# Channel Analytics for V2X Communication

Maqsood Ahamed Abdul Careem
Department of Electrical and Computer Engineering
University at Albany, SUNY, Albany, NY 12222
mabdulcareem@albany.edu, +1-518 409 9302

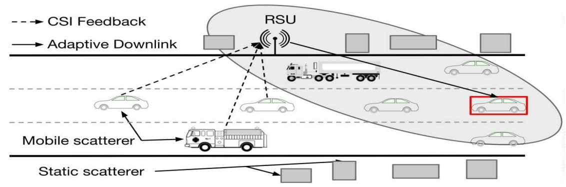
Aveek Dutta
Department of Electrical and Computer Engineering
University at Albany, SUNY, Albany, NY 12222
adutta@albany.edu

***Abstract*—Recommending channel characteristics for V2X communication has the distinct advantage of pre-conditioning the waveform at the transmitter to *match* the expected fading profile. The difficulty lies in extracting an accurate model for the channel, especially if the underlying variables are uncorrelated, unobserved and immeasurable. Our work implements this prescience by assimilating the Channel State Information (CSI), obtained as a feedback from vehicles, over time and space to adjust the modulation vectors such that the channel impairments are significantly diminished at the receiver, improving the Bit Error Rate (BER) by $96\%$ for higher order modulations. To account for the multivariate, non-stationary V2X channel, a tensor decomposition and completion approach is used to mitigate the effects of sparsity and noise in the CSI measurements.**

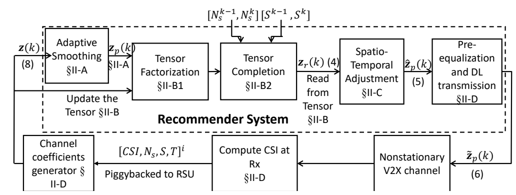
## I. Introduction

Recommender systems are designed to bridge the gap between the desired and actual behavior of an unknown process by iteratively tracking patterns in the outcomes. This reduces the ambiguity and uncertainty in the decision making process. Wireless communication between a Vehicle (V) to Anything (X), V2X is analogous to a recommender system, where the receiver can significantly reduce its packet error rate, if the transmitter (Road-Side Unit (RSU) or another vehicle) uses the *recommended* signal parameters based on historically observed channel profiles, obtained as a feedback from receivers. Intuitively, if transmitter pre-conditions waveform with inverse of expected channel, received signal will be minimally distorted.

This problem is complicated due to unknown and immeasurable relationships among the factors contributing to the channel fading profile, that also vary over space and time. Most importantly, the localized scattering from nearby vehicles, road-side features like buildings and vegetation, Doppler spectrum and path-loss, are either stochastic variables or time-variant. Collectively, these properties make the V2X channel statistically non-stationary [1]. Our goal in this work is to rely on measurable parameters like vehicle density ($N_s$), vehicle location, mapped into quasi-stationary segments ($S$) [2] and the CSI feedback ($CSI$) to construct a non-stationary time series (indexed by time of reception, $T$). The CSI from receivers captures a wide variety of channel characteristics across a stretch of road under different scattering environments. Broadband communication using Orthogonal Frequency Division Multiplexing (OFDM) used in the standards advocated for WAVE also captures the channel profile in frequency domain. Figure 1b shows the channel recommender system for V2X communication. It operates on the quadruplet, $[CSI, N_s, S, T]^i$, obtained from vehicle $i$. The first step is to pre-process the CSI using an adaptive filter to dampen the effects of non-linearities in the estimation process in the receiver and the uplink channel. This is used in the second




(a) CSI based channel analytics at transmitter.

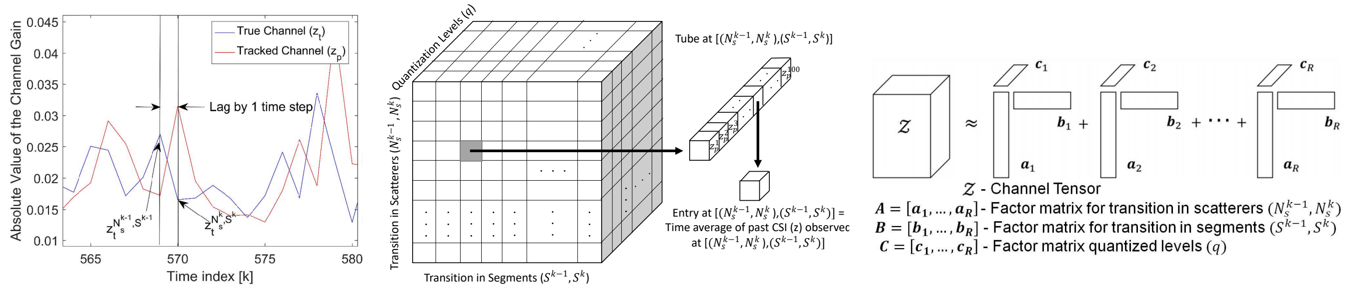



(b) V2X Channel recommender system.

Figure 1: (a) Elliptical zone of scatterers inducing time-space-frequency non-stationarity. (b) V2X Channel recommender

step to predict the downlink channel profile for any target vehicle in the road, according to its position and the scattering environment. This is accomplished by constructing a third order tensor containing the transitions for number of scatterers, $[N_s^{k-1}, N_s^k]$ and segment number, $[S^{k-1}, S^k]$ from the last observed CSI in time-step $k$ and the corresponding error in the recommended channel. This is described in §II-B,C. After this adjustment, the final step is to pre-condition the waveform, such that the receiver estimates an almost flat fading across all subcarriers (in §II-D). This step eliminates any need for complex receiver side algorithms and is compatible with conventional pilot based equalization. As recommender system evolves with more spatio-temporal CSI, the gap between the recommended and true channels gets asymptotically small leading to significant improvement in accuracy of predictions. This enables a broader set of reliable network services, like traffic-aware caching and multi-user downlink scheduling.

*Non-stationary V2X Channel:* V2X channels are modeled using the Geometric Stochastic Channel Model (GSCM), which is the basis of widely used WINNER channel model [2]. The V2X channel at time $k$ and for the $n^{th}$ OFDM subcarrier, depends on the number of scatterers at time $k$, $N_s(k)$, Doppler frequency, the angle of departure (AoD) and angle of arrival (AoA), complex channel gains and path delays for each sub-path. The AoAs and AoDs are functions of the transmitter (RSU or vehicle) location, vehicle (receiver) location, and number of scatterers in each (elliptical) scattering zone that are stochastically distributed [3]. The path delay (and consequently the channel impulse response) collectively depend on these factors. Non-stationarity over space, time and vehicular density affect the reliability and latency of data transmission, which has been validated by measurement campaigns [1].




(a) Lag in tracked and true channel. (b) An illustration of tensor $\mathcal{Z}$ and its entries. (c) Illustration of tensor factorization of tensor $\mathcal{Z}$.

Figure 2: Tensor factorization of tensor $\mathcal{Z}$ yields matrices, $\mathbf{A} = [\mathbf{a}_1, ..., \mathbf{a}_R]$, $\mathbf{B} = [\mathbf{b}_1, ..., \mathbf{b}_R]$ and $\mathbf{C} = [\mathbf{c}_1, ..., \mathbf{c}_R]$ which represent the factor matrices for transition in number of mobile scatterers, transition in segments and quantized levels respectively.

## II. Channel Recommendation System

The CSI is a quantized estimate of the downlink channel that can be used to adjust the parameters for future transmissions. However, the high dynamics of the V2X network requires agile scheduling of packets at the RSU for links with different scattering environment and location. Hence, the CSI may become obsolete and the RSU has the added burden of making unique recommendations for every downlink packet. To address this problem we design a recommender system that has four stages as shown in figure 1b: *A) Adaptive Smoothing:* Iteratively tracks and smooths the non-stationary noise in the CSI (similar to [3]), *B) Tensor Factorization & Completion:* This step generates channel recommendations to account for the change in the scattering environment and location of vehicles over time. *C) Spatio-Temporal Adjustment:* The output of steps A and B is fused to form the recommended downlink channel profile for the next packet, and *D) Pre-Equalization:* The downlink waveform is pre-equalized using the recommended channel profile, to achieve flat fading at the receiver. RSU processes the channel state, received as a quadruplet $[CSI, N_s, S, T]^i$ for each vehicle $i$ (piggy-backed on acknowledgement packet).

### A. Adaptive Smoothing

Adaptive smoothing of non-stationary noise in the CSI is performed by a combination of autoregression (AR) and Kalman filtering. The CSI obtained from various vehicles are combined using a noisy autoregressive (AR) model (random walk), the weights of which are tracked by a Kalman filter [3]. However, this iterative approach results in a lag between the tracked channel and the actual channel, due to one time-step delay in CSI feedback path (figure 2a). Hence, an additional smoothing step [4] is employed to mitigate the effect of this lag and any undesired transients in the received CSI. We denote it by $\mathbf{z}_p(k)$ and use it in §II-B and §II-C. Although smoothing, reduces transients, it is unable to maintain low error vector magnitude (EVM) for higher modulations, and a single smoothing filter is unable to simultaneously track the channel over multiple vehicles and locations.

### B. Tensor Completion & Factorization

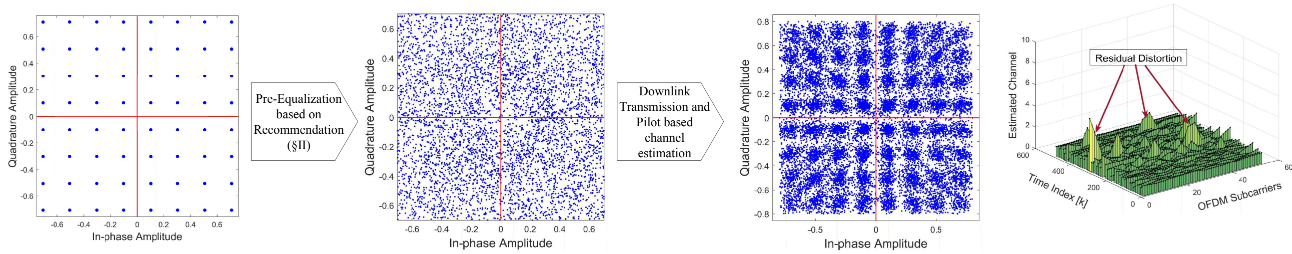
There is a disconnect between the smoothed and actual channels (which depends on the current scattering environment and location of the receiver, figure 2a). This information is embedded in the CSI, which consequently captures the deviation due to the change in the scatterers and the receiver location. We construct a 3D tensor, shown in figure 2b to record these deviations and use them to make adjustments (details in §II-C) to the smoothed channel, $\mathbf{z}_p(k)$. The measurement channel, $\mathbf{z}(k)$ derived from the CSI (see §II-D) is recorded in the tensor corresponding to the change in the scatterers $(N_s^{k-1}, N_s^k)$ and segments $(S^{k-1}, S^k)$ and the corresponding output of the smoothing filter, $\mathbf{z}_p(k)$, quantized to level $q$. Cell values are updated as a running average of all measurement channels that are mapped to that particular cell, and hence contain the historical deviations observed for a given change in $N_s$ and $S$ and the corresponding quantized level for $\mathbf{z}_p(k)$. Other latent factors also affect these deviations. Moreover, key challenges in this tensor-based procedure are, sparsity (due to the large size of the tensor database (see §III) and unobserved CSI entries) and noisy data in the tensor (due to incomplete filling of cells). These result in missing or corrupt adjustments. To account for these factors, we introduce tensor factorization & completion. At each time step $k$, the channel tensor is, 1. Updated with the measurement channel, $\mathbf{z}(k)$, 2. Factorized (§II-B1) into a factor model to capture the latent structure of the underlying process, 3. Reconstructed using the factorized model (§II-B2) to extract missing entries, and finally 4. The completed tensor is used to generate recommendations, $\mathbf{z}_r(k)$ which is used to adjust the smoothed channel, $\mathbf{z}_p(k)$ (§II-C) for location and scattering environment of a vehicle.

*1) Tensor Factorization:* This stage captures the latent structure of channel tensor by expressing it as the sum of component rank-one tensors. Figure 2c shows the tensor factorization of the third order channel tensor. The notations for tensors, matrices, vectors and elements are similar to [5]. Let $\mathcal{Z}$ be the 3-way channel tensor of size $I \times J \times K$, and rank $R$. Channel tensor decomposition is defined by factor matrices **A**, **B**, and **C** (defined in figure 2c) that minimizes the objective,

$$f_{\mathbf{W}}(A,B,C) = \underbrace{\frac{1}{2}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\left\{w_{ijk}\left\{z_{ijk} - \sum_{r=1}^{R} a_{ir}b_{jr}c_{kr}\right\}\right\}^2}_{\text{Error function}}$$

$$+ \underbrace{\frac{\lambda}{2}\sum_{r=1}^{R}\left\{\sum_{i=1}^{I}||a_{ir}||^2 + \sum_{j=1}^{J}||b_{jr}||^2 + \sum_{k=1}^{K}||c_{kr}||^2\right\}}_{\text{Regularization term}} \quad (1)$$

The *error function* is employed to account for CSI noise in the channel tensor and the weighted version of the error function addresses the sparsity by ignoring missing data and




(a) Before compensation (b) After Pre-equalize (c) Rx constellation (d) Equalized channel at $R_x$

Figure 3: High-level system performance: a) Constellation of ideal 64-QAM symbols for downlink transmission. b) Ideal I/Q vectors are pre-equalized with recommended channel profile, $\tilde{\mathbf{z}}_p(k)$. c) Received symbol constellations using linear interpolation equalizer. d) Equalized channel in time & frequency domain. Estimated channel is largely flat and achieves low BER.

modeling only the known entries. Minimizing this objective function ensures that the recommendations, $\mathbf{z}_r(k)$ accurately represents the discrepancy in channel tracking, even in the case of missing entries. $\mathcal{W}$ denotes a weight tensor, with entries of '1' or '0', when $z_{ijk}$ is known or missing respectively. The *regularization term* penalizes the size of the latent factors and consequently avoids over-fitting the noise in the measurement channel, $\mathbf{z}(k)$ and ensures the generality of $\mathcal{Z}$. $\lambda$ balances the modeling error and the complexity of the latent structure. For convenience the objective function in (1) is expressed as,

$$f_{\mathcal{W}}(\mathbf{A},\mathbf{B},\mathbf{C})=\frac{||\mathcal{Z}-[\![\mathbf{A},\mathbf{B},\mathbf{C}]\!]||^2_{\mathcal{W}}+\lambda(||\mathbf{A}||^2+||\mathbf{B}||^2+||\mathbf{C}||^2)}{2} \tag{2}$$

Here $[\![\cdot]\!]$ is the Kruskal operator shorthand notation, $||\cdot||$ refers to the Frobenius-norm for matrices or two-norm for vectors, and $||\mathcal{Z}||_{\mathcal{W}}$ is the $\mathcal{W}$-weighted norm of $\mathcal{Z}$. The objective function in (2) is minimized by a nonlinear gradient-based optimization, to find the latent factor matrices $\mathbf{A}, \mathbf{B}, \mathbf{C}$. This is easily extended to account for multiple lanes, direction of traffic, varying speeds of vehicles and simultaneous multi-vehicle downlink by extending (2) to a higher-dimensional tensor factorization problem (for N-way tensor, $\mathcal{Z}$) defined by,

$$f_{\mathcal{W}}(\mathbf{A}^{(1)},..,\mathbf{A}^{(N)})=\frac{||\mathcal{Z}-[\![\mathbf{A}^{(1)},..,\mathbf{A}^{(N)}]\!]||^2_{\mathcal{W}}+\lambda\sum_{n=1}^{N}||\mathbf{A}^{(n)}||^2}{2}$$

where $[\![\mathbf{A}^{(1)},...,\mathbf{A}^{(N)}]\!]=\sum_{r=1}^{R}\mathbf{a}_r^n\circ...\circ\mathbf{a}_r^n$, and latent factor matrices for transition in number of scatterers, segments, lanes, direction of traffic, vehicle speed etc... are defined as $\mathbf{A}^{(n)}=[\mathbf{a}_1^N,...,\mathbf{a}_R^N]$. for $n=1,...,N$, This shows the adaptability of the recommender to address a variety of V2X scenarios.

*2) Tensor Completion:* This stage, reconstructs the tensor $\hat{\mathcal{Z}}$ (Recommendation tensor) from the computed factorization model $(\mathbf{A}, \mathbf{B}, \mathbf{C})$ in (2) and is given by,

$$\hat{\mathcal{Z}}=[\![\mathbf{A},\mathbf{B},\mathbf{C}]\!]=\sum_{r=1}^{R}\mathbf{a}_r\circ\mathbf{b}_r\circ\mathbf{c}_r \quad \text{or} \quad \hat{z}_{ijk}=\sum_{r=1}^{R}a_{ir}b_{jr}c_{kr}$$

where '$\circ$' is the outer product. Recommendation tensor, $\hat{\mathcal{Z}}$ is used to obtain recommendations, $\mathbf{z}_r(k)$ corresponding to smoothed channel, $\mathbf{z}_p(k)$. Let the smoothed channel for $N$ subcarriers be, $\mathbf{z}_p(k)=[z_p(k,1), z_p(k,2)\dots z_p(k,N)]^T$. At each iteration $N$ recommendations $(z_r(k,n))$ are made where,

$$z_r(k,n)=\hat{\mathcal{Z}}[(N_s^{k-1},N_s^k),(S^{k-1},S^k),q_n] \tag{3}$$

for all $n=1,\dots,N$. Here, $\hat{\mathcal{Z}}[(N_s^{k-1},N_s^k),(S^{k-1},S^k),q_n)]$ is the entry of $\hat{\mathcal{Z}}$ at index $[(N_s^{k-1},N_s^k),(S^{k-1},S^k),q_n]$ as in figure 2b and $q_n$ is the quantization level of $z_p(k,n)$. Then the recommended channel for $N$ subcarriers is,

$$\mathbf{z}_r(k)=\begin{bmatrix}z_r(k,1) & z_r(k,2) & \dots & z_r(k,N)\end{bmatrix}^T \tag{4}$$

Since the actual channel is complex valued, two separate tensors are used to recommend the channel for the I/Q vectors.

### C. Spatio-Temporal Adjustment

At each time step $k$, smoothed channel $\mathbf{z}_p(k)$ is improved to $\hat{\mathbf{z}}_p(k)$ (recommended channel) by incorporating recommendations, $\mathbf{z}_r(k)$ from (4) using a normalized weighted average:

$$\hat{\mathbf{z}}_p(k)=(1-\alpha_k)\mathbf{z}_p(k)+\alpha_k\mathbf{z}_r(k)) \tag{5}$$

where $\alpha_k$ is the normalization weight at time step $k$. Since, the smoothed channel is adjusted with recommendations based on scattering environment and location of vehicle, this step alleviates lag and disparity in $N_s$ and $S$ and accounts for non-stationarity of channel over time, space and vehicle density.

### D. Pre-equalization at Transmitter

The waveform of the downlink packet is pre-equalized such that when convolved with the true channel, the net effect is a flat fading at the receiver, that can be easily equalized using pilot based linear interpolation methods commonly used in V2X communication. The pre-equalized channel, $\tilde{\mathbf{z}}_p(k)$ is,

$$\tilde{\mathbf{z}}_p(k)=\mathbf{1}./\hat{\mathbf{z}}_p(k) \tag{6}$$

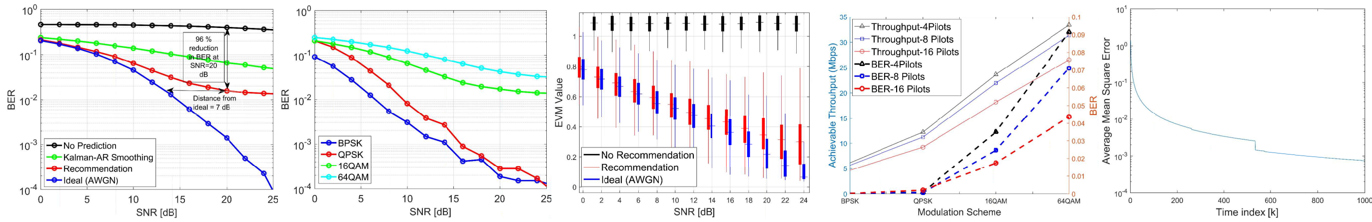
$\tilde{\mathbf{z}}_p(k)$ represents the inverse of the expected fading profile of the true channel, $\mathbf{z}_t(k)$ (see §III). Hence, the resultant channel, $\mathbf{z}_f(k)$, as estimated by the receiver vehicle is given by,

$$\mathbf{z}_f(k)=\mathbf{z}_t(k)\odot\tilde{\mathbf{z}}_p(k)+\mathbf{w}(k) \tag{7}$$

$\mathbf{w}(k)$ captures noise and estimation errors and $\odot$ is Hadamard product. CSI, $\mathbf{z}_f(k)$ captures the interaction between true and pre-equalized channels ($\mathbf{z}_t(k)$ and $\tilde{\mathbf{z}}_p(k)$). At the transmitter, measurement channel $\mathbf{z}(k)$ is computed, from (5) and (7),

$$\mathbf{z}(k)=\mathbf{z}_f(k)\odot\hat{\mathbf{z}}_p(k)+\mathbf{w}(k)=\mathbf{z}_f(k)./\tilde{\mathbf{z}}_p(k)+\mathbf{w}(k) \tag{8}$$

$\mathbf{z}(k)$ represents the error in the recommendation along with added system and numerical noise in the feedback loop. This forms the new input to the recommender system (in §II-B). Figure 3 shows the constellation diagram for a packet with 64-QAM modulation, which is pre-equalized by using the recommended channel and the equalized constellation at the receiver with the corresponding channel profile are shown. These results show that the channel recommender system works very well for higher order constellations as well. While residual distortion may remain at the receiver, the penalty in BER for those cases are minimal.




(a) BER for 16-QAM with 16 pilot tones. (b) BER for different modulation with 16 pilot tones. (c) EVM distribution for 16QAM-16 pilot tones (d) Throughput&BER for distinct modulations,pilots (e) Reduction in MSE with more CSI entries in tensor.

Figure 4: Performance of Recommendation system at the Receiver and the accuracy of the Recommender at the Transmitter.

## III. Experiments and Results

The V2X channel was modeled using WINNER channel toolbox in Matlab (accurately reflects real V2X channels [6]), and was used to emulate a schedule of downlink transmissions (i.e., the true channel $\mathbf{z}_t$), by randomly selecting a segment at each time step and selecting the channel state for that segment. In reality, this schedule is not observed by the vehicles, but is used here to evaluate the accuracy and performance of the recommender system. This simulated test-bed gives the freedom to address a variety of different scenarios of the V2X channel and scattering environment that may not be observed in measurement campaigns. Figures 4a and 4b show the BER performance, corresponding to an OFDM packet using different modulation and coding at carrier and sampling frequencies of 5.9GHz and 10MHz. Figure 4a shows the BER for 16-QAM modulation and $1/2$ coding, with and without (as in conventional 802.11p) channel recommendation (with pilot-based linear interpolation equalization at the receiver). The well compensated frequency selective fading of V2X channel (figure 3d) results in a BER improvement by two orders of magnitude, which is very encouraging. In contrast, conventional receiver algorithms are simply not sufficient to track the channel over space, time and frequency, hence performing much worse even at high SNR. This is a motivating reason to adopt a channel recommender at transmitter. Channel recommender requires only 7 dB more SNR to achieve same BER as ideal case. Figure 4b shows the BER for different modulations and the ability of the algorithm to support higher order modulations with very low BER. Figure 4c shows an almost ideal performance of EVM upto 16dB SNR.

In 802.11p, the inserted pilot tones are used to estimate the channel. While incorporating more pilot tones, improves the channel estimation at the receiver and results in a lower BER & EVM performance and more accurate channel prediction, it reduces the theoretical throughput. Figure 4d shows that while the transmission throughput reduces with increasing number of pilots, the drop in the *achievable* throughput is relatively less, since the BER also decreases. Hence, we can choose higher order modulations for V2X transmission to achieve higher throughput, while maintaining the same BER. Figure 4e shows the improvement in accuracy (Mean Square Error (MSE) between the recommended and true channel coefficients) of the channel recommender with time. As more entries are recorded, MSE reduces since the sparsity and noise in the tensor reduces.

This system can be extended to facilitate simultaneous multiuser downlink communication using Multiuser-MIMO which exploits recommended channel to precode waveforms to increase spatial multiplexing in dense vehicular networks. In V2V communication, since recommendation requires knowledge of vehicle topology, the RSU or a cloud based infrastructure should share this information with each vehicle. Currently we are conducting a measurement campaign, where the transmitter (RSU (laptop on road-side) or vehicle) and the receiver (vehicle) are equipped with Ettus USRP B210 radio, which also provides accurate timing and location using board-mounted GPS. Digital cameras mounted on the roof of the vehicle capture changes in scattering environment. Experiments are being conducted in areas with different scattering densities at different times of the day. The testbed will also enable research in proactive content caching, multiuser scheduling and other edge networking paradigm.

## IV. Conclusion

This work shows the power of recommender systems when applied to highly dynamic wireless environments like V2X networks. Through modelling, analysis and simulations, we draw three conclusions: 1) The channel recommender is able to successfully predict the V2X channel to obtain 96% lower BER in spatio-temporal, non-stationary channels by resulting in an almost flat fading profile at the receiver, 2) This enables higher modulation schemes to be used in V2X communications for high throughput, and 3) The accuracy of the recommender system improves with time, asymptotically achieving an MSE of $10^{-3}$. The encouraging results from this work will form the core of robust and highly reliable V2X networks supporting demanding mobile applications.

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