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Short-Term Prediction of Signal Cycle on an Arterial With Actuated-Uncoordinated Control Using Sparse Time Series Models

Bahman Moghimi, Abolfazl Safikhani, Camille Kamga, Wei Hao, and Jiaqi Ma

***Abstract*— Traffic signals as part of intelligent transportation systems can play a significant role in making cities smart. Conventionally, most traffic lights are designed with fixed-time control, which induces a lot of slack time (unused green time). Actuated traffic lights control traffic flow in real time and are more responsive to the variation of traffic demands. For an isolated signal, a family of time series models, such as autoregressive integrated moving average (ARIMA) models, can be beneficial for predicting the next cycle length. However, when there are multiple signals placed along a corridor with different spacing and configurations, the cycle length variation of such signals is not just related to each signal's values, but it is also affected by the platoon of vehicles coming from neighboring intersections. In this paper, a multivariate time series model is developed to analyze the behavior of signal cycle lengths of multiple intersections placed along a corridor in a fully actuated setup. Five signalized intersections have been modeled along a corridor, with different spacing among them, together with multiple levels of traffic demand. To tackle the high-dimensional nature of the problem, a penalized least-squares method is utilized in the estimation procedure to output sparse models. Two proposed sparse time series methods captured the signal data reasonably well and outperformed the conventional vector autoregressive model—in some cases up to 17%—as well as being more powerful than univariate models, such as ARIMA.**

***Index Terms*— Fully actuated signal, cycle length, time series, LASSO, HGLASSO.**

I. Introduction

TRAFFIC signals are one of the most significant components of the emerging system of smart cities. They have been designed to control the demand in a way to improve traffic flow and reduce crashes in urban networks. There have been many developments of controlling logic. The first generation of signal control logic was Pre-Times (Fixed) signal control. In fixed control systems, the value of the green time and cycle length were fixed regardless of demand variation, which could induce a lot of slack time - the green time that is not being used by system users. Although some attempts have been made to have different fixed-time signal logics by the time of day (a.m. and p.m. peak, midday, night time, etc.), this approach still imposes a lot of slack time on users. Subsequently, adaptive signal control has been designed to use information from the historical data of the past 5 or 10 minutes to update signal control parameters (including cycle length, split, and offset) and optimize timing and phasing to reduce user delays. There have been many adaptive control packages developed [1]–[4]. At the same time, with the rise of intelligent technologies such as detectors, sensors, wireless communication, vehicle-to-vehicle, and vehicle-to-infrastructure communications, signals have recently been designed intelligently using actuated control [5], [6]. Actuated control was presented to capture the demand at every second or even at a tenth of a second.

Fully actuated logic controls traffic signals in real time. It captures the underlying characteristics of the demand every second or even every tenth of a second. The control system collects traffic data through sensors, loop detectors, video, or radar. The actuated signal matches supply to demand in real time. It has the feature of compensation which means if a phase assigns more time to one direction because of reasons like emergency evacuation or transit signal priority, it compensates and allocates more time to the conflicting phases in the next cycle. The efficient fully actuated control operates so quickly that it results in shorter splits, cycle lengths, and therefore less delay to users [7]. Features enabling actuated signal control to operate as quickly as possible include: 1) using upstream/extension detectors, rather than over stop-line detectors, for gap detection, 2) using non-simultaneous gap-out logic instead of simultaneous gap-out 3) having shorter critical gaps, and 4) having shorter minimum green times [7]. Since, in actuated control, the signal cycle length is changing from time to time; this logic makes it difficult to provide good coordination among signals placed along a corridor.

To predict actuated control signal cycle, some previous studies tried to predict the expected traffic flow loaded over signal(s) for a short period ahead, and based on such traffic flow prediction, signal timing can be set [30]–[32]. However, in fully actuated setup, the behavior of signal cycle runs itself without being controlled exogenously. This research aims

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B. Moghimi and C. Kamga are with the Department of Civil Engineering, The City College of New York, New York, NY 10031 USA (e-mail: smoghim000@citymail.cuny.edu; ckamga@ccny.cuny.edu).

A. Safikhani is with the Department of Statistics, Columbia University, New York, NY 10027 USA (e-mail: as5012@columbia.edu).

W. Hao is with the Changsha University of Science and Technology, Changsha 410205, China (e-mail: haoweicsust@yahoo.com).

J. Ma is with the College of Engineering and Applied Science, University of Cincinnati, Cincinnati, OH 45221 USA (e-mail: jiaqi.ma@uc.edu).

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to capture the behavior of signal cycle using time series techniques and then utilize it to make a prediction.

The precise prediction of signal cycle length can be beneficial when it comes to intelligent traffic management, predicting travel time, emergency evacuation, and transit signal priority (TSP). Considering traffic signal priority for the emergency vehicle (e.g. ambulance) or transit (e.g. bus), the control logic attempts to change the signals' timing such that the movement of an ambulance or a bus gets facilitated. In other words, an ambulance/bus should face green light anytime it reaches traffic signal. This priority approach would result in less delay and travel time to emergency vehicles and transits. It is proven that having a longer prediction of transit arrival time can cause even less delay to transit with less impact on general traffic [8]–[11]. More specifically, with knowing transit arrival time for a longer horizon, actuated signal control can adjust itself slightly without making an abrupt decision. In other words, if the logic knows that approaching transit/bus will be at the target signal at a specific time in the future, say a fraction of the cycle length, the logic can extend or compress the cycle to some extent (depending on the different parameters). Also, together with knowing about the next value of cycle, the control logic should know about longer horizon transit arrival time in order to analyze which scenario can better match it with the signal green light, resulting in much less delay for transit/bus. Hence, in predictive TSP, with more accurate predictions of signal cycle lengths, signal priority performance can be potentially improved, and subsequently, transit's travel time, passenger delay, crowding, and reliability can also be improved.

Although actuated signal control has a lot of benefits, the prediction of the next cycle length is not an easy task since it varies from cycle to cycle. It is cumbersome to predict actuated signal cycle for an isolated signal and even more difficult to predict when there are multiple signals placed along a corridor. With regard to estimating signal cycle length for actuated control, Lin's study [12] developed a deterministic model to estimate the average green time and cycle length using headway distribution for estimating the extension green period. As a continuation of Lin's research, Akcelik's research [13] presented a model to estimate average green time with respect to minimum green, queue clearance time, and green extension time. More recently, Furth *et al.*'s study [7] introduced a new model to estimate actuated signal cycle length based on lost times. Seven lost time components were introduced. The evaluation of cycle length behavior on an isolated signal is performed based on the change of different levels of demand, detector setback, critical headway, and number of lanes per approach. Wadjas and Furth's research [10] used a simple adaptive logic that takes the average of the last five cycles to predict the next value of cycle length and thereby used the predicted value to adjust the signal cycle through compression or expansion to provide priority for transit.

In this research, a multivariate time series model is presented to predict the next values of cycle length for each signal located along a corridor. Time series models have been deployed in transportation research studies in the last decades. Univariate time series modeling has been used in the study by Barua *et al.*'s study [14] to predict the traffic arrival demand; and Williams and Hoel's study [15] predicted the seasonal variation of freeway traffic conditions. Meanwhile, multivariate time series modeling has been taken into consideration in transportation-related problems such as forecasting the relative velocity in roads [16] and predicting the traffic speed on a downstream link [17]. In this article, with the use of sparse multivariate time series modeling, the prediction of signal cycles is presented for multiple traffic lights in a corridor.

In the next section, we describe how fully actuated control is programmed and implemented in this study. Then, the structure of time series models from univariate ARIMA models to multivariate VAR models, and further, sparse time series models are introduced. Subsequently, the outputs from all of the time series models for different levels of demand and spacing are discussed and analyzed. Finally, the last section presents the main findings, conclusions, and discusses future work.

II. Methodology

Fully actuated control logic for five signalized intersections in a corridor is developed in this research. The developed controlling logic is based on standard actuation which turns the phases from green to red if the detected gap is larger than the minimum critical gap (gap-out) or exceeds the maximum green (max-out). The developed actuated control uses an upstream detector and is based on non-simultaneous gap-out logic. For left-turn phases, the logic skips the phase if there is no left-turn call. The logic uses a dynamic minimum green which updates the car counts between upstream and stop-line detector (cars-in-the-trap). It increments car counts by every upstream-detection and decrements it by every stop-line-detection.

Each traffic signal consists of many phases, some of which run concurrently and others that are in conflict which make up the critical phase. Each critical phase includes the green time and change interval (amber and all red time). Meanwhile, the duration of each phase can be a combination of some variables like the number of cars stopped during a red light, the stochastic arrival demand and platoon of cars dispatched from upstream intersections, the spacing between two adjacent signals, and other related variables. Therefore, in actuated control, each phase's queue length, split time, and obviously, signal cycle all changes from time to time. This research aims to determine if there is any covariance between the current value of a cycle length and its previous cycle lengths, and, more importantly, if there is any covariance among the datasets for different adjacent signals. For example, the study will investigate whether there is a correlation between the current value of the cycle length of a target intersection and its closest upstream signal or its next closest upstream signal, and so on. If there is any correlation among the datasets from different neighboring intersections, how we can make real-time prediction with lots of parameters. To do so, the fully actuated control logic is being modeled using microsimulation traffic software called VISSIM, and then the cycle length data is considered from the time series modeling perspective to capture variability and correlation among signals.

A. Time Series Model

Time series models are popular statistical models designed for data sets which are indexed by time. Time series models have been applied in different scientific areas including finance, water resources, climate change, transportation, etc. [18]–[21]. The main objective of time series models is to understand the behavior of the data over time and to decipher the dependence among such data points in order to predict the future. In this section, ARIMA and VAR models are introduced briefly as important and interpretable families of time series models in the univariate and multivariate, respectively.

1) ARIMA Model: Dealing with one data set, a univariate time series model such as the Auto Regressive Integrated Moving Average (ARIMA) model is a powerful yet simple statistical tool. Suppose one has the data set X_1, X_2, …, X_n, which are observed through time; i.e. $X_1$is the observation at the first time point, $X_2$is the observation at the second time point, etc. The Auto Regressive Moving Average ($ARMA$) model assumes that the current value of a time series is a linear combination of past observations combined with a linear combination of noises in the past observations. More specifically, the time series X_t is called $ARMA(p, q)$ if

$$X_t - \phi_1 X_{t-1} - \cdots - \phi_p X_{t-p} = Z_t + \theta_1 Z_{t-1} + \cdots + \theta_q Z_{t-q} \tag{1}$$

where Z_t is considered as white noise with mean 0 and variance $\sigma^2 (WN\left(0, \sigma^2\right))$, ϕ_1, ϕ_2, …, ϕ_p are called ARconstants, and θ_1, θ_2, …, θ_q are called MAconstants. In the above model, the current data point depends on the past p observations throughϕ_i's and the past q observation noises through θ_i's. ARIMA models are a simple extension of ARMA models allowing for some nonstationary behavior in the model by applying a differencing operator to the data first. It is referred to the research [22] for more details about the properties of ARMA and ARIMA models.

2) VAR Models: Vector Auto-Regressive (VAR) models are extensions of AR models in the multivariate setup. Due to the existence of spatial indexing in our data set, here VAR models are introduced using some sampling locations in the d-dimensional Euclidean space. More specifically, Suppose $s_1, s_2, \ldots, s_k$ are k fixed locations in $\mathbb{R}^d$ at which the response variable $\left\{y_t = \left(y_t\left(s_1\right), y_t\left(s_2\right), \ldots, y_t\left(s_k\right)\right) \in \mathbb{R}^k\right\}_{t=1}^{T}$ has been observed over a period of time with length T. Then, y_t follows a VAR model if it can be written as a linear combination of few part observations at arbitrary locations in the following way

$$y_t = \nu + \Phi^{(1)} y_{t-1} + \cdots + \Phi^{(p)} y_{t-p} + u_t, \quad t = 1, 2, \ldots, T, \tag{2}$$

where $\nu \in \mathbb{R}^k$ the intercept parameter, $\Phi^{(i)} \in \mathbb{R}^{k*k}$ the i-th lag coefficient matrix, and $\left\{u_t \in \mathbb{R}^k\right\}_{t=1}^{T}$ is a mean zero k-dim white noise with covariance matrix $\sum_u$. Also, p is the maximum time lag allowed in the VAR model. In practice, the model will be fitted for several values of p and the best one will be chosen based on the predictive performance of each model. It's obvious that in VAR model defined in equation (2), the current value of time series at a certain location might depend on the previous observed values at "different" locations. This allows for many more parameters to be introduced in the model and is in fact the main difference between the univariate AR and VAR models.

B. Regularization Method for Parameter Estimation

Parameter estimation for ARIMA models is rather simple [22]. However, in VAR model where the number of time series components are high, classical parameter estimation is problematic due to a large number of parameters in the model. Specifically, there are $k(kp+1)$ parameters to estimate, and if k is large compared to T, we may need to reduce the size in our estimation procedure. The linear regression compact matrix form of above formulation can be written as follows:

$$\mathrm{Y} = \Phi \mathrm{Z} + \mathrm{U} \tag{3}$$

Where

$$\begin{cases} \mathrm{Y} = [y_1 \ldots y_t] & (k * T); \\ \Phi = \left[\Phi^{(1)} \ldots \Phi^{(p)}\right] & (k * k.p); \\ z_t = \left[y'_{t-1} \cdots y'_{t-p}\right]' (kp * 1); & \\ \mathrm{Z} = [z_1 \ldots z_T] & (kp * T); \\ \mathrm{U} = [u_1 \ldots z_T] & (K * T); \\ \Phi_i^{(l:p)} = \left[\Phi_i^{(l)} \ldots \Phi_i^{(p)}\right] & (1 * \mathrm{k}(\mathrm{p} - \mathrm{l} + 1)). \end{cases} \tag{4}$$

In equation (4), Y is the matrix of all observations, Z is the matrix of all past observations with respect to Y, U is the matrix of concatenated noises, and Φ is the matrix of all transition matrices. When $k$is small, least squares method can be utilized for parameter estimation [22]. In order to deal with the high-dimensionality of the model when$k \gg T$, penalized least squares method are developed for parameter estimation. More specifically,

$$\hat{\Phi} = argmin_{\Phi} \left\{\frac{1}{2} \|Y - \Phi \mathrm{Z}\|_2^2 + \lambda \Omega\left(\Phi\right)\right\}, \tag{5}$$

where λ is the tuning parameter to be selected by a rolling scheme $(0 < T_1 < T_2 < T)$ [23]–[25], and $\Omega$is the penalty function on the parameters Φ.

For this study, the following two penalty functions are chosen:

1) Sparse VAR With LASSO–Least Absolute Shrinkage and Selection Operator: The elementwise L_1 penalty known as LASSO [26].

$$\Omega\left(\Phi\right) = \sum\nolimits_{i=1}^{p} \left\|\Phi^{(i)}\right\|_1 \tag{6}$$

2) Sparse VAR With HGLASSO–Hierarchical Group LASSO: This penalty function (Nicholson et al., 2014; Nicholson et al., 2017) penalizes the higher lag coefficients in a grouped way.

$$\Omega\left(\Phi\right) = \sum\nolimits_{i=1}^{k} \sum\nolimits_{j=1}^{k} \sum\nolimits_{l=1}^{p} \left\|\Phi_{ij}^{(l:p)}\right\|_2. \tag{7}$$

Note that in equation (7), $\Phi_{ij}^{(l:p)}$ is the vector of AR parameters to capture the effect of the i-th time series on the $j-th$ one in the last $p - l + 1$time lags. Therefore, the higher time lag parameters are present multiple times in the penalty function introduced in equation (7). This forces the last time lags to be set to zero much faster than the first time lag parameters. This is why this penalty function is called the "hierarchical" group LASSO. Solving optimization problems with the form of equation (5) have been studied extensively under different penalty functions [26]. Due to the hierarchical structure of the group penalties, especially in HGLASSO, this study applies the proximal gradient method introduced in Jenatton *et al.*'s study [27]. Further, the convergence rate of the proximal gradient method has been improved in Beck and Teboulle's research [28] by introducing the Fast Iterative Soft-Thresholding Algorithm (FISTA). It is worth noting that the optimization problem (5) can be split over the rows of $\hat{\Phi}$, which here is denoted by $\hat{\Phi}_i$ for the $i-th$ row, $i = 1, \ldots, k$. This makes it possible to scale the computation even for high values of k by parallel computing methods. In FISTA, a sequence of matrix coefficients $\hat{\Phi}_i\,[r]\,, r = 1, 2, \ldots$ is introduced iteratively through

$$\hat{\phi} = \hat{\Phi}_i\,[r-1] + \frac{r-2}{r+1}\left(\hat{\Phi}_i\,[r-1] - \hat{\Phi}_i\,[r-2]\right)$$
$$\hat{\Phi}_i\,[r] = Prox_{s\lambda\Omega}\left(\hat{\phi} - s\nabla f_i(\hat{\phi})\right), \tag{8}$$

with $f_i\,(\Phi_i) = \frac{1}{2}\,\|Y_i - Z_i\Phi_i\|_2^2\,, \nabla f_i\,(\Phi_i) = -Z_i'(Y_i - Z_i\Phi_i)$ the vector of derivatives of $f_i\,(\Phi_i)\,, Y_i$ and Z_i are the $i-th$ row of Y and Z, respectively. s is the step size (here we choose s to be $1/\sigma_1(Z_i)^2$ where $\sigma_1(Z_i)$ is the largest singular value of Z_i), and

$$Prox_{s\lambda\Omega}\,(u) = argmin_v\left(\frac{1}{2}\,\|u - v\|^2 + s\lambda\Omega\,(v)\right). \tag{9}$$

The proximal function (9) has a closed form for both penalty functions (6) & (7) defined above (See for example algorithm 2 in Nicholson *et al.*'s study [24]). As for the tuning parameter selection, the time points are divided into three parts (usually equally distanced)$0 < T_1 < T_2 < T$. The estimation procedure for fixed values of λ will be applied for the first part, i.e. $t = 1, 2, .., T_1$. Then, the mean squared prediction error (MSPE) for predicting one step ahead is calculated over all k time series components on the time

interval $[T_1 + 1, T_2]$:

$$MSPE = \frac{1}{k(T_2 - T_1)}\sum\nolimits_{i=1}^{k}\sum\nolimits_{t=T_1+1}^{T_2}(Y_i\,(t) - P_{T_1}Y_i\,(t))^2, \tag{10}$$

where $P_{T_1}Y_i\,(t)$ is the best linear predictor of $Y_i\,(t)$ based on the first T_1 observations. Now,

$$\hat{\lambda} = argmin_{\lambda}MSPE\,(\lambda)\,. \tag{11}$$

The model performance then can be quantified by the MSPE on the last part of the data, which is on the time interval $[T_2 + 1, T]$. Note that several parameter estimation methods are introduced in this section, and hence we need to distinguish them. For that, in the following sections, VAR stands for least squares estimation (i.e. when $\lambda = 0$ in the estimation procedure (5)), LASSO stands for penalized estimation with LASSO penalty, and HGLASS stands for penalized estimation with HGLASSO penalty.

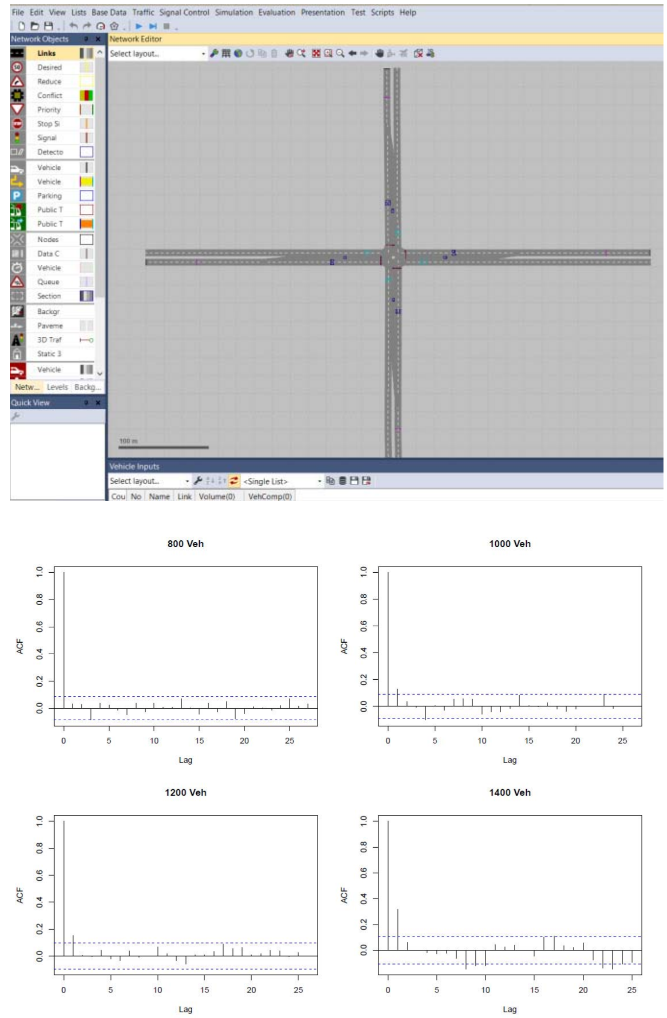

Fig. 1. Isolated actuated signal layout in VISSIM, and sample ACF over different levels of demand.

III. General Results

In order to understand signal cycle behavior in a corridor, one should first take a look at such behavior at an isolated intersection. Thereby, the behavior of the signal cycle of an isolated signal is briefly discussed here. It has been studied by Moghimi *et al.* [29] that the behavior of a signal cycle can be captured by using the univariate time series model, the ARIMA model. Figure 1 demonstrates the autocorrelation function (ACF) over signal cycle data, acquired for different levels of demand which were loaded on an isolated signalized intersection with two critical phases. As seen, as the demand increases from 800 veh/hr to 1400 veh/hr, the correlation between two consecutive signal cycles becomes more pronounced. This indicates that the behavior of signal cycle under fully actuated control can be analyzed through time series models, specifically when the level of demand is medium or high. Moreover, given that there is a significant correlation between datasets, a more precise prediction will be needed. Meanwhile, when there are left-turn phases, for signals with more than two critical phases, applying the linear regression over skipping indicators and then using ARIMA model could result in a smaller prediction error.

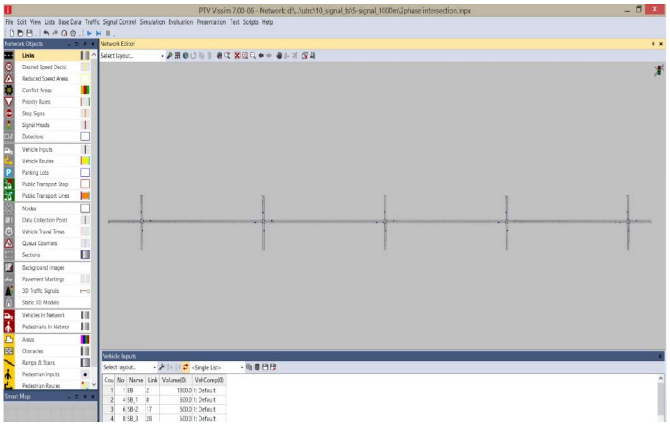

Fig. 2. Signalized corridor layout in VISSIM.

For more details, the reader is referred to Moghimi *et al.*'s research [29].

In this paper, multivariate time series models on signal cycle data along a corridor are developed and analyzed. To do so, a corridor of five signalized intersections is modeled using VISSIM microsimulation which is depicted in Figure 2. The signal control logic is programmed in C++, using VISSIM's application programming interface (API). In the developed model, at every time step of the simulation, detector information is passed from the simulation to the controller and then the signal phase state is returned to the simulation program. The corridor is an eastbound one-way street with two lanes. Each controller runs under fully actuated control with two critical phases. To see the covariance of demand from one signal to another, the demand on cross streets is set as 600 veh/hr and the demand volume on west entry streets changes from 800 veh/hr to 1600 veh/hr, with the increment of 200 veh/hr, as a realization of how the street functions from off-peak to peak hour conditions. The minimum and maximum green times are defined as 12 seconds and 50 seconds, respectively. Upstream detectors were located about 2 seconds of travel time from the stop line. Various spacing is modeled in this research, including 200 meters, 500 meters, and 1000 meters. For each scenario, the VISSIM simulation was run for 5 hours following a 15-minute warm-up period. Subsequently, the time series models defined earlier were applied over the cycle length data coming from the traffic simulation. To illustrate the variability of cycle length among the intersections, the boxplot for the eastbound demand of 1200 veh/hr and spacing of 500 m for all intersections as an example is plotted in Figure 3.

The prediction procedure is as follows: for each time series, the last 75 observations (the last 75 signal cycles) are excluded for the prediction purpose and then different prediction models are applied. Different prediction models are 1) averaging the last 5 cycles, 2) the univariate ARIMA model, 3) the multivariate VAR model, 4) the multivariate LASSO model, and 5) the HGLASSO model. To evaluate the performance of each method, a Mean Squared Prediction Error (MSPE) as shown in equation (10) is used. The lower the MSPE the better the model performance. More specifically,

$$MSPE = \frac{1}{5*75}\sum_{i=1}^{5}\sum_{t=T+1}^{T+75}\left(Y_i\left(t\right) - P_T Y_i\left(t\right)\right)^2, \quad (12)$$

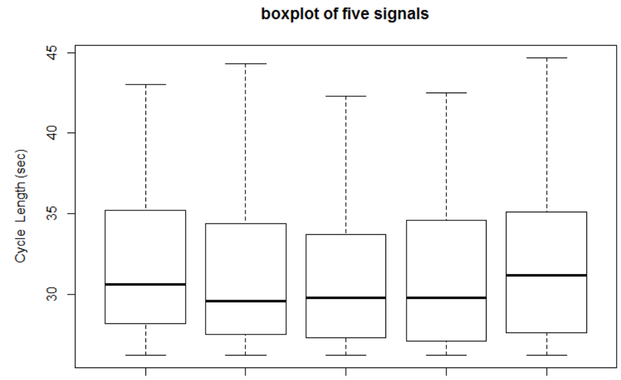

Fig. 3. Boxplot of five signal cycle length for eastbound demand of 1200 veh/h and spacing of 500 m.

TABLE I

MSPE OF ALL MODELS WITH METERS SPACING BETWEEN SIGNALS

Spacing	200 meters				
EB Volume (v/hr):	800	1000	1200	1400	1600
MSPE.avg	39.2	38.5	30.4	47.9	90.8
MSPE.univ	31.4	32.0	25.2	40.4	76.3
MSPE.var	26.9	31.7	22.4	36.8	66.9
MSPE.LASSO	26.8	30.8	22.1	35.4	66.1
MSPE.HGLASSO	26.8	30.8	22.1	35.4	66.1

TABLE II

MSPE OF ALL MODELS WITH DIFFERENT LEVELS OF DEMAND HAVING 500 METERS SPACING

	Spacing	**500 meters**				
	EB Volume (v/hr):	**800**	**1000**	**1200**	**1400**	**1600**
1 lag	**MSPE.avg**	29.1	32.0	31.7	50.2	85.7
	MSPE.univ	26.1	29.1	25.2	39.4	70.4
	MSPE.var	26.0	28.2	17.3	31.0	58.0
	MSPE.LASSO	25.2	27.5	17.3	31.0	56.5
	MSPE.HGLASO	25.2	27.5	17.3	31.0	56.5
2 lags	**MSPE.univ**	26.5	29.1	25.6	39.6	70.4
	MSPE.var	28.7	31.3	17.9	33.7	62.0
	MSPE.LASSO	25.3	27.9	17.3	31.0	57.4
	MSPE.HGLASSO	25.2	27.8	17.3	31.0	57.2

where T is the last observed cycle length used for parameter estimation, $Y_i\left(t\right)$ is the t-th cycle length observed at the i-th intersection, and $P_T Y_i\left(t\right)$ is the best linear predictor of $Y_i\left(t\right)$ based on the first T observations (See [22] for more details).

To evaluate the variation of signal cycles along the corridor, different scenarios were analyzed including a signalized corridor with spacing between signals varying from 200m, 500m, and 1000m, along with loading different levels of demand for each scenario. The prediction performance for the three spacing scenarios, 200m, 500m, and 1000m, are shown in Tables 1, 2, and 3, respectively. Noteworthy, the results shown in Table 1, 2, and 3 are the combined MSPE results of all 5 simulated intersections.

Table I shows the results of the five models with 200 meters spacing, and the levels of demand ranging from 800 veh/hr to 1600 veh/hr. As seen, all four time series models, at all levels of demand, perform better as compared to the conventional method of averaging the last 5 cycles. Moreover, the multivariate models, VAR, LASSO, and HGLASSO, outperformed the univariate model statistically; with the gaps

TABLE III
MSPE OF ALL MODELS WITH 1000 METERS SPACING BETWEEN SIGNALS

	Spacing	1000 meters				
	EB Volume (v/hr):	800	1000	1200	1400	1600
1 lag	MSPE.avg	29.7	23.6	33.7	53.2	69.8
	MSPE.univ	26.5	20.4	27.9	43.4	57.6
	MSPE.var	27.3	21.8	24.8	42.5	46.5
	MSPE.LASSO	26.0	20.2	24.5	41.9	46.7
	MSPE.HGLASSO	26.0	20.2	24.5	41.9	46.7
2 lags	MSPE.univ	26.5	20.4	28.0	43.5	58.1
	MSPE.var	30.7	23.4	26.2	43.9	48.6
	MSPE.LASSO	26.4	20.3	25.3	40.7	45.5
	MSPE.HGLASSO	26.0	20.2	24.9	40.9	45.6
3 lags	MSPE.univ	26.5	20.4	28.2	43.6	58.1
	MSPE.var	33.6	25.2	29.2	46.7	53.4
	MSPE.LASSO	26.6	20.4	25.4	40.5	46.0
	MSPE.HGLASSO	26.0	20.3	24.9	40.7	46.0

between their values becoming wider as the demand increases. This is due to the fact that, as demand increases, the effect of neighboring intersections becomes stronger, and therefore the multivariate models VAR/LASSO/HGLASSO outperform the univariate model since they account for this effect.

Table II reports the MSPE for the five models with 500 meters spacing at various levels of demand. As was found from simulation with 200m spacing, the time series models outperformed the averaging one. Also, the multivariate time series models (VAR and Sparse VAR models) have lower errors as compared to the univariate and averaging models. For example, for the eastbound demand of 1200 veh/hr, the averaging method resulted in the MSPE of around 31 where this amount is reduced to around 25 with the use of ARIMA model. The prediction error is further lowered to around 17 by applying the multivariate time series models developed here. This gap in MSPE has widened for higher demands of 1400 veh/hr and 1600 veh/hr. From this result, it is found that the LASSO and HGLASSO models have the smallest MSPE of all listed models.

Table III reports the MSPE of the five models with a 1000m spacing between signals and various levels of demand for different maximum time lags allowed p as explained after equation (2) in the methodology section. Specifically, the $i-th$ row (lag i) is related to prediction results with considering i previous time lag from history of the cycle data (i.e. $p = i$ in the description of both ARIMA and VAR model), for $i = 1, 2, 3$. Since the results are worse for higher time lags (i.e. 4 or higher), the MSPEs reported in table III are up to the time lag 3. With a very large distance between signals, the platoon arrival pattern functions differently. In a sparsely-spaced signalized corridor, the platoon of cars is not as dense, large, and imminent as it is in a more closely spaced signalized corridor. For such cases, it is better to penalize some of the AR coefficients to achieve better prediction accuracy. Therefore, the Sparse VAR models can be more useful in this regard. It is noteworthy that, with 1000 m spacing, 2 or 3 time lags are better for the model since it takes 1 or 2 cycles on average for the platoon of cars to pass from the upstream intersection to the downstream one. The LASSO and HGLASSO models have similar performance when the lag $p = 1$ since there is no hierarchical effect in this case. As p increases, the effect of the hierarchical penalty will be more apparent. For example, for a spacing of 1000m, EB volume 800 and 1200, when $p = 3$, HGLASSO outperforms LASSO with the reduction of more than 2% in MSPE.

Considering the results shown in the tables above, it can be concluded that, when there is more than one signal, multivariate time series is a better tool for understanding the behavior of signal cycles. Meanwhile, it is found that the multivariate models used in this study, including VAR, LASSO, and HGLASSO, can achieve lower mean square prediction errors for signal cycle length as compared to the two other models - averaging the last five cycles and the univariate ARIMA model. Also, when the signals are closely spaced, such as 200 meters apart, the behavior of adjacent signals is highly correlated with one another; they are relatively behaving the same as compared to a corridor with signals spaced far apart. On the other hand, when the signals are spaced closely, the correlation between signals within one cycle is strong, while in a corridor of far-spaced intersections, the correlations between them exist *after* the travel time between them, which can be measured as 2 or 3 cycles apart for 500 m and 1000 m spacing, respectively. Meanwhile, the Sparse VAR models perform better in predicting the next value of signal cycle among the five models, when the distance between signals is high (1000 meters) and the demand is high as well. Such mathematical findings can be interpreted in practical research that has been conducted by transportation scholars on self-organizing signal control [5], [29]. It indicates that when signals are closely spaced, those signals should be synchronized together by having the same cycle length. When they are spaced far apart, because there is a dependency with a time lag (travel time between signals), a platoon-based coordination can better provide coordination among signals.

IV. PARTICULAR CASE

Figure 4 shows the sample ACFs of the simulated signal cycle data for the 5 signals spaced 500 meters apart with an eastbound volume of 1200 veh/hr, which indicates the existence of a strong temporal dependency, especially between neighboring intersections. The graphs located along the diagonal represent the sample ACF for the data itself and the other graphs represent the correlation between two different signals. For instance, the graph labeled "Srs 4 & Srs 5" shows the correlation between the time series for signal 4 and that for signal 5. It is notable that the ACF on the signal 5 is more pronounced, which due to the fact that the simulation case is a one-way street and signal 5 is the last intersection receiving all traffic flows.

Considering the spacing of 500 meters and the speeds of the cars, it takes about a half cycle or one cycle for the cars to

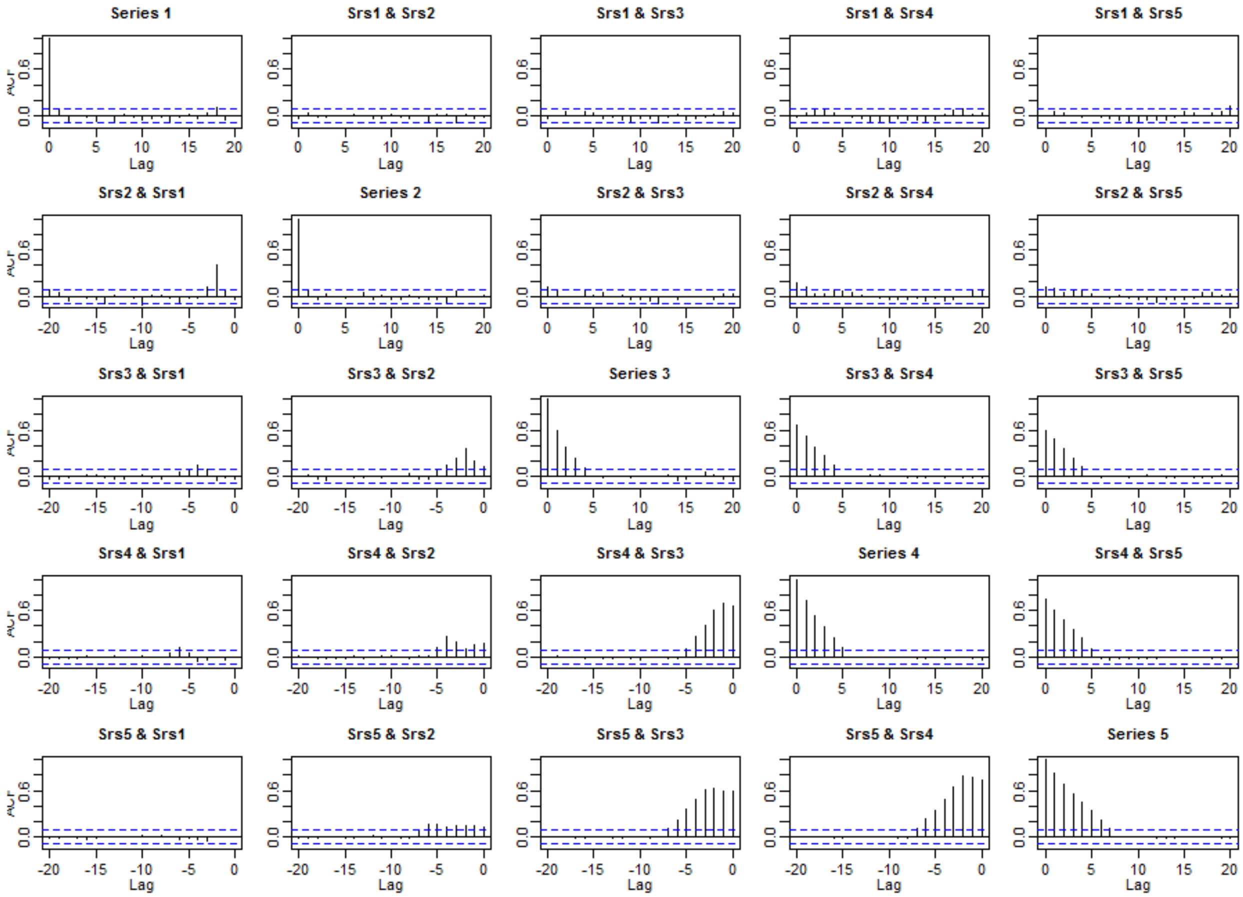

Fig. 4. Sample ACF of the five signals with 500 m spacing and 1200 veh/hr demand.

travel from one signal to the next. Hence, using the correlation of the previous two lags between signal cycles data can better predict the next value of the target cycle length. Figure 5 shows the $\Phi^{(i)}$ matrices among signals having two lags for both the VAR and HGLASSO models

Figure 6 shows the predicted values for the last 75 observations. The black line is the actual time series, the green line is the average of the last five cycles, the blue line is the *ARIMA* model, the pink line is the VAR model, the yellow line is the LASSO model, and the red line is the HGLASSO model. As it can be seen, the multivariate models including the VAR, LASSO, and HGLASSO (pink, yellow, and red lines) perform well in capturing the true observations' oscillation.

A. Results for Signal5

Since signal 5 is the last intersection in the one-way street simulation set-up shown in Figure 2, it has a more pronounced correlation from its upstream signals than the other signals do. Table IV shows the mean squared prediction errors for the fifth signal. The results are for using one lag, two lags, and three lags in all of the prediction models for street-spacings of 200 m, 500 m, and 1000 m, respectively. As before, all the time series models perform better than the conventional cycle averaging model. Meanwhile, multivariate models outperform the univariate ARIMA model. Moreover, among the three multivariate models, the two sparse models in this paper-LASSO and HGLASSO–have lower prediction errors than the conventional VAR model. This reduction in MSPE is in some cases as high as 17% (the difference in the error from VAR model to LASSO model for the case of 1000 m spacing and 1600 veh/hr volume).

TABLE IV
MSPE of All Models for Different Levels of Spacing and Demand for the 5th Signal

Spacing	**200 m**				
EB Volume (v/hr)	**800**	**1000**	**1200**	**1400**	**1600**
MSPE.avg	49.3	53.7	34.5	38.1	76.5
MSPE.univ	42.6	45.0	29.1	31.0	74.6
MSPE.var	41.2	40.0	28.4	28.1	67.5
MSPE.LASSO	39.0	38.9	27.6	27.5	65.6
MSPE.HGLASSO	39.0	38.9	27.6	27.5	65.6
Spacing	**500 m**				
EB Volume (v/hr)	**800**	**1000**	**1200**	**1400**	**1600**
MSPE.avg	35.6	37.8	28.4	86.7	84.0
MSPE.univ	33.0	33.0	24.8	69.2	66.5
MSPE.var	30.9	30.7	18.8	62.5	58.0
MSPE.LASSO	30.1	32.7	17.6	57.5	51.9
MSPE.HGLASSO	30.5	32.1	17.5	57.4	50.9
Spacing	**1000 m**				
EB Volume (v/hr)	**800**	**1000**	**1200**	**1400**	**1600**
MSPE.avg	38.7	16.6	41.8	66.9	57.2
MSPE.univ	32.4	14.9	37.4	58.0	50.4
MSPE.var	38.7	15.4	39.8	55.9	45.5
MSPE.LASSO	31.5	14.7	36.1	50.5	37.4
MSPE.HGLASSO	31.1	14.8	35.2	49.7	39.6

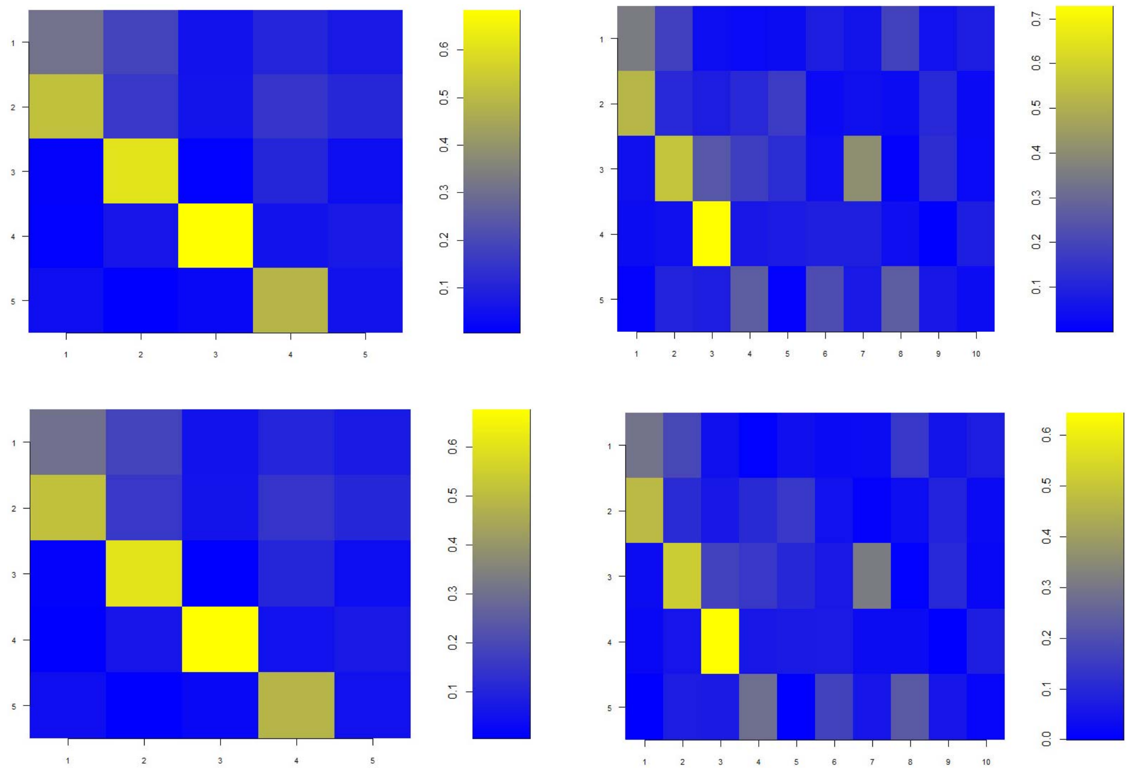

Fig. 5. The top row shows the VAR coefficient matrix with one and two lags; and the bottom row shows the HGLASSO coefficient matrix with one and two lags.

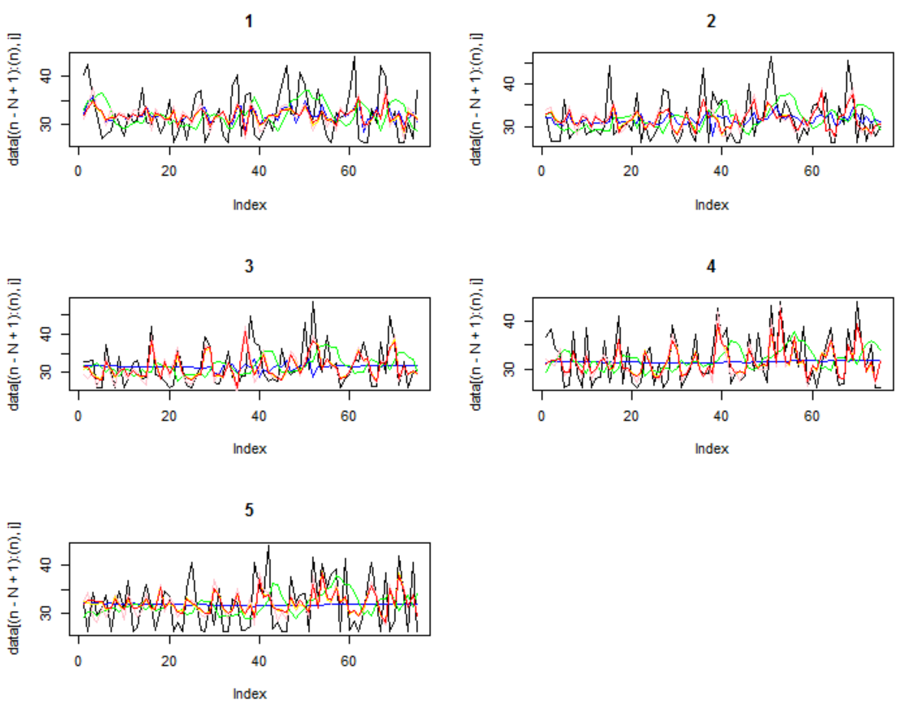

Fig. 6. Predicted values of all prediction models for the five signals over the last 75 cycles (black line = actual observation, green line = averaging; blue line = ARIMA; pink line = VAR; yellow line = LASSO; red line = HGLASSO).

B. Results for Two-Way Street

Table V demonstrates the results of the analysis of a two-way street on the same corridor with 500 meters spacing, under different combinations of demand (the time lag p=2 in this table). As it can be seen, even after making the simulated street as two-way, the two proposed sparse time series models (LASSO and HGLASOO) outperformed the other listed models. For example, for the case of east bound (EB) having a demand of 1200 veh/hr and west bound (WB) with 1000 veh/hr demand, the mean squared prediction error (MSPE) resulted in 33.19 for LASSO and 32.98 for HGLASSO. Using sparse models have reduced the

TABLE V
MSPE OF ALL MODELS ON A TWO-WAY STREET INCLUDING 5 SIGNALS WITH 500 m SPACING UNDER DIFFERENT COMBINATIONS OF DEMAND

	EB_1200v_ WB_600v	EB_1400v_ WB_600v	EB_1200v_ WB_800v	EB_1400v_ WB_800v	EB_1200v_ WB_1000v	EB_1400v_ WB_1000v
MSPE.avg	27.92	41.18	36.75	65.76	37.52	54.83
MSPE.univ	24.12	32.72	32.00	55.28	33.76	44.12
MSPE.var	25.82	34.54	32.32	56.34	35.94	47.55
MSPE.LASSO	23.83	31.48	31.41	52.88	33.19	41.83
MSPE.HGLASSO	23.65	31.34	31.17	53.73	32.98	41.65

prediction error around 12% as compared to the averaging method. It is worth noting that for two-way streets, due to the complex networks of traffic, time series models with additional structure on the components respecting the traffic network or high-dimensional graphical models with intersections as nodes may give more satisfactory results in terms of prediction. Developing comprehensive and rigorous modeling framework for predicting cycle length over two-way streets with different configurations or even more complex networks is out of the scope of the current paper, and will be investigated in our future projects.

V. CONCLUSIONS AND FUTURE STUDIES

This research analyzed the variation of signal cycles in a fully actuated set-up along a corridor for varying levels of traffic demand and signal spacing. The results derived from a VISSIM simulation for different scenarios were studied. It was found that time series models are strong statistical tools for capturing signal cycle behavior and predicting this behavior reasonably well, not only for isolated signals but also for multiple signals along a corridor. This research introduced a data-driven, statistical tool, the multivariate time series VAR, LASSO, and HGLASSO models, for predicting actuated cycle length for signals placed along a corridor. The results revealed that when there is a significant correlation between signal cycles, multivariate time series models can perform fairly well. Moreover, two sparse time series models, LASSO and HGLASSO, were found to outperform the conventional VAR model. The reason is that the sparse models penalized some of the statistical parameters and forced them to be zero to improve prediction accuracy. This study is mostly focused on one-way streets. However, the situation could be different in two-way streets, with platooning comes at different times in the two directions. This makes the cycle length prediction more difficult. Predicting cycle length in two-way streets with different configurations or even more complex networks is an interesting direction for the future research. Also, a spatial-temporal autoregressive (STAR) method [33] could be developed to compare with the introduced sparse time series models. Furthermore, the use of accurate cycle length prediction in actuated signal control will be applied to predictive transit signal priority.

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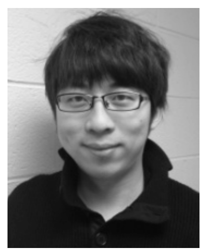
Bahman Moghimi received the M.S. degree in transportation engineering from Northeastern University, Boston, MA, USA. He is currently pursuing the Ph.D. degree in transportation engineering with The City College of New York. His main research interests include traffic signal control and transit signal priority.

Abolfazl Safikhani received the Ph.D. degree in statistics from Michigan State University. He is currently an Assistant Professor with the Department of Statistics, Columbia University, New York, NY, USA. His main research interests include massive spatial data modeling and high-dimensional statistics.

Camille Kamga received the Ph.D. degree in civil engineering (transportation) from The City University of New York. He is currently an Associate Professor with the City College of New York, and the Director of the University Transportation Research Center, Manhattan, NY, USA. In that role, he works closely with federal, regional, and state transportation planning and policy organizations. He has published many papers in the research area of transportation.

Wei Hao received the Ph.D. degree from the Department of Civil and Environmental Engineering, New Jersey Institute of Technology. He is currently a Professor with the Changsha University of Science and Technology, China. His areas of expertise include traffic operations, ITS, planning for operations, traffic modeling and simulation, connected automated vehicles, and travel demand forecasting.



Jiaqi Ma is currently an Assistant Professor with the Department of Civil Engineering, University of Cincinnati. Prior to that, he was a Research Scientist with the FHWA Turner Fairbank Highway Research Center, Leidos, Inc. His areas of expertise include traffic operations, intelligent transportation systems, connected automated vehicles, planning for operations, and traffic modeling and simulation. He is a member of the TRB Standing Committee on Vehicle-Highway Automation, the IEEE ITS Society, the ITS Midwest, and the American Society of Civil Engineers.