Multivariate Short-Term Traffic Flow Forecasting Using Time-Series Analysis

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***Abstract*—Existing time-series models that are used for short-term traffic condition forecasting are mostly univariate in nature. Generally, the extension of existing univariate time-series models to a multivariate regime involves huge computational complexities. A different class of time-series models called structural time-series model (STM) (in its multivariate form) has been introduced in this paper to develop a parsimonious and computationally simple multivariate short-term traffic condition forecasting algorithm. The different components of a time-series data set such as trend, seasonal, cyclical, and calendar variations can separately be modeled in STM methodology. A case study at the Dublin, Ireland, city center with serious traffic congestion is performed to illustrate the forecasting strategy. The results indicate that the proposed forecasting algorithm is an effective approach in predicting real-time traffic flow at multiple junctions within an urban transport network.**

***Index Terms*—Multivariate, prediction methods, time series, traffic flow.**

I. Introduction

THE implementation of intelligent transportation systems to provide dynamic traffic control requires continuous forecasting of traffic conditions in the near (short-term or less than 1 h [1]) future. Short-term traffic forecasting is an important tool in following the evolution of traffic conditions over time in a transport network. This type of advanced forecasting methodologies, having a time horizon of 15 min or less [1], can provide information to support short-range operational modifications to improve the efficiency of the network at a finer scale. With the increasing need to develop more adaptive (site and time specific) traffic management systems, considerable research attention has been focused on short-term traffic forecasting.

Well-known short-term forecasting algorithms can broadly be classified into univariate and multivariate approaches. The univariate approach is based on the modeling of traffic-condition-related variables (such as speed or flow or occupancy) using observations from any single site, whereas the development of a single model by considering several sites for input and output is termed as the multivariate approach. Unlike univariate models, these models are capable of capturing the temporal and spatial evolution of traffic conditions over time in a transportation network. However, due to the ease of computation, univariate models are more common in short-term traffic-forecasting literature [2].

Both multivariate and univariate models can be developed using different empirical and theoretical techniques [3]. The empirical approaches (nonparametric and parametric) employ a fairly standard statistical methodology and/or a heuristic method for traffic flow forecasting without referring to the actual traffic dynamics. The nonparametric techniques include nonparametric regressions (e.g., [4]) and neural networks (e.g., [5] and [6]). Due to their intrinsic multi-input nature, neural network models are often favored among the space-time or multivariate models [7]. The parametric techniques include different time-series models, such as linear and nonlinear regression, historical average algorithms (e.g., [8]), smoothing techniques (e.g., [8] and [9]), and autoregressive linear processes (e.g., [9]–[13]). Of all the autoregressive linear processes, seasonal autoregressive integrated moving average (SARIMA) models (e.g., [13] and [14]) perform better than other time-series techniques ([1] and [15]).

With a few exceptions [2], [13], [16], [17], most of the literature in short-term traffic forecasting is univariate in nature. The available multivariate empirical models in the short-term traffic forecasting literature are mainly multivariate variations of the existing univariate parametric statistical models, e.g., the multivariate autoregressive integrated moving average (ARIMA) model [2] and the space-time ARIMA model [17]. Another type of multivariate time-series model based on state-space methodology was introduced as a short-term traffic forecasting technique by Stathopoulos and Karlaftis [18]. These models can account for the dimension of space in a transport network. However, the models are computationally demanding as the multivariate nature involves the estimation of a large number of parameters.

In this paper, a new multivariate structural time-series (MST) model using the seemingly unrelated time-series equation (SUTSE) has been chosen to model the traffic flow time-series observations from multiple junctions within a congested urban transportation network. In the case of urban transport networks, the traffic flows are not strictly located on the same routes or sharing the same paths due to the existence of ubiquitous sink/sources and excessive merging and diverging maneuvers. As a result, the multivariate short-term traffic flow forecasting models become complex and require tedious calculations that are associated with route choice. Since a SUTSE model does not use cause-and-effect relationships among the variables, this model will computationally be more efficient while considering multivariate traffic flow observations.

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The SUTSE model introduced by Harvey [19] is a type of MST model. In MST, the evolution of different components of time-series data such as trend, seasonal, cyclical, and calendar variations with time can separately be modeled. The verification of the stationarity conditions in the time-series data sets is not critical in MST and missing observations, and exogenous variables such as traffic flow observations of other upstream junctions can relatively easily be incorporated in these models [19]–[21]. In addition to the computational efficiency in multivariate form, the aforementioned characteristics lend additional advantages to the SUTSE model and significantly distinguish the SUTSE model from the classical autoregressive moving average (ARMA) class of models.

II. Theoretical Background

The structural time-series model (STM) methodology is a particular time-series analysis technique that is set up in terms of components that have a direct physical interpretation [19]. The different components of an STM are the (deterministic and stochastic) trend, seasonal, cyclical, and calendar variations, together with the effect of explanatory variables and interventions (outlier and structural breaks). The basic principle behind the STM is similar to that of the Holt–Winters exponential smoothing model [9], [14] but more complex. Multivariate STMs are a straightforward extension of univariate STMs and involve less computational complexities than the other existing multivariate time-series techniques. An overview of the univariate and multivariate STM definitions is given in this section. A detailed discussion on this subject is available in [19] and [21]. A software package called Structural Time-Series Analyser, Modeller and Predictor (STAMP) 6.0 [22], [23] is used in this study to model traffic flow observations using STMs.

A. Univariate STM Methodology

A univariate STM is formulated based on the unobserved components, which have a direct interpretation in terms of the temporal variability of a time-series data set. Consequently, the evolution of components such as trend or seasonality over time and their contribution to the final predictions can clearly be observed. A univariate STM for a time-series data set $\mathbf{y}$ can be described by the following general equation involving all possible types of temporal components in its form

$$y_t = \mu_t + \gamma_t + \psi_t + \nu_t + \varepsilon_t, \qquad \varepsilon_t \sim \text{NID}(0, \sigma_\varepsilon^2)\ t = 1, \ldots, T \tag{1}$$

where y_t is the observed data at an instant of time t, μ_t is the trend, γ_t is the seasonal component, ψ_t is the cycle, ν_t is the first-order autoregressive component, and ε_t is the irregular or random error component. The random error is assumed to follow a normal identical distribution (NID) with zero mean and variance σ_ε^2. For the purpose of traffic flow modeling, the univariate and multivariate STMs are considered to comprise stochastic trend, seasonality, and irregular components. Hence, (1) reduces to the following form:

$$y_t = \mu_t + \gamma_t + \varepsilon_t, \qquad \varepsilon_t \sim \text{NID}\left(0, \sigma_\varepsilon^2\right). \tag{2}$$

Stochastic trend component μ_t represents the long-term movement in a time series, which can be extrapolated into the future. In case of traffic flow observations over a few weeks from a developed urban transport network, this long-term movement does not show any significant gradient and should be modeled for the local fluctuations. A Markov model of the stochastic trend can be considered for this purpose (change of slope is not considered), i.e.,

$$\mu_t = \mu_{t-1} + \eta_t, \qquad \eta_t \sim \text{NID}\left(0, \sigma_\eta^2\right). \tag{3}$$

The variance of irregular component σ_ε^2 and the variance of stochastic trend (level) σ_η^2 are mutually uncorrelated. Process μ_t collapses to a linear trend if $\sigma_\eta^2 = 0$. The periodic nature of the time-series data set is chosen to be modeled using a trigonometric specification of the seasonal component as this ensures a smooth change as observed in traffic flow time-series data, i.e.,

$$\gamma_t = \sum_{j=1}^{\left[\frac{s}{2}\right]} \gamma_{j,t} \tag{4}$$

where each $\gamma_{j,t}$ is generated by

$$\begin{bmatrix} \gamma_{j,t} \\ \gamma_{j,t}^* \end{bmatrix} = \begin{bmatrix} \cos\lambda_j & \sin\lambda_j \\ -\sin\lambda_j & \cos\lambda_j \end{bmatrix} \begin{bmatrix} \gamma_{j,t-1} \\ \gamma_{j,t-1}^* \end{bmatrix} + \begin{bmatrix} \omega_{j,t} \\ \omega_{j,t}^* \end{bmatrix}, \begin{matrix} j = 1, \ldots, \frac{s}{2} \\ t = 1, \ldots, T \end{matrix} \tag{5}$$

where $\lambda_j = 2\pi j s^{-1}$ is the frequency (in radians), and seasonal disturbances ω_t and ω_t^* are mutually uncorrelated random normal disturbances with zero mean and common variance σ_ω^2. The superscript $*$ in (5) signifies a minimal realization of the state vector in the state-space form [19]. When s is even, (5) at $j = (s/2)$ collapses to

$$\gamma_{j,t} = \cos\lambda_j \gamma_{j,t-1} + \omega_{j,t}. \tag{6}$$

Equations (2)–(5) define the STM used in this study. The disturbances of the individual components of the STM (σ_ε^2, σ_η^2, and σ_ω^2) mentioned in these equations are all mutually uncorrelated. Variances σ_ε^2, σ_η^2, and σ_ω^2 denote the extent to which the individual components such as the trend or seasonal component will vary with time and are called hyperparameters [24]. Equations (2)–(5) are generally solved in state-space form using Kalman-filter-based algorithms [19], [25]. The hyperparameters and the components are estimated using the maximum-likelihood estimation method.

In some cases, the time-series observations to be modeled have dynamic relationships with some other independent variables. They are called explanatory or exogenous variables, and inclusion of these variables in the STM may improve the forecasting precision of the models. Inclusion of the explanatory variables changes the first part of (1) to the following form:

$$y_t = \mu_t + \gamma_t + \psi_t + \nu_t + \sum_{i=1}^{k} \sum_{\tau=0}^{q} \Delta_{i\tau}\, x_{i,t-\tau} + \varepsilon_t \tag{7}$$

where $x_{i,t-\tau}$ is an exogenous variable, k is the total number of exogenous variables, τ is the time lag, and $\Delta_{i\tau}$ is a set of unknown constants. The significance of τ is that, in some cases, the lagged value of the dependent variable can be considered as an exogenous variable in the STM.

B. Multivariate STM Methodology

Multivariate time-series data can chiefly be classified into two distinct types: 1) panel data and 2) interactive data [19]. The time-series data sets in panel data are subjected to the same or similar influences or environments, but the individual elements do not interact with each other. As the variables follow a similar temporal nature, they can jointly be modeled. In contrast, multivariate interactive time-series data sets have some behavioral relationships among themselves and dynamically interact with each other. This distinction is important in identifying the suitable type of MST analysis technique. The multivariate traffic flow observations obtained from different stations within the same transport network are modeled in this paper as panel data. The rationale behind the treatment is explained in detail in the next section.

The panel data are modeled by an MST technique referred to as SUTSE. In the SUTSE model, it is assumed that the different time-series data sets are not interrelated through any physical cause-and-effect relationships between them. However, they are subjected to the same overall environment, thus statistically linking themselves within a multivariate framework. In the STM regime, SUTSE modeling is possible by allowing the various components to be contemporaneously correlated [19].

The univariate equations described in the previous subsections can easily be extended to the SUTSE model as

$$\boldsymbol{y}_t=\boldsymbol{\mu}_t+\boldsymbol{\gamma}_t+\boldsymbol{\varepsilon}_t, \qquad \boldsymbol{\varepsilon}_t\sim \mathrm{NID}(0,\boldsymbol{\Sigma}_\varepsilon), \qquad \boldsymbol{t}=1,\ldots,\mathbf{T} \tag{8}$$

where $\boldsymbol{y}_t$ is a vector of $N \times 1$ time-series observations which depends on the unobserved trend component $\boldsymbol{\mu}_t$, seasonal component $\boldsymbol{\gamma}_t$, and irregular component $\boldsymbol{\varepsilon}_t$, which are also vectors. $\boldsymbol{\Sigma}_\varepsilon$ is the $N \times N$ variance matrix of the irregular disturbances. In the multivariate regime, (3)–(6) change in a similar manner as (2). The various unobserved components of the univariate STM now become vectors in the MST model, and the disturbances of these components become $N \times N$ variance matrices.

The inclusion of explanatory variables in the MST model is simple and similar to the univariate approach described in (7). The model is described as

$$\boldsymbol{y}_t = \boldsymbol{\mu}_t + \boldsymbol{\gamma}_t + \sum_{\tau=0}^{q} \boldsymbol{\delta}_\tau \boldsymbol{x}_{t-\tau} + \boldsymbol{\varepsilon}_t \tag{9}$$

where $\boldsymbol{x}_t$ is a vector of $k \times 1$ explanatory variables. The elements of the unknown parameter matrix $\boldsymbol{\delta}_\tau$ can be specified to be zero, thereby excluding certain explanatory variables from particular equations.

Process $\boldsymbol{y}_t$ is said to be homogeneous if all linear combinations of its N elements have the same stochastic properties. In a multivariate homogeneous system, the disturbance matrices are required to satisfy the following:

$$\boldsymbol{\Sigma}_k = q_k \boldsymbol{\Sigma}_* \quad \text{and} \quad \boldsymbol{\Sigma}_{\,\varepsilon} = h\boldsymbol{\Sigma}_* \tag{10}$$

where $q_k, k = 1,\ldots$; g and h are nonnegative scalars; and $\boldsymbol{\Sigma}_*$ is an $N \times N$ matrix. In a SUTSE model, the assumption of homogeneity (where reasonably applied) decreases the computational complexity to a great extent.

One of the major advantages of the STM methodology is its transparency [21]. In an STM, the different components that make up the time series are separately modeled, unlike the SARIMA methodology (e.g., [13] and [14]), where the trend and seasonal components are eliminated by differencing. Hence, in an STM, it is easy to understand the evolution and contribution of each of the components in the final results. In a multivariate regime, MST models are straightforward vector extensions of univariate STMs. SUTSE models do not involve the estimation of huge covariance matrices, compared with vector ARMA models. Due to the recursive and Markovian nature of STMs, any known structural change at a given instant of time is easy to implement. On the other hand, the stationary form of SARIMA models does not allow the inclusion of such abrupt or unusual structural changes. Treatment for missing values in a time series is also very simple in STM equations. Explanatory variables, outliers, structural breaks, etc. can also easily be modeled in an STM framework, as described before. The introduction of these variables in SARIMA models requires tedious computational effort. The STM is more general and flexible and can easily be transferred from the univariate to the multivariate regime, compared with the ARIMA class of models.

III. Methodology

A multi-input–multi-output short-term traffic flow forecasting model, where the number of input intersections is more than number of output intersections, is proposed in this study for efficient modeling of traffic in a congested urban transport network. A SUTSE model has been chosen to model the traffic flow time-series observations from multiple junctions within a congested urban transportation network.

Unlike the previous multivariate traffic flow models developed for urban transport networks [17], [18], the locations of the sites of data collection within the transport network are not required to be considered in the proposed methodology. The aim of this approach is to develop a multivariate traffic flow forecasting model for multiple intersections within a transport network, which are not strictly situated on the same route or sharing the same path within the network. As a consequence, a cause-and-effect relationship need not explicitly be assumed while considering simultaneous traffic-flow observations. Hence, the route choice and traffic merging and diverging information are not required. This is ideal for modeling time-series observations within a SUTSE framework since the behavioral relationship among the variables is not required to be considered.

As exogenous variables, the current traffic flow observations at an immediate upstream junction can be considered to further

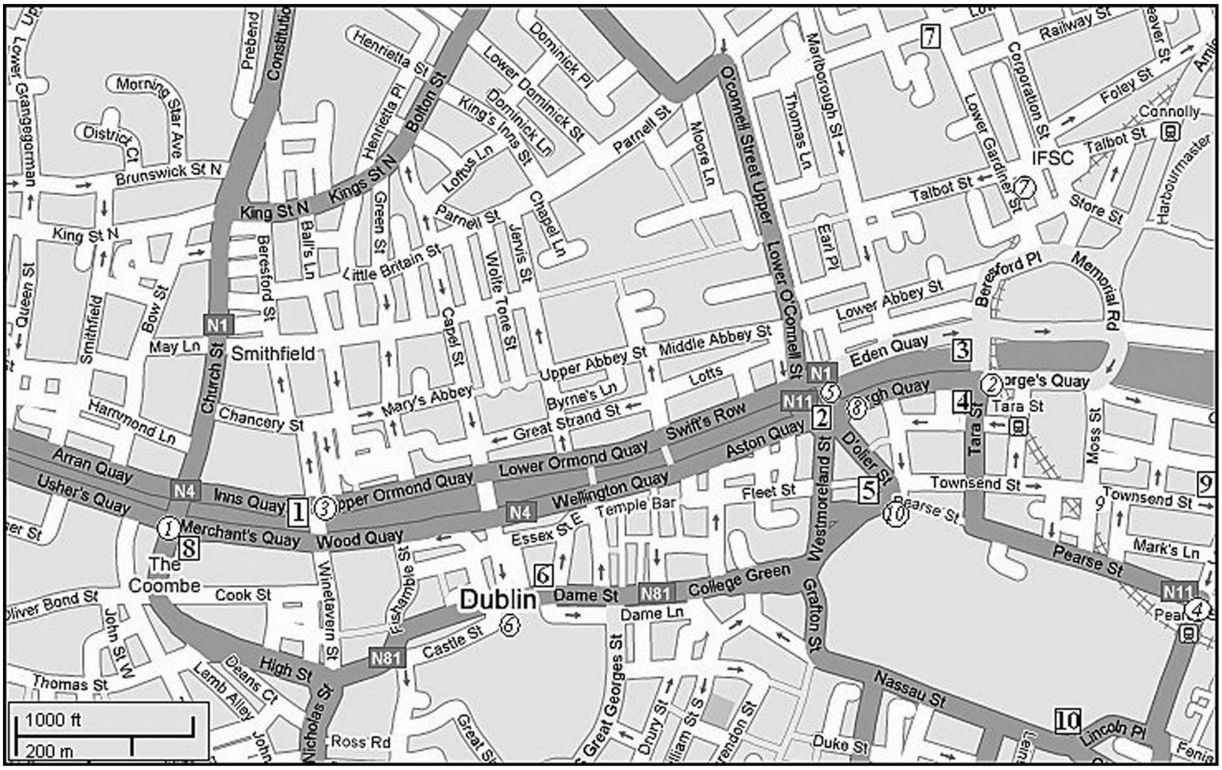

Fig. 1. Map of the chosen transport network.

aid the prediction of the traffic flow at the relevant downstream junction in the future. These observations at an immediate upstream junction are a good statistical estimate of the traffic volume observations at the downstream junction, without having to resort to any assumption of physical dependence between the two junctions. Consequently, where possible, the single most effective upstream junction that significantly contributes to the efficiency of the prediction process has been included as explanatory variables to the MST model equations. For other upstream junctions, the coefficient of the exogenous variable is considered to be zero, as it do not provide a good statistical estimate.

IV. Application of the Proposed MST Model

A. Traffic Flow Observations From an Urban Transport Network

The proposed multivariate SUTSE traffic flow forecasting methodology is applied to a congested urban transportation network at the city center of Dublin to illustrate the effectiveness of the forecasting strategy. A network of ten intersections within the transport network is chosen for this purpose.

The time interval of traffic volume data aggregation is unique to the data collection system of the existing urban traffic control system of any city. The data interval can vary from a few seconds to 1 h. Short-term forecasting algorithms that are applicable to a traffic management system should have a prediction horizon of 15 min or less [8]. The univariate traffic flow observations obtained over each 15-min interval from the inductive loop detectors situated at these ten intersections and their nearest available upstream junctions are modeled using the proposed multivariate traffic flow model.

The location of the sites and their respective distances can be chosen at random. However, it is important to ensure that all the time-series data sets are contemporaneously correlated. For example, the average travel time between the two sites sharing the same route or path within the network is less than 15 min (i.e., the data collection time interval) to ensure that the time-series data sets do not have any physical or behavioral dependence.

In Fig. 1, a map of the chosen urban transport network at the city center of Dublin is shown. In the map, the directions of the traffic movements in the network are shown with arrows. The ten chosen junctions that are modeled using the multivariate SUTSE methodology are shown by numbered squares in the map. The nearest available upstream junction to each of the ten chosen junctions is marked with a numbered circle. The distance between an intersection and its nearest available upstream junctions, along with the number of traffic maneuvers between them, can be found in the figure. The ten intersections at which the proposed multivariate short-term traffic flow model is applied for forecasting are termed as output intersections in the rest of the text. In Table I, further details about the ten output intersections are given, along with the name of the nearest upstream intersections at which traffic flow observations are available. The distance of the respective upstream intersection and the number of existing major and minor traffic maneuvers between the upstream and output intersections are also provided in the table.

The traffic flow observations used for all the chosen intersections were recorded from November 3, 2003, at 6:30 A.M.

TABLE I
DETAILS OF THE TEN OUTPUT JUNCTIONS

Station in Map	Intersection Name	Data Collecting Loop-Detectors	Upstream Junction & Loop-Detectors	Distance with Upstream Junctions	No. of Manoeuvres in between
1	TCS 26	4, 5, 6	TCS 182 (1, 2)	0.4 km	1 major and 2 minor
2	TCS 196	10, 11, 12, 13	TCS 193 (5, 6, 7)	0.3 km	1 major and 1 minor
3	TCS 17	5, 6, 7, 8	TCS 183 (5, 6, 7)	0.9 km	3 major and 2 minor
4	TCS 183	1, 2, 3, 4	TCS 26 (4, 5, 6)	0.7 km	2 major and 1 minor
5	TCS 232	1, 2, 3, 4	TCS 146 (1, 2, 3, 4)	0.1 km	1 minor
6	TCS 49	1, 2,	TCS 48 (1, 2)	0.2 km	none
7	TCS 166	1, 2, 3	TCS 188 (3, 4)	0.3 km	1 minor
8	TCS 193	1, 2, 3, 4	TCS 232 (6, 7)	0.9 km	3 minor
9	TCS 439	1, 2, 3	TCS 196 (6, 7, 8, 9)	0.2 km	1 minor
10	TCS 269	1, 2, 3	TCS 196 (10, 11, 12, 13)	0.8 km	2 major and 1 minor

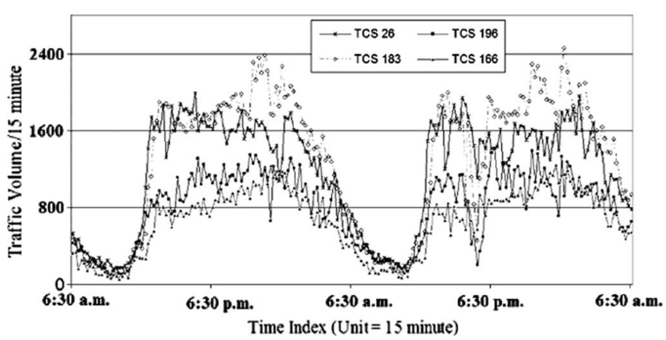

Fig. 2. Plot of the two-day traffic volumes from output intersections.

to November 26, 2003, at 6:30 A.M., excluding weekends. A cross-sectional time-series plot of the traffic flow observations from four output intersections during November 4–5, 2003, is shown in Fig. 2 to retain clarity of the figure. This plot illustrates the definite temporal similarity among the traffic flow observations at the various stations. This condition was verified to hold true for all ten chosen output stations. The output junctions at which the modeled direction of traffic is on the routes toward the city center have high traffic volumes during the morning peak hours. The junctions at which the modeled direction of traffic is on the routes away from the city center have higher traffic volumes during the evening peak hours than the morning peak hours. The cross-correlational structure of the ten chosen junctions is presented in tabulated form (see Table II). It is apparent from the table that the 15-min aggregate traffic flow time-series observations from the ten output junctions are highly correlated without having a time-dependent cause-and-effect relationship. This satisfies the previously mentioned condition of simultaneous dynamic evolution of a system under a common environment for the SUTSE multivariate model. Additionally, the presence of cointegration, which is central to the idea of the SUTSE model, helps to ensure the appropriateness of the proposed approach.

The 15-min aggregate univariate traffic volumes from the aforementioned loop detectors in the upstream junctions are used as explanatory variables in the SUTSE model equations. The 15-min aggregate traffic flow observations at an immediate upstream junction can be considered to be a good statistical estimate of the traffic volume observations at the downstream junction, without the assumption of physical dependence between the two junctions. The use of this exogenous variable is effective where there is a limited number of diverging and merging maneuvers taking place in between the junctions. In (9), the elements of the matrix are chosen such that the forecasts from each intersection is affected only by the change at its upstream junction and not by the changes at other upstream intersections.

B. Time-Series Model

Stationarity is not central to the formulation of STMs. However, all the traffic flow time-series information used in this paper for modeling can be reduced to a stationary form by "differencing." The second-order stationarity of the time-series data sets used in the MST model are checked by plotting the autocorrelation functions (ACFs) of the data sets. As an example, the correlograms of the traffic flow time-series data sets from stations 1, 4, and 8 are shown in Fig. 3. In the plots, the two dotted lines, which are nearly parallel to the x-axis of the plot, denote the 95% confidence interval for the ACF. If the value of the ACF is within this band, then it can be considered negligible or equal to zero. The three correlograms in the upper row of the figure show large ACF values in a periodic manner. This is a clear indication of the seasonality of the data. The seasonal differencing of the data sets has been performed. The correlograms of the three "seasonally differenced" traffic data sets are also plotted (see Fig. 3). These plots confirm the stationarity of the seasonally differenced time-series data sets. To ensure stationarity, seasonal differencing has been performed on all the modeled traffic flow time-series data sets.

All of the ten series of traffic flow observations are modeled using homogeneous SUTSE models with (3)–(6) and (9) in their vector forms. In the proposed MST model, the value of τ in (9) changes from 1 to 96 according to the step of prediction. The estimated values of the trend/level component and the standard deviations of the disturbances of the components are provided in Table III. The elegance of the STM lies in the meaningful depiction of the components, as shown in Fig. 4. In the figure, the trend, seasonality, and random error components (obtained from the traffic flow observations collected from output station 2, as an example) are individually shown in three different subplots. Subplot A shows the original traffic flow data series, along with the trend component, as simulated and predicted from the proposed multivariate model. Subplots B and C show the seasonal and irregular components, respectively,

TABLE II
CROSS-CORRELATION COEFFICIENTS OF THE TRAFFIC FLOW TIME SERIES AT THE TEN OUTPUT JUNCTIONS

Correlation coefficient	Station 1	Station 2	Station 3	Station 4	Station 5	Station 6	Station 7	Station 8	Station 9	Station 10
Station 1	1.000	0.863	0.910	0.880	0.911	0.860	0.810	0.824	0.890	0.893
Station 2	0.863	1.000	0.827	0.898	0.851	0.799	0.839	0.908	0.843	0.825
Station 3	0.910	0.827	1.000	0.861	0.872	0.866	0.787	0.787	0.869	0.882
Station 4	0.880	0.898	0.861	1.000	0.895	0.831	0.947	0.922	0.922	0.896
Station 5	0.911	0.851	0.872	0.895	1.000	0.850	0.826	0.841	0.946	0.920
Station 6	0.860	0.799	0.866	0.831	0.850	1.000	0.699	0.727	0.864	0.859
Station 7	0.810	0.839	0.787	0.947	0.826	0.699	1.000	0.910	0.853	0.834
Station 8	0.824	0.908	0.787	0.922	0.841	0.727	0.910	1.000	0.843	0.811
Station 9	0.890	0.843	0.869	0.922	0.946	0.864	0.853	0.843	1.000	0.922
Station 10	0.893	0.825	0.882	0.896	0.920	0.859	0.834	0.811	0.922	1.000

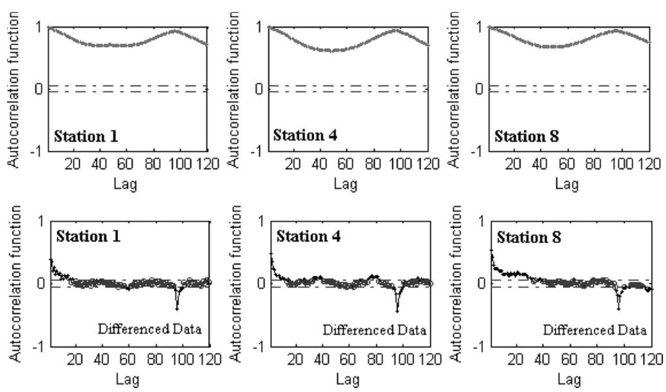

Fig. 3. Correlogram of the original and difference traffic flow time-series observations at output stations 1, 4, and 8.

TABLE III
ESTIMATES OF THE PARAMETERS AND HYPERPARAMETERS

Station in Map	μ_t	σ_ε	σ_η
1	268.77	33.877	9.4979
2	206.92	31.621	9.3628
3	136.44	19.427	6.3258
4	303.04	28.569	12.665
5	296.63	25.842	10.937
6	147.77	17.535	13.214
7	146.32	17.076	3.4146
8	206.42	23.496	9.1426
9	123.99	17.871	3.4507
10	106.81	14.500	2.1109

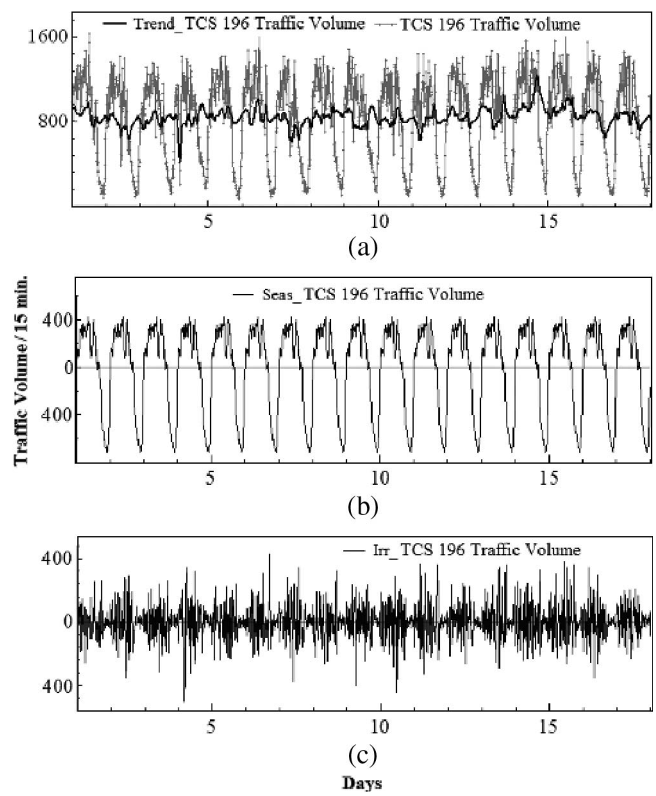

Fig. 4. Plots of the individual components of the STM.

which were simulated and predicted from the MST model. The hyperparameter estimates (see Table III) and the plot of the seasonal component show that the seasonality is deterministic in nature. On the other hand, the trend component is stochastic and depicts the within-day local fluctuations in the data. The trend component varies about a zero mean value, validating the assumption that there is no slope component latent within the traffic flow data set.

C. Forecasts From the Proposed MST Model

The proposed MST model is a multistep forward-prediction algorithm. The current traffic flow observations at the ten chosen output stations and the ten respective upstream junctions are used to predict traffic flow at the output junctions 24 h ahead into the future (96 points). As the model considers daily seasonality, the SUTSE model can predict a season or 96 steps ahead into the future without any loss of accuracy, owing to the fact that the forecast function solely depends on the current estimates of the seasonal effects [19]. The prediction of the proposed MST model is achieved in state-space form, employing Kalman-filter-based algorithms.

The prediction accuracy of the proposed model in the form of mean absolute percentage error (MAPE) and root-mean-square error (RMSE) values is presented for one step, four steps, and 50 steps ahead into the future for each of the ten output junctions as an example that illustrates the robustness of the MST model (see Table IV). The real-life traffic flow

TABLE IV
COMPARISON OF THE UNIVARIATE SARIMA AND MST MODELS

Station ⟶	1	2	3	4	5	6	7	8	9	10
MAPE of MST (%)										
(t+1) one step ahead	5.86	10.2	12.81	7.29	6.24	7.5	3.84	6.83	7.5	10.09
(t+4) 1hr or four steps ahead	5.81	10.3	12.74	7.21	7.89	7.44	3.83	6.25	6.9	9.89
(t+50) 12.5hrs or fifty steps ahead	5.89	10.9	12.66	7.4	6.52	7.96	4.94	6.20	7.4	10.1
MAPE of SARIMA (%)										
(t+1) one step ahead	10.68	11.61	12.73	7.79	8.31	13.10	7.65	7.16	8.83	11.18
(t+4) 1hr or four steps ahead	10.00	12.04	12.88	7.76	9.08	14.00	7.45	6.63	8.14	10.99
(t+50) 12.5hrs or fifty steps ahead	11.02	12.7	11.24	7.07	8.6	15.56	8.32	7.12	8.45	10.94
RMSE of MST (veh/min)										
(t+1) one step ahead	0.90	2.15	1.33	1.34	1.71	1.25	0.60	0.44	0.63	0.95
(t+4) 1hr or four steps ahead	0.53	2.43	1.43	0.85	1.27	0.98	0.32	0.48	0.68	0.96
(t+50) 12.5hrs or fifty steps ahead	1.32	1.99	1.64	2.21	1.74	1.07	0.71	1.28	1.05	1.04
RMSE of SARIMA (veh/min)										
(t+1) one step ahead	1.35	4.35	1.23	1.50	2.38	1.60	0.91	1.58	1.30	1.34
(t+4) 1hr or four steps ahead	2.15	2.69	1.44	1.67	2.76	1.09	1.09	0.95	1.16	1.01
(t+50) 12.5hrs or fifty steps ahead	2.56	2.23	1.7	2.25	2.33	1.54	1.15	1.36	1.22	1.00

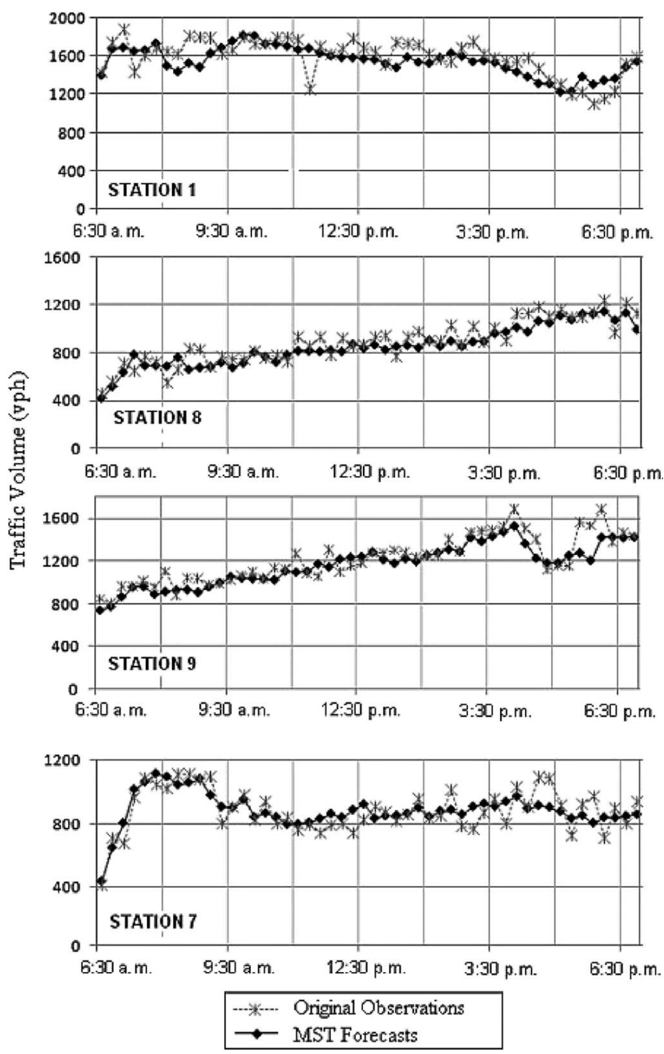

Fig. 5. Multistep-ahead forecasts from the output intersections from the SUTSE model.

observations obtained on November 26, 2003, from 6:30 A.M. to 8:00 P.M., are compared with the forecasts obtained from the MST model in Fig. 5. To retain clarity, the forecasts at four out of the ten chosen output junctions are plotted in

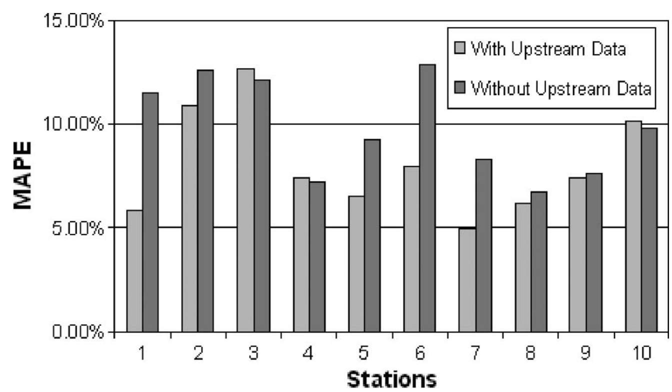

Fig. 6. Multistep-ahead forecasting errors from the chosen intersections.

Fig. 5 as examples. The MAPE values of the proposed MST model for the forecasts obtained from each of the ten output junctions (with and without considering the influence of the upstream junctions) are shown in Fig. 6 in the form of a bar diagram. Among the ten output stations in seven cases, there is a maximum of one major traffic maneuver taking place between the upstream and output junctions. It is observed from Figs. 5 and 6 that the MAPE values for the forecasts at the seven output stations improve when the traffic flow observations from the nearest available upstream junctions are incorporated in the SUTSE model as explanatory variables. In the remaining three cases, where the upstream junction is situated at a distance from the output junction and there are two or more major traffic maneuvers taking place between the junctions, the MAPE values do not improve with the inclusion of the exogenous variable. In such cases, the traffic flow at the nearest upstream junction cannot be considered as a good statistical estimate at the downstream output station due to the presence of excessive merging and diverging maneuvers. It can be observed from Figs. 5 and 6 that higher average traffic volumes are associated with lower MAPE values. As the daily traffic volume significantly fluctuates between peak and off-peak hours, it can be concluded that the MAPE values of the forecasts are less during peak hours. These MAPE values are associated with higher average traffic volumes. The variation in prediction accuracies at the ten output stations are also significantly affected by the variability of the traffic flow, the regularity/irregularity of the traffic dynamics, and the relative presence or absence of lane-blocking incidents. Removal of outliers from the traffic flow data caused by incidents is thus recommended for the improvement of the prediction accuracy.

The MAPE and RMSE values for one step, four steps, and 50 steps ahead into the future from the univariate SARIMA $(2,0,1)(0,1,1)_{96}$ [14] model for the traffic flow observations at the ten output intersections are shown in Table IV, in comparison with the values from the proposed MST model. In most of the cases, the proposed multivariate traffic flow time-series model proved to be more accurate than the ordinary univariate SARIMA model for short-term forecasting of traffic volume in a congested urban network.

V. Conclusion

This paper has presented a SUTSE model for developing a multivariate short-term traffic flow forecasting algorithm for an urban signalized transport network. The application of STM is new to short-term traffic-condition-related studies. The model is capable of and useful for simultaneous modeling of traffic conditions at multiple intersections in an urban signalized transport network, where it is difficult to model the existing paths and turning movements.

The SUTSE model is computationally more efficient than some of the other existing multivariate short-term traffic flow forecasting methodologies. The checking for stationarity conditions is not critical to the development of the model. The developed SUTSE model can separately trace the evolution of each individual component (trend, seasonality, etc.) of the traffic flow data over time. Consequently, the deterministic nature of the seasonal component of the traffic volume observations from junctions at urban signalized arterials has been established. The MST model can additionally include the effect of changes in traffic conditions at one or more immediate upstream junctions to improve the predictions at the downstream output junction. The proposed multivariate traffic flow time-series model has superior forecasting accuracy, compared with the forecasts separately obtained for each output station using the univariate SARIMA model.

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