied extensively in traffic flow theory, and the intelligent-driver-model (IDM) as well as its extensions have been shown to be able to accurately model real-world, microscopic vehicle dynamics. Using the IDM model and by treating vehicle location as a part of the “state” of a vehicle, we can derive the dynamic model of the vehicle. (Details of the derivation can be found in [14].) Given that the model is nonlinear, we use the Unscented Kalman Filter (UKF) to estimate vehicle locations. By treating the model parameters as a part of the system state and introducing random walks to the parameter evolution, the microscopic model can also be adapted according to the individual driving behavior of vehicles in different real-world settings. Besides vehicle location estimation, the above approach to vehicle location estimation can be applied to a vehicle itself to filter out its own location measurement errors for improved localization accuracy.

The IDM model focuses on the longitudinal movement of a vehicle along a specific lane, and it does not directly
model behavior such as lane change and turn. Since it is more difficult to model those behavior accurately, we propose, for effectiveness of real-world deployment, not to explicitly model those behavior and resort to event-based quick diffusion of vehicle state to address the impact of lane change and turn; that is, a vehicle immediately shares its new location right after it changes lane or turns. Together, these mechanisms enable vehicles to be aware of one another’s locations, thus enabling the effective use of the gPRK model in V2V networks.

V. EXPERIMENTAL ANALYSIS

Considering the lack of large-scale, field-deployed V2V network testbeds for evaluating link layer scheduling mechanisms, we implement our CPS scheduling framework in the widely-used ns-3 network simulator, and we experimentally analyze the behavior of CPS by integrating high-fidelity ns-3-based wireless network simulation and SUMO-based vehicle dynamics simulation.

A. Methodology

Multi-dimensional high-fidelity simulation. High-fidelity simulation of V2V networks requires high-fidelity simulation of V2V wireless channels and vehicle mobility dynamics. For V2V wireless channels, we implement in ns-3 a channel model based on real-world measurement data that capture large-scale path loss, small-scale fading, and real-world complexities such as anisotropic, asymmetric wireless signal attenuation. For vehicle mobility dynamics, we use the SUMO simulator that simulates vehicle traffic flow dynamics at high-fidelity based on real-world road and traffic conditions of Detroit, Michigan, USA. For integrated, high-fidelity simulation of V2V wireless channels and vehicle mobility, we integrate SUMO simulation with ns-3 simulation through the traffic control interface (TraCI) of SUMO.

CPS assumes that each vehicle has a location sensor (e.g., GPS and/or SLAM) which reports its real-time locations. To simulate location measurement errors, our experimental analysis assumes that the error is a Gaussian variate with zero mean and a standard deviation of four meters, a localization accuracy achievable by today’s GPS systems.

Protocols. To understand the benefits of CPS in scheduling inter-vehicle communications, we comparatively study the following representative V2V network protocols:

- **802.11p**: the MAC protocol of the IEEE 802.11p standard which uses CSMA/CA to coordinate channel access and interference control. This is the MAC protocol used in existing field deployments of DSRC implementations (e.g., those by USDOT).
- **DCC**: an ETSI standard that, on top of the 802.11p protocol, uses congestion, power, and rate control to mitigate inter-vehicle interference and improve communication reliability.
- **AMAC**: the ADHOC MAC protocol which is a slot-reservation-based TDMA protocol based on the protocol interference model. In the protocol, vehicles transmit in their reserved slots without carrier sensing. If collisions are detected in a certain time slot of the TDMA frame, vehicles will release the slot and reserve another slot.
- **VDDCP**: a TDMA-based MAC protocol that, based on the protocol interference model, first allocates non-overlapping sets of time slots to different roads and then let vehicles on each road compete for channel access in a slot-reservation-based TDMA manner as in AMAC.

To understand the benefits of the geometric approximation of the PRK model by the gPRK model, we also study a variant of CPS, denoted as OCPS (for Oracle CPS), that is the same as CPS except for its use of the PRK model. In OCPS, we assume that, after a vehicle has a new estimate for the signal power $P(C, R)$ from another vehicle $C$ to itself, the newly estimated $P(C, R)$ is known to every other potentially interfering vehicle through some oracle without requiring any control signalling packet exchange as we have discussed in Section IV-A; this way, the costly and sometimes infeasible signal-map-related control signalling overhead is gone, and OCPS can be executed in our simulation environment.

**Network settings.** For understanding protocol behavior in real-world settings, we consider an urban network consisting of vehicles in midtown Detroit of Michigan, USA. As shown in Figure 5, the urban network consists of freeway I-75 and city roads in midtown Detroit, and it spans an area of 3km $\times$ 3km. In the network, vehicle speed limits range from 40km/h (i.e., 25mph) on small city streets to 120km/h (i.e., 75mph) on I-75. Our study considers normal vehicle traffic flow conditions, and the average bumper-to-bumper distance ranges from one meter to 20 meters.

We set the desired broadcast communication range as 150 meters and the desired broadcast reliability as 90%. For protocols that do not use transmission rate and power control (i.e., protocols other than DCC), the transmission rate is set as 6Mbps, and the transmission power is set at a value that ensures that the signal-to-noise ratio (SNR) in the absence of interference is 6dB above the SNR for ensuring 90% communication reliability for links of length 150 meters. Each vehicle transmits a data packet every 100 milliseconds, a frequency needed for many active safety and networked vehicle control applications in V2V networks. The size of each data packet is 1,500 bytes.

We have experimented with other network settings such as on freeways and when the broadcast reliability requirement is 95%. We have observed phenomena similar to what we will present in Section V-B due to the limitation of space, we relegate the detailed discussion to.

**B. Experimental Results**

**CPS vs. existing protocols.** For different protocols, Figure 6 shows the boxplot of communication reliability from each vehicle to its receivers. Figure 7 shows the concurrency (i.e., number of concurrent transmissions) in the network. Figure 8
Enabling accurate, agile identification of interference relations among vehicles, our gPRK-based cyber-physical approach to interference modeling and transmission scheduling ensures predictable interference control and application-required broadcast reliability, as shown in Figure 6. Implicitly assuming a protocol interference model and using a contention-based approach to medium access control, 802.11p and DCC do not ensure predictable control of interference and thus do not ensure application-required communication reliability. Through congestion, power, and rate control, DCC improves the reliability of 802.11p, but the broadcast reliability is still quite low in DCC (i.e., being ~6% in our study). Assuming an inaccurate protocol interference model and unable to address the challenge of high vehicle mobility to TDMA scheduling, the TDMA protocols AMAC and VDDCP cannot ensure predictable interference control, and the communication reliability from senders to receivers tend to be quite unpredictable, ranging from very low to very high and varying over time. In AMAC and VDDCP, the slot reservation tends to be unreliable in the presence of vehicle mobility and inter-vehicle interference, thus the concurrency in AMAC and VDDCP tends to be quite low too, as shown in Figure 7. The fact that the reliability is unpredictable while the concurrency is low in AMAC and VDDCP demonstrates the importance of accurately identifying inter-vehicle interference relations in an agile manner in the presence of vehicle mobility, as is accomplished in our CPS framework.

The concurrency in 802.11p and DCC is the highest among all the protocols, but their throughput is quite low due to the low communication reliability in both protocols, as shown in Figures 8 and 9. Due to the low concurrency and the unpredictable, often-low communication reliability in AMAC and VDDCP, the throughput is low in both protocols. Ensuring application-required reliability while maximizing channel spatial reuse, CPS enables significantly higher throughput than other protocols do.

To improve communication reliability, retransmission is needed in other protocols, which significantly increases the communication delay, as shown in Figure 9. The low concurrency and the unpredictable communication reliability in AMAC and VDDCP make their communication delay the largest among all the protocols.

CPS vs. OCPS. Figure 10 shows the empirical cumulative distribution function (CDF) of the communication reliability from each vehicle to its receivers in CPS and OCPS. We see that OCPS achieves a much higher communication reliability than other existing protocols, with the minimum communication reliability being 75% and the reliability being no less than the required 90% for about 85% of the links from a broadcast sender to its receivers. Nonetheless, the communication reliability of about 15% of the links is less than the required 90% in OCPS, while CPS ensures the required reliability for all the links. The reason for this is because, in OCPS, even though the existence of an oracle addresses the signalling overhead challenge in PRK-based scheduling, it is still difficult to precisely track the highly-dynamic signal power from one vehicle to another in the presence of vehicle mobility, which makes it difficult to precisely track inter-vehicle interference relations and thus difficult to ensure predictable communication reliability. In CPS, the gPRK model and the precise tracking of vehicle locations through well-understood vehicle dynamics enable precise tracking of inter-vehicle interference relations and thus enable predictable interference control and predictable communication reliability, showing the benefits of using the geometric approximation of the PRK model in V2V networks.

VI. RELATED WORK

IEEE 802.11p is a well-studied industry standard specifying the medium access control mechanisms for inter-vehicle communication. Inheriting basic WiFi mechanisms such as CSMA and thus unable to ensure predictable interference control, 802.11p-based solutions do not ensure predictable link reliability [16], [29]. To improve the reliability of inter-vehicle communications, schemes that control information exchange load as well as packet transmission power and rate have been proposed [22]. Not addressing the fundamental limitations of CSMA in interference control, these schemes lead to the loss of network throughput and increase in communication delay while still being unable to ensure predictable communication reliability [29], as we have shown in Section V.

TDMA schemes [2], [8] have also been proposed for inter-vehicle communications. Based on the protocol interference model which is inaccurate and cannot ensure predictable interference control, however, these schemes cannot ensure pre-
dictable communication reliability. Multi-scale schemes have also been proposed to first allocate non-overlapping sets of time slots to different roads and then let vehicles on each road compete for channel access in a TDMA manner [13], [20], [11]. Assuming a protocol interference model in both road-level scheduling and vehicle-level scheduling, however, these schemes do not ensure predictable communication reliability. Schemes have also been proposed to first partition space into geographic regions such as rectangles or hexagons and then schedule transmissions based on geographic regions [18], [24]. Assuming a protocol interference model, however, these schemes do not ensure predictable communication reliability either. Resource allocation mechanisms have also been proposed to improve communication throughput between vehicles as well as between vehicles and transportation infrastructures [30]. Focusing on network throughput, these work do not consider ensuring predictable, controllable reliability in vehicular communication, and, due to throughput-reliability tradeoff [23], the high throughput usually comes at the cost of low communication reliability.

VII. CONCLUDING REMARKS

For predictable reliability of inter-vehicle communications, we formulate and apply the gPRK interference model to predictable interference control in V2V networks. Our approach to gPRK-based interference modeling effectively leverages cyber-physical structures of V2V networks. Based on the cyber-physical, gPRK-based approach to interference modeling, our Cyber-Physical Scheduling (CPS) framework ensures predictable reliability of inter-vehicle communications. Ensuring predictable interference control and communication reliability in the presence of vehicle mobility, our cyber-physical approach to interference modeling and data transmission scheduling is expected to enable the development of mechanisms for predictable timeliness, throughput, and their tradeoff with reliability in inter-vehicle communications. While our focus in this study is on inter-vehicle communications, the basic methodologies can be extended to enable predictable communication reliability between vehicles and transportation infrastructures such as traffic lights. These are future directions worth pursuing.

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