Cyber-Physical Scheduling for Predictable Reliability of Inter-Vehicle Communications

Chuan Li⋆, Hongwei Zhang†, Jayanthi Rao‡, Le Yi Wang⋆, George Yin⋆
⋆Wayne State University, {chuan,lywang,gyin}@wayne.edu
†Iowa State University, hongwei@iastate.edu ‡Ford Research, jrao1@ford.com

***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, for lightweight control signaling and effective interference relation estimation, CPS leverages the physical locations of vehicles to define the gPRK interference model as a geometric approximation of the PRK model; for effective use of the gPRK model, CPS leverages cyber-physical structures of vehicle traffic flows, particularly, the spatiotemporal interference correlation as well as the macro- and micro-scopic vehicle dynamics. 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 [10], [16]. One basis for this vision of networked vehicle control (e.g., active safety and fuel economy control [10]) 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*, that is, satisfying the packet delivery ratios as required by vehicle control applications [26]. Given the different impact that communication reliability, delay, and throughput have on networked vehicle control [26], [25] and the inherent tradeoff between communication reliability, delay, and throughput [22], [27], the optimal operation of networked vehicle systems also requires controlling the tradeoff between communication reliability, delay, and throughput, for which controlling communication reliability in a predictable manner according to the vehicle control requirement is also a basis [20], [27].

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% [18], [28]. 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 [10]. 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 other, 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 [27] 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 [28] 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 (i.e., packet delivery ratio).*

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 explain the design of CPS in the rest of the paper.

II. Preliminaries

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) [10]. Given the significance of single-hop broadcast (e.g., for real-time networked vehicle control [10]) 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 (as defined by Che et. al [4]) 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 ratio (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 [27], [28]. The protocol model is local and suitable for distributed protocol design, but it is inaccurate and does not ensure reliable data delivery [19]. 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 [27], [28]. 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 [27] 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 $P(C',R) < \frac{P(S,R)}{K_{S,R,T_{S,R}}}$, where $P(C',R)$ and $P(S,R)$ are 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. As shown in Figure 1, the PRK model defines, for each link $\langle S,R\rangle$, an exclusion region (ER) $\mathbb{E}_{S,R,T_{S,R}}$ around the receiver R such that a node C is in the ER (i.e., $C \in \mathbb{E}_{S,R,T_{S,R}}$) if and only if $P(C,R) \geq \frac{P(S,R)}{K_{S,R,T_{S,R}}}$. Every node $C \in \mathbb{E}_{S,R,T_{S,R}}$ is regarded as interfering and thus shall not transmit concurrently with the transmission from S to R. The PRK model is generically applicable to different wireless networks since it only assumes that the packet delivery reliability along a link is a non-decreasing function of the signal-to-interference-plus-noise-ratio (SINR) at the receiver, which generally holds for wireless communications [27].

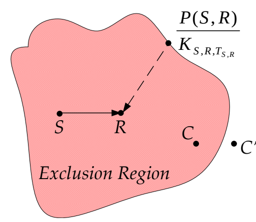

Fig. 1: PRK interference model

For predictable interference control, the parameter $K_{S,R,T_{S,R}}$ of the PRK model needs to be instantiated for every link $\langle S,R\rangle$ according to in-situ, potentially unpredictable network and environmental conditions (e.g., data traffic load and wireless signal power attenuation). To this end, Zhang et. al [28] have formulated the PRK model instantiation problem as a regulation control problem [8] 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 [28]. 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 [17], and the resulting PRK-based scheduling protocol is denoted as PRKS [28]. Through extensive measurement study in the high-fidelity Indriya [5] and NetEye [11] wireless network testbeds, Zhang et. al [28] 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 [28].

III. Cyber-Physical Scheduling (CPS) Framework

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 show in [15], 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 [15]. In the gPRK model, interference relations among vehicles are defined based on inter-vehicle distance, and nodes closer-by may be regarded as interfering with one another since they tend to introduce stronger interference to one another. In particular, 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

$$D(C', R) > D(S, R) K_{S,R,T_{S,R}}, \tag{1}$$

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 defines, for each link $\langle S, R\rangle$, an exclusion region (ER) $\mathbb{E}_{S,R,T_{S,R}}$ around the receiver R such that a node C is in the region (i.e., $C \in \mathbb{E}_{S,R,T_{S,R}}$) if and only if $D(C, R) \leq D(S, R)K_{S,R,T_{S,R}}$. As we show in [15], the gPRK model is amenable to distributed, feedback-control-theoretic approach to model instantiation, and the instantiated gPRK model captures the impact of complex vehicular wireless channels and potential vehicle localization errors (e.g., due to imperfect GPS).

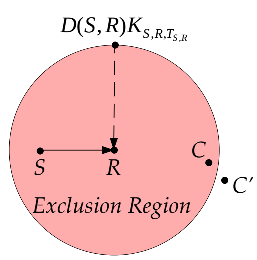

Fig. 2: gPRK model

Vehicle mobility also makes vehicle locations and thus inter-vehicle interference relations highly dynamic. For enabling vehicles to accurately identify their mutual interference relations, we propose to leverage *spatiotemporal interference correlation and macroscopic vehicle dynamics* to quickly adapt gPRK model parameters. In particular, 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 macroscopic clustering behavior applies to both free-flow and congested traffic and for both highways and urban roads [24]. 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 [6], [7], [21], [24], [9], [2]. The relative stability in cluster membership and intra-cluster vehicle spatial distribution makes it feasible to accurately instantiate/adapt the gPRK model parameters for the links between vehicles of the same cluster, and these stable links in turn enable online, adaptive instantiation of the gPRK model parameters of transient links by leveraging the spatial correlation between gPRK model parameters of close-by links as well as the temporal correlation of gPRK model parameters of a same link [15].

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 by leveraging well-understood *microscopic vehicle dynamics models* such as the intelligent-driver-model (IDM) and its extensions [15], [24].

Using the above methods of addressing vehicle mobility that leverage the cyber-physical structures of V2V networks (particularly, spatiotemporal interference correlation, physical vehicle location, as well as macro- and micro-scopic vehicle dynamics), 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 [28]. To realize the above methods, we propose the Cyber-Physical Scheduling (CPS) framework for inter-vehicle communications as shown in Figure 3. In this framework, time is divided into a consecutive sequence of time slots, with each time slot being long enough for completing the transmission and processing of a control or data packet. As in PRKS [28], the transmissions of control signaling packets (e.g., those containing gPRK model parameters and vehicle locations) and data packets are separated in frequency or in time so that there is no interference between control packet transmission

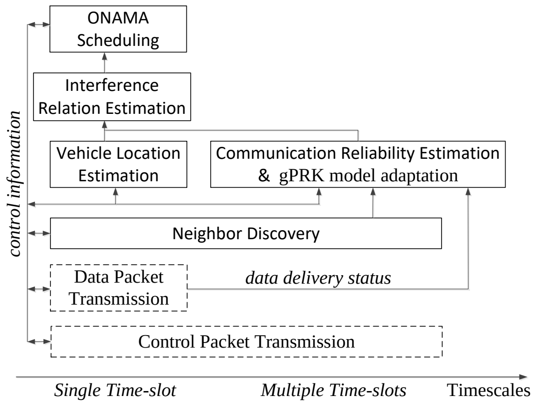

Fig. 3: Cyber-Physical Scheduling (CPS) framework

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 [17].

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 3 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.

IV. 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 [1] 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 [13].

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 multi-path fading, anisotropic, asymmetric wireless signal attenuation, and the impact of vehicles and surrounding objects (e.g., buildings, bridges) on vehicular wireless channels [12]. 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 [13]. 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, as shown in Figure 4. With the TraCI interface, ns-3 can query any desired information (e.g., locations of individual vehicles) from SUMO anytime. When a simulation starts, ns-3 first invokes SUMO with its local configuration files, as shown by link *a* of Figure 4; during a ns-3 simulation, ns-3 continuously queries vehicle state information (e.g., locations) from SUMO, as shown by link *b* of Figure 4.

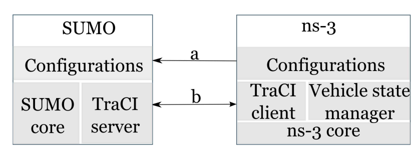

Fig. 4: Integration of SUMO with ns-3

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 [18]. 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 [23].
- *AMAC*: the ADHOC MAC protocol [3] 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 [14] 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 effectiveness 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. Interested readers can find the detailed discussion in [15].

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.

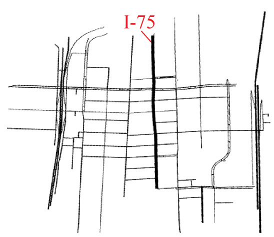

Fig. 5: V2V network in Detroit, Michigan, USA

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 [10]. 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 IV-B; due to the limitation of space, we relegate the detailed discussion to [15].

B. Experimental Results

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 at a time slot) in the network, Figure 8 shows the network throughput that is computed as the number of packets successfully delivered to receivers in every time-slot duration (i.e., 2.5ms), and Figure 9 shows the packet delivery delay when packet retransmission is used to ensure the application-required reliability for protocols that would be unable to ensure the application-required reliability otherwise (i.e., protocols other than CPS).

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. Moreover, this is achieved while having considered the complex, real-world vehicular wireless channels and vehicle localization errors as discussed in Section IV-A.

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 $\sim$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

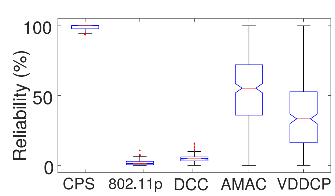

Fig. 6: Reliability

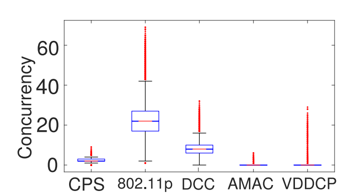

Fig. 7: Concurrency

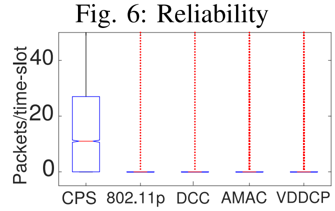

Fig. 8: Throughput

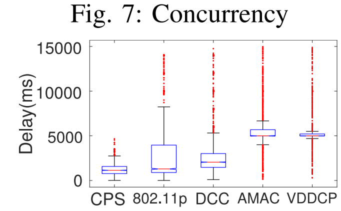

Fig. 9: Delay

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 6. 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.

V. 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, thus further enabling wireless-networked vehicle control [10], [16]. 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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