How Cars Talk Louder, Clearer and Fairer: Optimizing the Communication Performance of Connected Vehicles via Online Synchronous Control

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***Abstract*—The connected vehicles have been considered as a remedy for modern traffic issues, potentially saving hundreds of thousands of lives every year worldwide. The Dedicated Short-Range Communications (DSRC) technology is an essential building block of this promising vision. DSRC faces volatile vehicular environments, where not only wireless propagation channels but also network topologies vary rapidly. Moreover, traffic congestions during rush hours may lead to an unprecedentedly high density of broadcasting radios, resulting in compromised reliability, efficiency and fairness of DSRC.**

In order to optimize the performance of DSRC, we develop a novel Online Control Approach of power and Rates (OnCAR). Supported by systematic control theories, OnCAR performs stably even in the dynamic and unpredictable vehicular environments. To the best of our knowledge, OnCAR is the first solution to address the strong coupling between communication variables. It adopts a multi-variable control model to synchronously adjust transmission power and data rates, which are two major variables determining the performance of DSRC. In addition, OnCAR leverages receiver-side measurements of performance metrics to strike a balance between overall performance and fairness. Compared with the state of the art, OnCAR enhances the overall reliability and efficiency of DSRC by 23.7% and 30.1%, respectively. Meanwhile, these numbers are achieved with a 40.1% improvement in fairness.

I. Introduction

According to a study [1] led by the U.S. Department of Transportation (U.S. DOT), connected vehicles can avoid 74 percent of car crashes. This would save hundreds of thousands of lives and billions of dollars every year worldwide. To realize this promising vision, the U.S. DOT has committed to the use of Dedicated Short-Range Communications (DSRC) devices on new light-duty vehicles[1]. The DSRC technology enables a variety of safety-critical applications including adaptive cruise control, lane change assist, forward collision warning, and etc [2]. Reliability, efficiency and fairness of DSRC are major concerns for these new applications. While high reliability and efficiency bring a comprehensive understanding of traffic situations, good fairness protects overall safety from being jeopardized by a few vehicles oblivious to the surrounding.

Unlike its counterparts such as Wi-Fi and Zigbee [3], DSRC works in highly volatile vehicular environments. Rapid changes in wireless channels and network topology usually bring unpredictable disturbances. Moreover, traffic congestions during rush hours lead to communication congestions in the DSRC safety channel (i.e., Channel 172), compromising the driving safety. Rush hours are of vital importance, as the number of traffic accidents arrives its peak during them (statistics are to be presented in Section II).

To adapt to these unique environments, the transmission power and data rates (i.e., the modulation/coding rates) must be adjusted appropriately, as they are two fundamental variables dominating DSRC performance [4]. However, there is still a gap between the optimal performance and the performance provided by existing power and rate adaptation solutions. This is mainly due to the facts that 1) the strong coupling between communication variables has not been fully addressed, and that 2) heuristic algorithms have been adopted in volatile scenarios. Previous solutions either focus on the adaptation of one single variable (e.g., transmission power [5], [6] or data rates [7], [8]), or adjust them one by one [9], [10]. These sequential approaches could lead to error propagation in the two-stage variable adjustment, and thus performance degradation. In addition, heuristic algorithms may fail to provide consistent performance in highly dynamic environments.

Therefore, we are in need of a joint and online approach to control transmission power and data rates. This mission is non-trivial due to the following challenges. (i) The coupling between power and rates is implicit and hard to fully characterize in advance. (ii) Real-life traffic is dynamic, introducing rapid variations to network topology and wireless channels. (iii) The DSRC performance, especially the fairness, degrades due to the lack of feedback and coordination.

In order to allow connected vehicles to "talk" with each other louder (with increased efficiency), clearer (with enhanced reliability) and fairer (with improved fairness), we develop an **On**line **C**ontrol **A**pproach of power and **R**ates (OnCAR) based on systematic control theories. OnCAR takes the effective Packet Delivery Ratio (ePDR) as the metric of reliability and considers the effective throughput (eTPUT) as the metric of efficiency. It considers power and rate settings as inputs to the DSRC system, and takes ePDR and eTPUT as outputs that are adaptively and synchronously controlled by the inputs. In this way, OnCAR embraces the coupling in

[1]U.S. DOT, DSRC: The Future of Safer Driving, http://www.its.dot.gov/factsheets/dsrc_factsheet.htm.

its online Multiple-Input Multiple-Output (MIMO[2]) controller, and adapts to the traffic dynamics rapidly. At the same time, by adopting receiver-side measurements of these two metrics, OnCAR takes the performance of neighboring vehicles into consideration, and improves the fairness as well.

The **main contribution** of this paper is two-fold.

- We systematically study the critical problem of synchronous control of transmission power and data rates in DSRC. To the best of our knowledge, we are the first to tackle the strong coupling between power and rates in the context of connected vehicles.
- We develop OnCAR - an online control approach of power and rates for DSRC. OnCAR is fundamentally different from existing approaches in that it adjusts power and rates of DSRC in an adaptive, joint and synchronous manner based on systematic control theories. OnCAR improves the reliability, efficiency and fairness of DSRC by 23.7%, 30.1% and 40.1%, respectively.

The remainder of this paper is organized as follows. In Section II, we discuss two important observations that motivate our work, and present the challenges in developing OnCAR. In Section III, we present the design of OnCAR, and discuss how OnCAR tackles the challenges. In Section IV, we conduct trace-driven simulations to evaluate of OnCAR in large-scale networks and reveal several interesting findings. We discuss the related work in Section V, and conclude the paper in Section VI.

II. Observations and Challenges

A. Background of Dedicated Short-Range Communications

To foster the development of Vehicle Safety Communications (VSC), the DSRC technology has been actively promoted by the U.S. DOT. The most widely accepted DSRC protocol in North America employs IEEE 802.11p as its PHY and MAC layer standards [2]. There are several important features of the IEEE 802.11p based DSRC. First of all, DSRC functions in highly dynamic vehicular environments, where unpredictable disturbances may undermine DSRC performance. Secondly, among all the DSRC channels, Channel 172 is designated to exchange safety messages, which are broadcast with neither handshaking nor feedback. Furthermore, DSRC channel congestions can be really severe due to traffic jam during rush hours.

B. Observations and Challenges

In this paper, we consider **rush hours** (i.e., 16:00 to 20:00 in this paper) to be far more critical than other time periods. This is motivated by the following observation.

Observation 1: The number of traffic accidents arrives its peak during rush hours.

Observation 1 is supported by government sources such as Texas Motor Vehicle Crash Statistics[3], North Carolina Crash Data[4] and New York State Department of Motor Vehicles[5]. To

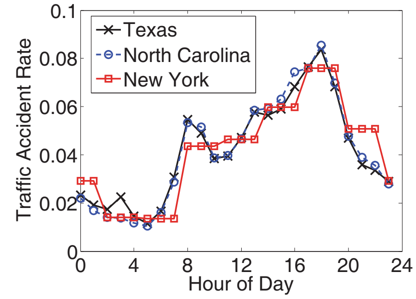


Fig. 1: Traffic accident rate across different time of day.

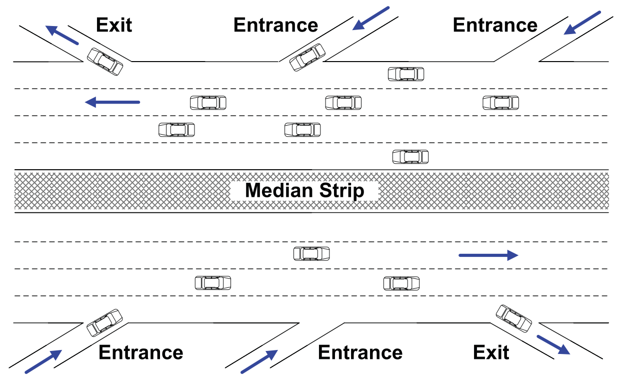


Fig. 2: The simulated highway scenario.

demonstrate and validate this observation, we use the crash data of year 2014 from Texas, and that of year 2013 from North Carolina and New York (the latest available data). Figure 1 presents the traffic accident rate, i.e., the percentage of traffic accidents, across different time of day. Figure 1 confirms Observation 1, as the peaks of traffic accident rates appear during rush hours for all three states. In addition, the shapes of accident rates are very similar in different states, indicating a strong correlation between traffic accident rate and time.

To improve DSRC performance during both rush and regular hours, the **coupling** between transmission power and data rates must be carefully considered. This is motivated by the second observation as follows.

Observation 2: The coupling between transmission power and data rates is implicit and complicated, and may lead to degraded performance of DSRC.

For example, higher transmission power could support higher data rates for higher DSRC throughput. Yet, it also intensifies the interference, to which higher data rates are vulnerable. Lower power could alleviate interference for better DSRC reliability. However, it only support lower data rates, which deliver less information for safety. In addition, packets with lower data rates may be more vulnerable to hidden terminals due to longer propagation delays. Such a correlation can hardly be captured by existing heuristics, resulting in degraded performance of DSRC.

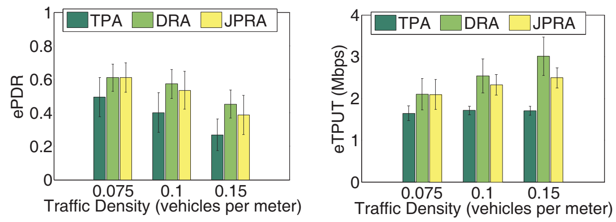
We further demonstrate Observation 2 with trace-driven ns-2 simulations in a bi-directional highway scenario as illustrated in Figure 2. This highway is of 2000 meters long and 30 meters wide with four lanes in each direction. There are two entrances and one exit along each direction.

[2]In this paper, the term MIMO refers to the multiple control inputs and control outputs of a control model [11].This is different from the concept of multiple antennas and multiple I/O data streams in wireless communications.

[3]http://www.txdot.gov/government/enforcement/annual-summary.html

[4]http://nccrashdata.hsrc.unc.edu

[5]http://dmv.ny.gov/about-dmv/statistical-summaries



(a) ePDR

(b) eTPUT

Fig. 3: Illustration of performance degradations due to negligence of the power-rate coupling.

We first implement a Transmission Power Adaptation (TPA) approach [5], [6] and a Data Rate Adaptation (DRA) approach [7], [8] (Both of them are state-of-the-art approaches on individual power or rate adaptation). TPA fixes the data rate as $3Mbps$ (the default data rate of DSRC) and adaptively adjusts transmission power. DRA fixes transmission power as $20dBm$ (the default power setting) and adaptively changes data rates. We then combine them sequentially to build a Joint Power and Rate Adaptation (JPRA) approach, which is extended from that proposed in [9]). JPRA first selects power based on TPA, and then chooses a rate based on DRA.

Figure 3 compares ePDR and eTPUT (i.e., metrics of reliability and efficiency, to be defined in Section II-C) of the three approaches under different traffic density conditions. We observe that the joint approach JPRA performs much worse than the individual approach DRA in terms of both ePDR and eTPUT. This result suggests that the data rates selected by JPRA are not well supported by the chosen transmission power. Adjusting these two variables one by one (which is common practice in existing solutions) can lead to a mismatched pair of power and rate settings.

This observation indicates that a good approach must calculate and conduct the adjustments of power and rates at the same time (i.e., *synchronously*), instead of changing them sequentially. To design such a joint and synchronous control approach for DSRC, we have to tackle several challenges.

Challenge 1: The coupling of variables, as well as their impacts on DSRC performance, is implicit and hard to be captured in advance.

Challenge 2: The vehicular environment is extremely volatile, introducing a variety of unpredictable disturbances to the control and adaptations of variables.

Challenge 3: Due to the high density during rush hours and the lack of coordination between vehicles, the overall fairness of DSRC is degraded by egocentric power/rate adaptations.

C. Metrics

In this paper, DSRC reliability is captured by the effective Packet Delivery Ratio (ePDR), DSRC efficiency is described by the effective throughput (eTPUT), and DSRC fairness is represented by the Coefficient of Variation (CV) of ePDR.

The ePDR of a vehicle i is defined as

$$\text{ePDR}_i = \frac{\sum_{j \in \Omega_i} N_r(i,j)}{\sum_{j \in \Omega_i} N_t(j)}, \tag{1}$$

where i and j are vehicle IDs, $N_t(j)$ denotes the number of packets transmitted by j, $N_r(i,j)$ represents the number of packets transmitted by j while successfully received by i, and Ω_i represents the set of neighbors within the effective range of i. Ω_i is expressed as

$$\Omega_i = \{j | j \neq i \ \text{ and } \ d(i,j) \leqslant d_{eff}\}, \tag{2}$$

where $d(i,j)$ is the distance between i and j.

The eTPUT of a vehicle i is defined as

$$\text{eTPUT}_i = N_r(i,j) \times \Gamma, \tag{3}$$

where Γ is the packet length of safety messages.

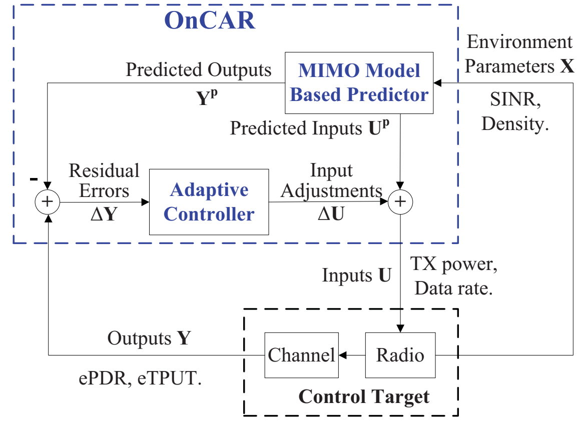


Fig. 4: Architecture of OnCAR.

III. Design of OnCAR

In this section, we present the design details of OnCAR. Note that OnCAR aims to improve the DSRC performance during both rush hours and regular periods.

A. Overview of OnCAR

We first introduce the fundamental components of OnCAR. Figure 4 presents the architecture of OnCAR. It is a controller that runs on each in-vehicle DSRC radio in a distributed manner. The objective of OnCAR is to optimize the system outputs (i.e., ePDR and eTPUT) of the target system by adjusting the system inputs (i.e., transmission power and data rates). Meanwhile, it takes the fairness into consideration. OnCAR is composed of a feed forward control loop and an adaptive feedback control loop. The feed forward loop provides a baseline initiation to the feedback loop, so as to increase the convergence speed of OnCAR. Moreover, the feedback loop improves the baseline initiation and further increases the performance of OnCAR.

To address Challenge 1, the feed forward loop utilizes a MIMO model based predictor. This predictor takes measurements of environment parameters (i.e., vector $\mathbf{X}$ of SINR value and neighbor density) to select a pair of transmission power and data rate settings to optimize ePDR and eTPUT. The selected pair is used as the predicted inputs (denoted as $\mathbf{U}^p$) to the target system. The parameters of this MIMO model are updated periodically. They describe the input-output mapping, and capture the coupling between two system inputs (i.e., transmission power and data rates) as well.

However, the MIMO model used in the predictor can only serve as an approximation of the dynamic target system. The predicted ePDR and eTPUT (denoted as predicted outputs $\mathbf{Y}^p$)

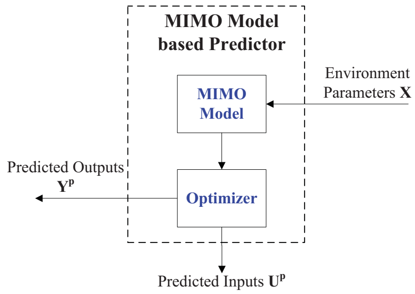


Fig. 5: Architecture of the MIMO model based predictor.

may be off from the measured ePDR and eTPUT (denoted as system outputs $\mathbf{Y}$), resulting in "residual" errors. In addition, the unpredictable disturbances in the vehicular environment enlarge these errors.

To address Challenge 2 and correct residual errors, we further develop an adaptive feedback control loop in OnCAR. This loop first compares the system outputs $\mathbf{Y}$ with the predicted outputs $\mathbf{Y}^p$ to calculate the residual errors (denoted as $\Delta\mathbf{Y}$). Then an online adaptive controller estimates a regression model of residual errors using these measurements. With this online trained regression model, the adaptive controller produces input adjustments (denoted as $\Delta\mathbf{U}$) to minimize the residual errors. The adaptive nature of this controller helps us cope with dynamic disturbances in the vehicular environment.

To address Challenge 3, OnCAR utilizes receiver-side measurements of system outputs and environment parameters to feed the aforementioned control loops. Adopting such measurements makes each vehicle to consider the performance of its neighbors, and thus improves the overall fairness.

B. Design of MIMO Model Based Predictor

The core module of the feed forward control loop in OnCAR is the MIMO model based predictor, whose architecture is shown in Figure 5. For every pair of power and rate settings in DSRC, the predictor first uses a MIMO model to predict its corresponding output of ePDR and eTPUT. Based on these outputs, an optimizer selects the best pair to maximize ePDR and eTPUT. This selected pair is then provided to the objective system as the predicted inputs $\mathbf{U}^p$, while the corresponding ePDR and eTPUT pair is provided to the feedback loop as the predicted outputs $\mathbf{Y}^p$. Note that measurements of environment parameters (i.e., SINR and neighbour density) are needed as the inputs of the MIMO model. We leave the detailed measurement process till Section III-D.

1) The MIMO Model: The mathematical expression of the MIMO model is a function F mapping the environment parameter vector $\mathbf{X}$ and input vector $\mathbf{U}$ to output vector $\mathbf{Y}$:

$$\mathbf{Y} = F(\mathbf{X}, \mathbf{U}). \tag{4}$$

Note that this MIMO model F is a general model that can generalize most existing algorithms. To achieve model parameters, we adopt an approach that is more consistent with industry practice. Considering the potentially large measurement results of DSRC from current and future industry simulations and tests, we propose to train the MIMO model with them. This approach can be easily applied by automobile industry in deployments with their test data. In this paper, the MIMO model is trained with fine grained ns-2 simulation traces. We collected training data of 244 pairs of inputs (i.e., power and rate settings $\mathbf{U}$) in 3660 traffic conditions. We also recorded SINR values, and collected another group of training data for environment parameters $\mathbf{X}$. The total size of training data is over $1TB$ in binary format. Applying the least squares model fitting technique [12] on the training data, we obtained our MIMO model F.

2) The Optimizer: Based on the MIMO model F and measurements of the environment parameters $\mathbf{X}$, the optimizer produces the predicted inputs and outputs. Denote the predicted inputs as $\mathbf{U^p} = \{u_1^p, u_2^p\}$, where u_1^p denotes the predicted selection of transmission power and u_2^p represents the predicted selection of data rate. Denote the predicted outputs as $\mathbf{Y^p} = \{y_1^p, y_2^p\}$, where y_1^p is the predicted ePDR and y_2^p is the predicted eTPUT. The optimizer is designed to maximize a weighted sum of y_1^p and y_2^p as follows.

$$\begin{aligned} \underset{\mathbf{U^p}}{\text{Maximize}} \quad & y_1^p + \lambda y_2^p, \\ \text{Subject to} \quad & \mathbf{Y^p} = F(\mathbf{X}, \mathbf{U^p}), \\ & u_1^p \in U_1, u_2^p \in U_2, \end{aligned}$$

where λ is a parameter that scales ePDR to the level of eTPUT, U_1 is a finite set of available power levels, and U_2 is a finite set of available data rates.

C. Design of Adaptive Controller

As mentioned in Section III-A, the predicted outputs $\mathbf{Y}^p$ of the MIMO model predictor may be off from the measured system outputs $\mathbf{Y}$. This leads to "residual" errors. In addition, these errors can be enlarged by the unpredictable disturbances in vehicular environments. To eliminate these errors and adapt to the dynamic environment, we further introduce an adaptive feedback control loop.

The key component of this adaptive feedback control loop is an adaptive controller, which is illustrated in Figure 6. This controller is composed of an online parameter estimator with a control law. The online estimator provides estimates of time-varying parameters at each control instant. Based on these estimates, the control law calculates control inputs to achieve the control objective. Here the control objective is to minimize the residual errors. The calculated control inputs are then used to adjust the predicted inputs given by the MIMO model based predictor. We adopt a direct adaptive control scheme [11] for this adaptive controller.

In the design of the parameter estimator, we apply a linear regression model to capture the relation between control inputs $\mathbf{S}(k)$ and control outputs $\mathbf{R}(k)$. Here $\mathbf{S}(k)$ represents the input adjustments $\Delta\mathbf{U}$ at time interval k, while $\mathbf{R}(k)$ corresponds to the residual errors $\Delta\mathbf{Y}$ at time interval k. Note that this regression model (which maps $\Delta\mathbf{U}$ to $\Delta\mathbf{Y}$) is different from the MIMO model F (which maps $\mathbf{U}$ and $\mathbf{X}$ to $\mathbf{Y}$). The adaptive feedback control scheme is described by a difference equation model as

$$A(q^{-1})\mathbf{R}(k) = B(q^{-1})\mathbf{S}(k) + e(k), \tag{5}$$

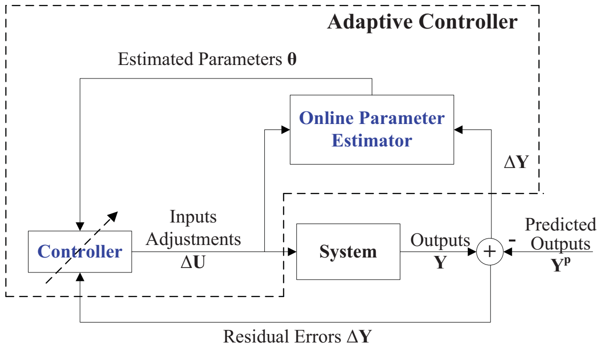


Fig. 6: Architecture of the adaptive controller.

where

$$A(q^{-1}) = 1 - a_1 q^{-1} - \cdots - a_n q^{-n}, \quad (6)$$
$$B(q^{-1}) = b_0 q^{-1} + \cdots + b_{n-1} q^{-n}, \quad (7)$$

q^{-1} is the back shift operator, n is the order of the regression model, and $e(k)$ is a sequence of independent, identically distributed (i.i.d.) random vectors with zero means. Note that the digital implementation of the controller introduces a one-step delay between the current control inputs and the corresponding control outputs. In this case, the control inputs at time interval $k-1$ (i.e., $\mathbf{S}(k-1)$) will affect the control outputs at time interval k (i.e., $\mathbf{R}(k)$).

In order to cope with the disturbances in the vehicular environment, the model parameters are updated periodically. At each sampling interval, control outputs are measured and fed into the online parameter estimator. The estimator combines these outputs with the corresponding past control inputs to estimate the model parameters $a_i (i = 1, \cdots, n)$ and $b_j (j = 1, \cdots, n)$. Based on these estimates, the controller calculates future control inputs to correct the residual errors. To this end, we apply a Recursive Least Square (RLS) scheme [13] for the online parameter estimator. Denote

$$\phi(k) = [\mathbf{R}(k-1), \cdots, \mathbf{R}(k-n), \mathbf{S}(k-1), \cdots, \mathbf{S}(k-n)]^T, \quad (8)$$

and

$$\theta(k) = [a_1(k), \cdots, a_n(k), b_0(k), \cdots, b_{n-1}(k)]^T. \quad (9)$$

We convert Eq. (5) to an RLS-friendly format:

$$\mathbf{R}(k) = \phi^T(k)\theta(k). \quad (10)$$

In Eq. (10), $\theta(k)$ denotes the true parameters to be estimated at time interval k. Applying the RLS algorithm, we can obtain the estimated parameters $\hat{\theta}(k)$ at time interval k. In detail, the RLS algorithm works by solving the following three equations.

$$\varepsilon(k) = \mathbf{R}(k) - \phi^T(k)\hat{\theta}(k-1), \quad (11)$$

$$\begin{aligned} P(k-1) &= P(k-2) - [1 + \phi^T(k)P(k-2)\phi(k)]^{-1} \\ &\quad \cdot P(k-2)\phi(k)\phi^T(k)P(k-2), \end{aligned} \quad (12)$$

$$\hat{\theta}(k) = \hat{\theta}(k-1) + P(k-1)\phi(k)\varepsilon(k). \quad (13)$$

The estimated parameters $\hat{\theta}(k)$ contain the estimates of model parameters a_i and b_j. The RLS algorithm updates Eq. (12) and (13) in each sampling interval, and thus the model parameters are estimated in an online manner. The initial condition of the above RLS algorithm is $P(-1) = p_0 I$, where $p_0 > 0$ and I is an identity matrix.

Based on the estimated parameters $\hat{\theta}(k)$, the control law is calculated by solving the following formula

$$\phi^T(k)\hat{\theta}(k) = \mathbf{R}^*(k), \quad (14)$$

where $\mathbf{R}^*(k)$ is the control reference. As stated in the beginning of this section, the adaptive controller aims to minimize the residual errors. Hence, we set $\mathbf{R}^*(k) = 0$. As defined in Eq. (8), $\phi(k)$ encapsulates past control outputs $\mathbf{R}(k-1), \cdots, \mathbf{R}(k-n)$, past control inputs $\mathbf{S}(k-2), \cdots, \mathbf{S}(k-n)$, and current control inputs $\mathbf{S}(k-1)$. By solving Eq. (14), we achieve current control inputs $\mathbf{S}(k-1)$. Note that $\mathbf{S}(k-1)$ correspond to input adjustments $\Delta\mathbf{U}$ in Figure 6.

Directly applying the control law based on Eq. (14) may result in large variations in two consecutive control inputs, jeopardizing the stability and convergence of OnCAR. In addition, abrupt oscillations of transmission power and data rate would introduce undesirable disturbances to neighbor vehicles. To address this issue, we integrate a smooth control mechanism in the control law. The corresponding smooth control law aims to minimize the following cost function

$$\begin{aligned} J =& E\{||W(\mathbf{R}(k+1) - \mathbf{R}^*(k+1))||^2 \\ &+ ||Q(\mathbf{S}(k) - \mathbf{S}(k-1)||^2\}, \end{aligned} \quad (15)$$

where $||.||$ is the 2-norm operation, W and Q are weighting matrices. Their relative magnitude controls the tradeoff between performance and stability. In this paper, W and Q are diagonal matrices, which are consistent with common practice. (Interested readers can refer to [11] for more details on settings of W and Q.) The goal of Eq. (15) can be interpreted as approaching the desired system outputs while controlling the changes of inputs.

***Theorem** 1:* The smooth control law is realized with the following control inputs

$$\begin{aligned} \mathbf{S}(k) =& \big((W\hat{b}_0)^T W\hat{b}_0 + Q^T Q\big)^{-1} \cdot \big(Q^T Q\mathbf{S}(k-1) \\ &+ (W\hat{b}_0)^T W(\mathbf{R}^*(k+1) - \hat{\theta}(k)\tilde{\phi}(k))\big). \end{aligned} \quad (16)$$

The proof of this theorem is reported in [14]. We skip the details for brevity.

D. Measuring System Outputs and Environment Parameters

As we mentioned earlier, OnCAR needs the measurements of system outputs (i.e., ePDR and eTPUT) and environment parameters (i.e., SINR and neighbor density) to feed the aforementioned MIMO model based predictor and adaptive controller. Adopting receiver-side measurements also motivates each vehicle to improve the performance of its neighbors, reducing selfish behaviors significantly. The reason is two-fold. 1) Due to the channel reciprocity[6] in DSRC, receiver-side measurements serve as a good estimation of a vehicle's own transmission performance. To enhance its own performance, a vehicle would improve receiver-side measurements. 2) Each vehicle would like to obtain more safety messages from its

[6]We are aware of the debate on the existence of channel reciprocity in general. In the context of DSRC, field tests [4] already confirmed the existence of channel reciprocity.

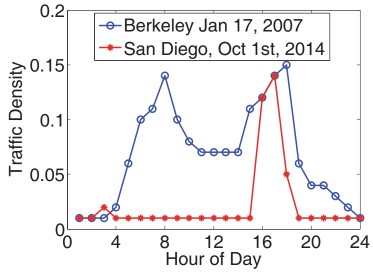


Fig. 7: Real-life traffic density traces.

neighbor, so as to enhance its own driving safety with more information. Therefore, each vehicle is also self-motivated to improve the performance of its neighbors.

The measurements of system outputs work as follows. At each sampling interval, each DSRC radio measures eTPUT by counting the number of received packets sent by neighbors within the effective range. To measure ePDR, each DSRC radio leverages the 12-bit sequence number in the sequence control field of an IEEE 802.11 MAC header. The expected number of transmitted packets is approximated by the difference between the maximum and minimum sequence numbers. Then ePDR is estimated as the ratio of the number of received packets to the expected number of transmitted packets.

To measure the density of neighbor, there exist several candidates such as the one proposed by Kong et al. in [15]. For the sake of robustness, in this paper, we resolve to a light-weight solution as follows. Each DSRC radio extracts the sender's MAC address encapsulated in the MAC header, and counts the number of neighbors based on this distinct MAC address. To measure the SINR value, each DSRC radio first measures the SINR value of each packet sent by a neighbor with the effective range. Then an average value of SINR is calculated.

IV. Trace-driven Evaluation

In this section, we evaluate OnCAR with trace-driven ns-2 simulations. We demonstrate that OnCAR perform consistently well all the time including rush hours. Concretely, we first present the performance improvement of OnCAR during the most critical period (the rush hours), with real-life traces. We then adopt simulations with synthetic traces to demonstrate that OnCAR bring improvements in all time periods.

A. Evaluation Setup

1) Traffic Traces: We establish real-life traffic scenarios with two real-life traffic data sets. One data set [16] records the traffic density of Berkeley on Jan. 17, 2007. The other data set [17] traces the traffic density of San Diego on Oct. 1st, 2014. The traffic densities of Berkeley and San Diego data sets are presented in Figure 7. In both scenarios, traffic density achieves the maximum value during rush hours.

Real-life traffic traces are mostly available in metropolis areas. There may be cases that are not covered by currently accessible traces. To cover as many those cases as possible, we also conduct simulations in ten synthetic scenarios representing a diverse group of traffic conditions.

Traffic data sets in the real-life and synthetic scenarios provide density information from the view of a highway. To generate microscopic vehicle dynamics, we combine the density information with a vehicle movement trace generator SUMO [7]. In this way, we obtain a set of traces on vehicle dynamics, which describe the time-varying speeds, positions and destinations of all vehicles on a bi-directional highway. This highway has a speed limit of 100 kilometers per hour. The layout of this highway has been illustrated in Figure 2. This highway is of 2000 meters long and 30 meters wide with four lanes in each direction. It has a median strip to separate two directions. Upon arriving at the end of one direction, vehicles re-enter the highway at the beginning of the other direction. There are two entrances and one exit along each direction.Vehicles that leave through the exits will re-enter the highway through the entrances.

2) DSRC Propagation Model: To capture the signal propagation in real DSRC scenarios, we adopt the field-test results reported in [18]. Due to the limited space, we report the model details in [14].

3) DSRC Radio Settings: Each DSRC radio follows the DSRC standards and broadcasts safety messages periodically on DSRC Channel 172. The broadcasting period of messages is 0.05 seconds. The effective range of communication is 300 meters. The data encapsulated in each packet is of 500 bytes, while the packet headers are added based on IEEE 802.11p protocols. The options of data rates include $3Mbps$, $6Mbps$, $12Mbps$, and $24Mbps$. The available transmission power ranges from $10dBm$ to $30dBm$, with a $2dBm$ step. In addition, each vehicle is equipped with one DSRC radio.

B. Approaches Studied

We implement and evaluate the following four power/rate adaptation approaches on our testbed.

• OnCAR is our proposed approach. It combines a MIMO model based predictor with an online adaptive controller. OnCAR runs on each vehicle distributively.

• Transmission Power Adaptation (TPA) is an individual transmission power adaptation approach. It is developed based on state-of-the-art individual power adaptation approaches proposed in [5], [6]. TPA uses a fixed data rate of $3Mbps$.

• Data Rate Adaptation (DRA) is an individual rate adaptation approach. It is implemented based on state-of-the-art individual data rate adaptation approaches proposed in [7], [8]. DRA fixes transmission power as 20dBm and adapts data rates based on its measured environment parameters (i.e., channel SINR and neighbor density).

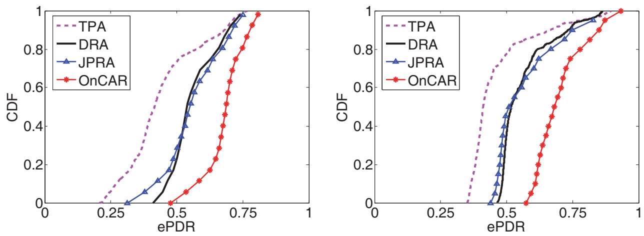
• Joint Power and Rate Adaptation (JPRA) is a joint and heuristic adaptation approach. We leverage state-of-the-art designs of joint approaches proposed in [9], [10], [19] to develop JPRA. It combines TPA and DRA sequentially: it first determines the transmission power, and then selects a data rate.

C. Evaluation in Real-life Scenarios

In this section, we present the evaluation results in both Berkeley and San Diego scenarios.

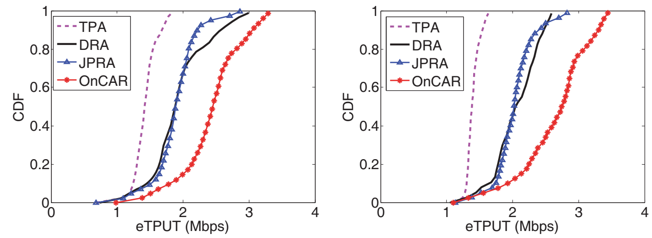
1) DSRC Reliability in Real-life Scenarios: We first evaluate the reliability in terms of ePDR. We focus the rush hours, i.e., $16:00$ to $20:00$. The Cumulative Distribution Functions (CDFs) of ePDRs at rush hours are presented in Figure 8. It

[7]Simulation of Urban Mobility: http://sumo-sim.org/



(a) Berkeley scenario. (b) San Diego scenario.

Fig. 8: CDFs of ePDRs in real-life scenarios at rush hours.



(a) Berkeley scenario. (b) San Diego scenario.

Fig. 9: CDFs of eTPUT in real-life scenarios at rush hours.

TABLE I: Statistics of ePDRs at rush hours of Berkeley.

Approach	mean	Improvement by OnCAR	max	min
TPA	0.4431	53.9%	0.7691	0.2084
DRA	0.5624	21.2%	0.8038	0.4091
JPRA	0.5593	21.9%	0.7686	0.3126
OnCAR	0.6818	−−	0.8469	0.4768

TABLE II: Statistics of ePDRs at rush hours of San Diego.

Approach	mean	Improvement by OnCAR	max	min
TPA	0.4631	51.2%	0.8973	0.3507
DRA	0.5636	24.2%	0.8650	0.4628
JPRA	0.5659	23.7%	0.9052	0.4387
OnCAR	0.7002	−−	0.9335	0.5728

TABLE III: Statistics of eTPUT at rush hours of Berkeley.

Approach	mean	Improvement by OnCAR	max	min
TPA	1.4287	70.3%	1.8768	0.6808
DRA	1.9280	26.2%	0.7364	3.0836
JPRA	1.8869	28.9%	0.6840	2.9088
OnCAR	2.4324	−−	0.9816	3.4264

TABLE IV: Statistics of eTPUT at rush hours of San Diego.

Approach	mean	Improvement by OnCAR	max	min
TPA	1.3986	88.9%	1.6732	1.1120
DRA	2.0479	29.0%	2.6728	1.0512
JPRA	2.0307	30.1%	2.9300	1.1288
OnCAR	2.6416	−−	3.5072	1.1040

is shown that OnCAR achieves the best reliability with the largest ePDR.

We summarize several statistics of ePDRs at rush hours in Table I (for Berkeley scenario) and Table II (for San Diego scenario). The statistics include mean, maximum and minimum values of ePDRs, as well as the mean ePDR improvements of OnCAR over other approaches. Compared with JPRA, OnCAR improves the average reliability of DSRC by 21.9% and 23.7%, respectively. Moreover, OnCAR achieves the highest minimum and maximum ePDR among all approaches. This suggests that the improvement in reliability benefits every vehicle. In addition, we observe that the joint approach JPRA achieves a lower ePDR than that of the individual approach of DRA. This again confirms that sequential adjustments of power and rates sometimes result in a mismatched pair of these two variables, leading to a compromised DSRC performance. The synchronous control adopted by OnCAR address this issue by embracing the strong coupling with a MIMO control model. It enables OnCAR to select the optimal choices of power and rates. Hence, OnCAR addresses **Challenge 1**, and greatly enhances DSRC reliability of all vehicles

2) DSRC Efficiency in Real-life Scenarios: We further evaluate the efficiency of OnCAR in terms of eTPUT. We present the CDFs of eTPUT for all approaches during rush hours in Figure 9. It is shown that OnCAR achieves the largest eTPUT and thus the best efficiency of DSRC. Therefore, we conclude that among all the approaches, OnCAR provides the highest efficiency of DSRC.

We also summarize the mean, minimum and maximum of eTPUT, as well as the mean eTPUT improvement by OnCAR over other approaches, in Table III and Table IV. Note that the unit of eTPUT in Table III and Table IV is Mbps. Compared with the state-of-the-art joint approach JPRA, OnCAR enlarges the overall efficiency of DSRC by 28.9% and 30.1%, respectively. Furthermore, we find that OnCAR's improvements in eTPUT is larger than that in ePDR (in terms of percentage). In other words, OnCAR further enlarges the eTPUT beyond the increment brought by an enhanced ePDR.

3) DSRC Fairness in Real-life Scenarios: The metric of fairness, i.e., the CV of ePDRs, is presented in Figure 10. It is shown that, in both scenarios, OnCAR achieves the lowest CV and hence the best fairness among all approaches. To quantify the improvement in fairness, we summarize the decreases in CV of ePDRs brought by OnCAR in Table V. Compared to JPRA, OnCAR improves the fairness across all vehicles by up to 44.0% and 40.1%, respectively. These improvements are brought by the receiver-side measurement mechanism of OnCAR. This mechanism establishes an implicit feedback loop, which forces vehicles to consider the performance of their neighbors. Therefore, OnCAR helps vehicles achieve enhanced reliability and improved fairness simultaneously, and indeed addresses **Challenge 3**.

4) Convergence in Real-life Scenarios: We further evaluate the convergence of different approaches. We compare OnCAR with JPRA, while omitting TPA and DRA as they only adjust

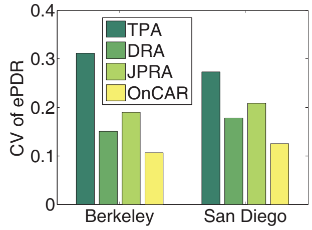


Fig. 10: CV of ePDR in real-life scenarios.

TABLE V: OnCAR's improvements in fairness over others.

Fairness Improvement	Berkeley	San Diego
Over TPA	65.8%	54.2%
Over DRA	29.4%	29.8%
Over JPRA	44.0%	40.1%

one individual variable. Due to the limitation of space, we focus on the convergence of San Diego scenario, and leave the details of Berkeley scenario in [14]. We extract the results at the very beginning of the simulations, when all vehicles just start to adapt their power and rates. Fig. 11 presents the selections of power and rates across time. It is demonstrated that power and rates of OnCAR converge much faster than those of JPRA. While OnCAR achieves a convergence of both variables in only 3 control iterations, JPRA requires almost 30 control iterations. This is because the sequential adaptation procedure in JPRA is sensitive and vulnerable to the dynamics in the environment. Changes in one variable sometimes evoke cascading oscillations across two variables for a relatively long period. OnCAR avoids this problem with a synchronous control of both variables. In this way, OnCAR addresses **Challenge 2** and increases the convergence speed.

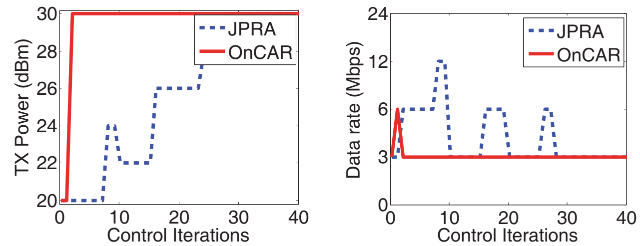
D. Evaluation in Synthetic Scenarios

In this section, we demonstrate that OnCAR achieves large improvements in both rush and regular periods. To this end, we establish ten synthetic scenarios, each of which is generated with an unique synthetic traffic density trace. The traffic density in each synthetic scenario varies randomly and arbitrarily across time, from 0.025 to 0.15 vehicles per meter. To better compare the approaches, we group simulation results into different sets according to the corresponding densities. Due to the limited space, we focus on the results of a low density set (i.e., density 0.075), a medium density set (i.e., density 0.1), a high density set (i.e., density 0.15). We summarize OnCAR's improvements in mean ePDRs, mean eTPUT and CV of ePDRs over other approaches in Table VI. It is confirmed that OnCAR delivers the most reliable, efficient and fair performance across different traffic densities.

V. Related Work

In this section, we only discuss the work that is most pertinent to ours, due to the space limitation.

Transmission power control and data rate adaptation in stationary wireless networks have been extensively studied. However, they cannot adapt to the dynamic vehicular environments directly. In mobile ad hoc networks (MANETs) and vehicular ad hoc networks (VANETs), power and rate



(a) Transmission Power.

(b) Data Rate.

Fig. 11: Convergence in San Diego Scenario.

TABLE VI: OnCAR's improvements in synthetic scenarios.

Density	**Approach**	ΔePDR	ΔeTPUT	ΔCV
0.075	TPA	39.7%	53.9%	65.8%
	DRA	12.9%	17.4%	39.1%
	JPRA	18.8%	21.0%	44.1%
0.1	TPA	63.7%	78.1%	62.8%
	DRA	21.0%	25.6%	27.2%
	JPRA	21.6%	31.0%	48.4%
0.15	TPA	87.0%	98.5%	45.3%
	DRA	42.4%	30.8%	26.9%
	JPRA	29.0%	35.7%	38.5%

adaptation methods explicitly consider the impact of mobility. For power control, Torrent-Moreno et al. in [20] developed a distributed power control method D-FPAV, which aims to improve the transmission fairness of safety-critical information. Guan et al. in [5] proposed to control the transmission range by adapting the power level of DSRC nodes. The proposed algorithm FPC requires feedback beacons from neighbouring vehicles. For rate adaptation, Holland et al. in [21] developed RBAR, which adapts the data rate based on a receiver-based SNR measurement approach. Chen et al. in [8] proposed a rate adaptation method named RAM to handle the channel asymmetry. Vutukuru et al. in [22] designed a rate adaptation method SoftRate, which adjusts the data rate according to the channel bit error rate. Shankar et al. in [7] proposed to leverage context information such as velocity and distance in rate adaptation and developed CARS based on this idea. However, the above-mentioned methods focus on either power control or rate adaptation, and may fail to select the optimal combination of both.

There also exist a number of joint adaptation methods. Nevertheless, most methods are based on handshaking or feedback messages, and thus are not suitable for DSRC safety communications. This is because DSRC safety communications are based on broadcast and provide neither handshaking nor feedback messages. Ramachandran et al. in [9] developed Symphony, which is a fully distributed synchronous two-phase power and rate adaptation strategy. The first step of Symphony is to estimate the best performance and selects the corresponding data rate. The second step is to tune transmission power to approach estimated performance with the selected data rate. However, tuning the power setting in the second step costs Symphony much time, and thus reduces Symphony's efficiency in the vehicular environment.

Other variables have also been utilized in reducing channel congestion and improving DSRC performance. CAM-DCC proposed by European Telecommunication Standards Institute (ESTI) in [23] and LIMERIC proposed by Bansal et al. in [24] are two candidates for the congestion control in DSRC. While CAM-DCC adjusts the generation rate of safety messages according to vehicle dynamics (e.g., position, heading and speed changes), LIMERIC adapts this rate based on the channel load. Huang et al. in [25] proposed a joint transmission probability and power adaptation method to enhance the safety of driving. Rawat et al. in [19] proposed to jointly select transmission power and contention window (CW) size. Zhang et al. in [6] improved QoS of VANETs with a joint adaptation of power and sub-carrier allocation. Tielert et al. in [10] designed a joint approach that adjusts transmission power and beacon frequency to reduce congestion and collisions in the wireless channels. Xiang et al. in [26] developed a context-aware data dissemination scheme, which adjusts the contention window size of CSMA according to the preference of information captured in each DSRC packet. Gao et al. in [27] designed a two-step network coding based data dissemination approaches, which separates the coding operation and the transmission operation into two threads. By carefully adjusting and scheduling these two threads, the proposed approach manages to reduce data dissemination delays. However, to achieve the optimal DSRC performance, these approaches should be integrated with power and rate control. Moreover, the coupling among control parameters (e.g., power, data rates, message generation rates, CW sizes, and etc.) have not been fully explored.

VI. Conclusion

In this paper, we develop and implement OnCAR to enhance the reliability, efficiency and fariness of DSRC by joint and synchronous control of transmission power and data rates. OnCAR handles the coupling between power and rates with a MIMO model based predictor to produce a synchronous pair of variables. Furthermore, OnCAR tackles the disturbances in the dynamic vehicular environment with an online adaptive controller. In addition, by adopting receiver-side measurements, OnCAR manages to deal with the lack of coordination between vehicles and improve fairness across all. Several interesting findings are revealed. (i) OnCAR achieves its largest improvement during rush hours. (ii) OnCAR enhances average reliability and at the same time improves fairness across all vehicles. (iii) OnCAR leverages a combination of high transmission power and high data rates to combat the network congestion.

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