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Comparison of Urban Traffic Prediction Methods between UTN-Based Spatial Model and Time Series Models

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Abstract— **A spatial short-term traffic flow prediction method based on the macroscopic urban traffic network (UTN) model is described and compared to the traditional time series forecasting methods. This paper presents a general macroscopic UTN model by adopting the transfer mechanism of vehicles between road links to represent the future distribution of vehicles in the whole network. Based on the model, we predict the short-term traffic flux without using any historical traffic data, which is completely different from previous approaches. Furthermore, to verify the effectivity of the UTN-based prediction model, we compare it to four classic models including two parametric and two nonparametric methods with the data produced by CORSIM, a commonly used microscopic traffic simulation software. Finally, the comparative results illustrate that the proposed method can reach the level of classic methods and predict the short-term traffic flow timely and accurately both for the steady or suddenly changed traffic states.**

I. INTRODUCTION

In recent decades, in order to solve or relieve the frequent traffic jams and fleetly climbing up accidents, intelligent transportation systems (ITS) emerged and are developing rapidly in urban transportation management (UTM). As one of the major elements of ITS and the key technology in the traveler information service systems (TISS) and advanced traffic management system (ATMS), accurate short-term traffic flow prediction can provide reliable guarantee for optimized control and guidance [1].

Since the early 1980s, based on the elaborate historical data, an increasing number of researchers attempt to predict accurate and timely traffic flow in less an hour instead of day time. Many various methods have been proposed to predict the traffic flow, on both freeways and urban roads. In general, previous prediction methods or models can be classified into two categories on the basis of the variables feeding into the prediction models: univariate time series model and spatio-temporal correlation model.

Univariate time series model takes advantage of historical traffic data on a single point location or a certain road link to predict the variation of traffic flow. During the initial stage of development of ITS, researchers have made use of the historical data to predict short-term traffic flow by different methods, mostly on freeways. For instance, prediction through Kalman filtering [2], nonparametric regression method such as k-nearest neighbor (k-NN) approach [3], autoregressive integrated moving average (ARIMA) [4], artificial neural network (ANN) approach [5]. On the basis of considering the traffic flow as time series, these approaches based on some assumptions about the statistical distribution of traffic flow mostly could promise well in freeway or a location on an artery in urban, instead of complicated and variable urban road networks.

Recent years, spatio-temporal correlation models are frequently used to predict traffic flow in urban arteries, in order to predict traffic flow more accurate and stable. Many researchers took account of historical traffic data at upstream locations or road links to excavate their influence to current traffic state. Stathopoulos *et al.* [6] developed a state space approach which fed on data from upstream roads to improve on the downstream locations. Besides, machine learning approaches have also been extensively utilized for short-term traffic flow forecasting, especially SVR [7], Bayesian network [8] and so on.

Although a quantity of prediction methods have mitigated difficulties in traffic flow prediction to a certain degree, some of models can not be in accordance with the substantial mechanism of traffic flow reasonably. For instance, some spatio-temporal models built the relationship between upstream links at time $t-1$ and current link at t. However, actually, the time interval to represent the best match or most influence between the current and historical or upstream traffic states is mutable other than one or several stationary time periods. On the other hand, these prevenient methods are proposed within the emphasis of matching the variational tendency of traffic variables using some function tools based on historical data or upstream links, without considering of the movement mechanism in the road network of the traffic flow. Consequently, these approaches could generate pleasing effect for normal traffic statuses, *i.e.,* the traffic flow changes smoothly or gradually, whereas, inaccurate predictions usually occur when traffic flow suddenly changes.

Therefore, in order to realize the traffic prediction by using the mechanism of traffic moving in the road network, Lin *et al.* [9] tried to predict the traffic flow in short term using the macroscopic urban traffic network (UTN) model, and obtained promising results. However, some approximations of the model parameters made the prediction lack of robustness. Afterwards, we modified the UTN model to make it more precise [10]. In this paper, we first briefly introduce the UTN model and propose a more general topological structure of UTN. Furthermore, for the purpose of testing the effectivity of our UTN-based prediction model, we compare it to

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the traditional time series models including parametric and nonparametric methods with the data produced by CORSIM, a commonly used software for microscopic traffic simulation.

The remainder of this paper is structured as follows: Section II is a brief overview of the urban traffic network model, including urban network topological structure, signalized link model, and speed-density model; the simulation case study is expounded in Section III, moreover, several traditional prediction approaches are implemented for comparison with our model; finally, some concluding remarks and directions for the future work are given in Section IV.

II. Overview of Urban Traffic Network Model

In this section, an introduction of the previous macroscopic urban traffic network (UTN) model proposed by Lin *et al.* [9], [11] and improved by Xu *et al.* [10] is briefly described.

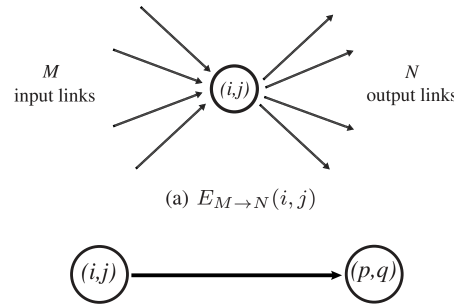
Considering the models described in the following sections, the notations are listed in Table I.

TABLE I
NOTATIONS DEFINED IN UTN

Variable	Description
T	sampling time interval (sec)
$v_m^0(i,j)$	free flow speed in the mth input link belongs to junction $E_{M\to N}(i,j)$ (m/s)
$v_m(i,j,k)$	average flow speed in the mth input link from link entrance to tail of the queue (km/h)
$C_m(i,j)$	capacity of the mth input link (veh)
$W_m(i,j)$	number of lanes in the mth input link
L_{veh}	average length of vehicles (m)
$s_{m,n}$	saturated flow rate turning from the mth input link to nth output (veh/s)
$\beta_{m,n}(i,j,k)$	turning rate from the mth upstream link to nth downstream link at time k
$d_{m,n}(i,j,k)$	number of vehicles discharge from the mth input link to the nth output at time k (veh)
$d_{in,n}(i,j,k)$	number of vehicles flow into the nth output link at time k (veh)
$d_{out,m}(i,j,k)$	number of vehicles discharge from the mth input link at time k (veh)
$x_m(i,j,k)$	number of vehicles waiting at the stop line in the mth input link at time k (veh)
$a_m(i,j,k)$	number of vehicles arriving at the tail of the queue in the mth input link at time k (veh)
$f_m(i,j,k)$	free space in the mth input link at time k (veh)
$r(i,j,k)$	density of vehicles in the link at time k (veh/m)
$q(i,j,k)$	flow rate in the link at time k (veh/s)
$g_{m,n}(i,j,k)$	signal symbol for vehicles departure from the mth input links to nth output, 1 when signal is green, 0 when signal is red

A. Urban Road Network Model

In the first instance, the urban traffic road network should be topologized according to its space structure. To suit this purpose, the basic components in a general road network (intersections and links) are characterized by their manners of connecting to each other. In [9]–[11], the basic elements of UTN were defined as "Cross", "T-shape", and "Source", and then further detailed by their directions. In this paper, a more general and flexible pattern is given in Fig. 1a and expressed as intersection element $E_{M\to N}(i,j)$. In the element, the variable M and N stand for the number of links input into and output from the intersection (i,j).



(a) $E_{M\to N}(i,j)$

(b) $L(i,j)(p,q)$

Fig. 1. UTN elements: (a) intersection element; (b) link element

Although a common urban road network can be decomposed into a quantity of $E_{M\to N}(i,j)$, the road network is unable to be built using $E_{M\to N}(i,j)$, as a result of its lack of directions of links. In other words, the element $E_{M\to N}(i,j)$ is only a matter of an intersection with number of links in and out, but can not represent the interaction between the upstream and downstream junctions. Therefore, to consummate the topological structure of our UTN, another basic link element $L(i,j)(p,q)$ is defined as the road link directing from the upstream intersection (i,j) toward downstream intersection (p,q), as Fig. 1b shows. At this point, a general UTN is able to reconstructed by two essential elements: intersection element $E_{M\to N}(i,j)$ and link element $L(i,j)(p,q)$. Under this definition of UTN model, the "Cross" intersection is conveniently expressed as $E_{4\to 4}(i,j)$, and $L(i-1,j)(i,j)$ denotes the left road segment directing to the junction.

After modeling the UTN, the macroscopic traffic behaviors at the signalized junction can be represented by mathematical formulas. Therefore, for the mth link pointing to $E_{M\to N}(i,j)$, the computational formula of $d_{m,n}(i,j,k)$ is given by

$$
d_{m,n}(i,j,k) =
\begin{cases}
\min\{x_{m,n}(i,j,k)+a_{m,n}(i,j,k), & \\
\quad f_{m,n}(i,j,k), & \text{if } g_{m,n}(i,j,k)=1 \\
\quad s_{m,n}(i,j)T\} & \\
0 & \text{if } g_{m,n}(i,j,k)=0
\end{cases}
\tag{1}
$$

where the saturated flow rate $s_{m,n}(i,j)$ is calculated by the mean discharge headway t_h; the waiting vehicles $x_{m,n}(i,j,k)$ and the arriving vehicles $a_{m,n}(i,j,k)$ at time k are expressed by the predefined turning rate.

B. Link Transmission Model

The link transmission mode (LTM) is originally based on the model proposed by Berg *et al.* [12]. To simulate a real road link, the basic diagram of road segment $L(i,j)(p,q)$ between two signalized junction shown in Fig. 1b is represented as follows:

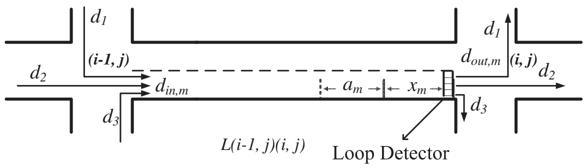


Fig. 2. Link transmission mode in UTN

Based on the assumption that there is no vehicle access or disappear in the process of vehicles transmission in the link, the free space of the mth input link in $E_{M\to N}(i,j)$ is updated by

$$\begin{aligned} f_m(i,j,k+1) = & f_m(i,j,k) - d_{in,m}(i,j,k) \\ & + d_{out,m}(i,j,k) \end{aligned} \tag{2}$$

where

$$d_{out,m}(i,j,k) = \sum_{n=1}^{N} d_{m,n}(i,j,k) \tag{3}$$

Since the number of vehicles that enter the nth output link can be calculated using its own upstream links. So we have

$$d_{in,m}(i,j,k) = \sum_{m=1}^{M} d_{m,n}(i,j,k) \tag{4}$$

At this point, the number of vehicles arriving at the tail of the waiting queues in the mth input link in element $E_{M\to N}(i,j)$, which is an essential variable in (1), can be represented as follows:

$$\begin{aligned} & a_m(i,j,k) = \\ & (\frac{T-\gamma_m(i,j,k)}{T}) d_{in,m}(i,j,k-\delta_m(i,j,k)-\sigma) \\ & + (\frac{\gamma_m(i,j,k)}{T}) d_{in,m}(i,j,k-\delta_m(i,j,k)-1-\sigma) \end{aligned} \tag{5}$$

where

$$\begin{cases} \delta_m(i,j,k) = fix\left(\frac{(C_m(i,j)-x_m(i,j,k))L_{veh}}{W_m(i,j)v_m(i,j,k)T}\right) \\ \gamma_m(i,j,k) = rem\left(\frac{(C_m(i,j)-x_m(i,j,k))L_{veh}}{W_m(i,j)v_m(i,j,k)T}\right) \end{cases} \tag{6}$$

and σ is the average time during which the vehicles passing through the junction freely.

Finally, the number of vehicles waiting in the queue in the mth input link turning to the nth output is updated by

$$x_{m,n}(i,j,k+1) = x_{m,n}(i,j,k) + a_{m,n}(i,j,k) - d_{m,n}(i,j,k) \tag{7}$$

C. Speed-Density Model

In order to model the UTN more logical and consummate, a speed-density model was introduced to build the relationship of average speed and vehicle density on the link segment by Xu *et al.* [10]. Herein, a speed-density model based on the macroscopic fundamental diagram (MFD) is described to make the average speed and travel time more close to the real traffic situation.

For the sake of simple and effective calculation, the triangular shape MFD is employed and defined by three values: the maximum flow rate q_m, the traffic jam density r_{jam} of the link, the velocity v^0 in the free flow state, as Fig. 3 shows.

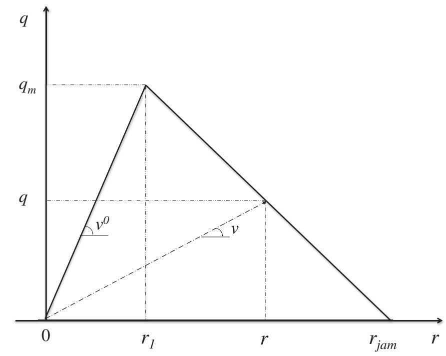


Fig. 3. Triangular shaped fundamental diagram

Furthermore, the triangular shaped curve consists of two vectors. The first one is the free flow side of the curve, in which the velocity identically equals to the free flow speed v^0. Another is the congested branch, which starts with the maximum flow rate q_m to the state with zero flow and jam density r_{jam}. The vertex of triangular shaped MFD (r_1, q_m) can be obtained by (8).

$$r_1 = q_m(i,j)/v_D^0(i,j) \tag{8}$$

Then, the average travel speed can be calculated as follows:

$$v_m(i,j,k) = \frac{q}{r} = \begin{cases} v_m^0(i,j) & 0 \le r < r_1 \\ \frac{q_m v_m^0(i,j)}{r_{jam} v_m^0(i,j) - q_m} \cdot \frac{r_{jam}-r}{r} & r_1 \le r \le r_{jam} \end{cases} \tag{9}$$

with $r = [1 - f_D(i,j,k)/C_D(i,j)]/L_{veh}$, $r_{jam} = W_D(i,j)/L_{veh}$, and $q_m = W_D(i,j)/t_h$.

Finally, $v_m(i,j,k)$ in (6) is updated to obtain a more accurate estimation to the vehicle delay time in the link.

III. Comparison of Prediction Models

Different from traditional forecasting methods, the proposed macroscopic-UTN-based prediction method is purely a kind of spatial model, taking advantage of the transfer mechanism of vehicles in the road network, instead of following the variation tendency of historical data. In this section, four classical time series models are first described. Afterward, the simulation case and evaluation criterion in our study are introduced. Finally, the prediction results are analyzed and compared.

A. Models for comparison

To evaluate the performance of our proposed prediction model, two parametric and two nonparametric methods are used as representative criterions for overall comparisons. The models for comparison are described as follows.

1) ARIMA: The ARIMA model is one of the most frequently used families of parametric models in time series prediction, which is due to its flexibility in approximating many stationary processes. The ARIMA model is the combination of the autoregressive (AR) and the moving average (MA) model. The ARIMA(p, d, q) model is obtained as follows:

$$\phi_p(B)\Delta^d z_t = \theta_q(B)a_t \tag{10}$$

where the backshift operator B defines $z_{t-p} = B^p z_t$; $\phi_p(B)$ and $\theta_q(B)$ are the AR(p) operator and MA(q) operator, respectively; $\Delta^d z_t = (1 - B)^d z_t$, and d is the order of differencing. In our experiment, ARIMA($4, 4, 4$) is employed to predict the traffic volume.

2) Kalman filter: As a recursive solution to the discrete-data linear filtering problem, the Kalman filter provides an efficient computational means to estimate the state of a process of dynamic linear systems, in the sense that it minimizes the mean squared error. The filter is very powerful in several aspects: it supports estimations of past, present, and even future states, and it can do so even when the precise nature of the modeled system is unknown. Kalman filter prediction model [2] is developed based on the Kalman filter theory with two sets of equations:

State equation: $x_k = F_{k,k-1}x_{k-1} + \omega_k, \quad x_k, x_{k-1} \in R^n$

Observation equation: $y_k = H_k x_k + v_k, \quad y_k \in R^m$

The Kalman filter used a predictor-corrector algorithm to estimate x_k. First a tentative estimate $\hat{x}_k^-$ is calculated based on the value of $\hat{x}_{k-1}$, the the measurement value y_k is used to further refine the value of $\hat{x}_k^-$ in order to obtain $\hat{x}_k$, which is the estimate of x_k.

3) K-nearest neighbors model: The k-NN nonparametric regression is also a classic model for short-term traffic flow prediction. In essence, the approach seeks the nearest neighbors of the current traffic state of the current link or single point (defined by independent variables) in a great variety of past traffic states.

Suppose the k nearest neighbors of current traffic state $\mathbf{x}_c(t)$ are $\mathbf{x}_i(t), i = 1, 2, \ldots k$. The forecasting value $\hat{Q}(t+1)$ calculated by the following equation using a simple weighted average approach [3]:

$$\hat{Q}(t+1) = (1/k)\sum_{i=1}^{k} \frac{Q_i(t)}{Q_{h,i}(t)} Q_{h,i}(t+1) \tag{11}$$

Here the traffic state pattern is defined as $\mathbf{x}(t) = [Q(t), Q(t-1), Q(t-2), Q_{h,i}(t), Q_{h,i}(t+1)]$. The euclidean distances between the states are calculated and ranked to find the k nearest neighbors $\mathbf{x}_i(t), i = 1, 2, \ldots k$ (k is equal to 5 in our experiment).

4) Artificial neural network: The ANNs are considered as a consolidated data-driven method for addressing the complex nonlinearity faced in transportation systems [5]. In this paper, the multilayer perceptron (MLP) is exploited for traffic flow prediction. The MLP-ANN is trained with multiple back-propagation in our study, the first step is propagating the input vectors towards the forward layers through the network. Second step is propagating the sensibilities from the last layer back to the first layer through the network. In the ANN, a three-layer network with 12 neurons in the hidden layer is built, and 5 previous traffic states are regarded as inputs. In addition, sigmoid tangent activation functions are used in the hidden layer and linear activation function is used in the output layer respectively.

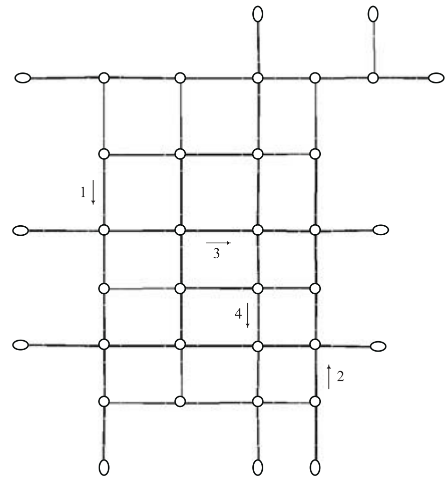


Fig. 4. An example of urban traffic networks

B. Data Description

In this paper, to evaluate the prediction ability of the method based on the UTN model, the reliable microscopic traffic simulation package TSIS-CORSIM exploited by FHWA [13] is employed to simulate the real urban surface traffic. An example of urban traffic networks shown in Fig. 4 is first built in CORSIM. The experiment continues 6 hours and repeats 20 times to generate historical data. In addition, we assign fix-timed signal time controller at all intersections. Towards every step of the prediction, the prediction model is fed with the initial traffic states that are detected on all over the traffic network, including number of the waiting vehicles, current number of vehicles on the link, the future signal information, and the future traffic flows feeding into the network.

Before the simulation case study, all the capacities of links $C_m(i, j)$, number of lanes $W_m(i, j)$, and the turning movement percentages $\beta_{m,n}(i, j, k)$ at the stop line are considered to be definite and known. Furthermore, the free flow speed, the average vehicle length L_{veh}, the mean discharge headway t_h are all set to fixed values. The time for which the vehicles pass through the junction freely σ is equal to $1.8s$. The sampling time interval T is set to $1s$, both for CORSIM and the proposed UTN model.

The output of our prediction model is the average traffic flux in 5 minutes, which denotes the mean traffic flow rate discharged from a link. In the urban network we studied, four typical links are selected to inspect the effectivity of the proposed UTN based prediction model, i.e., link 1, 2, 3, and 4 marked in Fig. 4.

TABLE II

ERROR ANALYSIS OF FIVE METHODS FOR THE FOUR TYPICAL LINKS

	Link 1	Link 2	Link 3	Link 4
UTN	**0.9742**	**0.7263**	1.6127	1.2432
ARIMA	1.2693	1.3643	1.1757	1.0821
Kalman	1.1030	1.2642	1.0935	**1.0643**
k-NN	1.0821	0.9167	**1.0057**	1.2624
ANN	1.5831	1.2865	1.6684	1.5087

C. Results and Analyses

As evaluating indicators, a different measure for forecasting error analysis the mean absolute scaled error (MASE), is adopted in this research to evaluate the performance of the proposed model and the classic time series methods. It is worth being noticed that MASE is a special measure of forecast accuracy proposed by Rob Hyndman [14]. Different from the traditional error measures, MASE is a kind of scaled error that takes account of the gradient of the actual values, therefore, in MASE, the prediction accuracy can be compared not only between different methods for same link but also between methods for different road links. Similarly, a smaller MASE indicates better prediction. MASE is defined as follows:

$$MASE = \frac{1}{K}\sum_{k=1}^{K}\left|\frac{Q_k - \hat{Q}_k}{\frac{1}{K-1}\sum_{k=2}^{K}|Q_k - Q_{k-1}|}\right| \quad (12)$$

where K is the total number of intervals during the experiment; Q_k denotes the average traffic flux generated by CORSIM and is treated as the actual value; $\hat{Q}_k$ is the prediction value produced by the compared models.

Fig. 5 and 6 give the traffic flux prediction results for link 1 and 2, respectively, including the UTN, ARIMA, Kalman, k-NN, and ANN methods. As the figures and Table II show, the prediction curve of the UTN model is more accordant with the actual value generated by CORSIM, and bears smaller errors than the other time series methods on link 1 and 2. Furthermore, through intensive observation of the prediction curves, we can conclude that the UTN model can predict the rapid rise or drop of traffic flow opportunely, unlike ARIMA's following such variations with a time lag.

The comparison diagram of link 3, which is located more centrally in the network, is shown in Fig. 7. Even though the link is located more central, which would accumulate more approximate errors (estimation of parameters and approximation of the LTM) in the UTN, the predictive curve can also match the actual value well. On the other hand, the historical data used for training in k-NN, ANN methods in the experiments is produced by repeating the simulation 20 times before hand, whereas the UTN model doesn't require any training process to implement the prediction.

In addition, the UTN-based model has a much lower computation complexity in contrast with the methods using quantities of historical data, e.g., k-NN. In our experiment, in a personal computer with a 2.8GHz processor and 4GB memory, the computing time for each prediction step is between 1 and 2 CPU seconds for the whole network shown in Fig. 4, with a titchy sampling time interval $T = 1s$. Therefore, the UTN-based prediction model can satisfy the requirement of real-time prediction.

Moreover, the flexibility and robustness of prediction methods are both important indicators besides the accuracy and operation speed. As combining the current observed values and the inherent properties of traffic networks to predict the short-term traffic flux on the links of the whole network without using any historical data, the UTN-based model can perform stably on both weekdays and holidays, even encountering special cases (e.g., severe weather, traffic accidents, large assemblies).

IV. CONCLUSIONS AND FUTURE WORKS

This paper first describes a spatial model of short-term traffic prediction, which is based on a general macroscopic UTN model. In this model, the transfer mechanism of vehicles between road links is made full use of to implement the prediction, therefore this model doesn't require any historical traffic data in the prediction. Then, in order to evaluate the performance of the spatial model, four classic time series forecasting methods are employed as the comparison objects. The comparing experiments are performed in the microscopic simulation package CORSIM. The experiment results illustrate that the spatial model bears better performance than the time series forecasting models.

Nonetheless, owing to the estimation of some parameters (e.g., turning rate at junctions, traffic flow fed into the network) and the approximation of the model, some inaccuracies are still induced in prediction on the links located in the center region of traffic networks, as the results in Table II show. Therefore, the UTN-based model still needs to be consummated in the future. In addition, we will continue to compare the UTN-based model to other approved prediction methods, such as support vector regression (SVR) and Bayesian networks.

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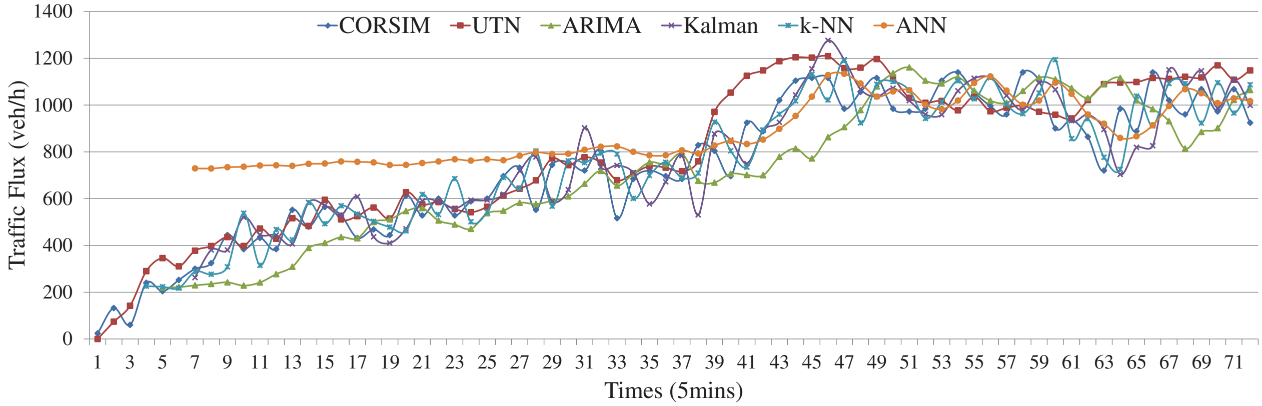

Fig. 5. Prediction of average traffic flux for link 1

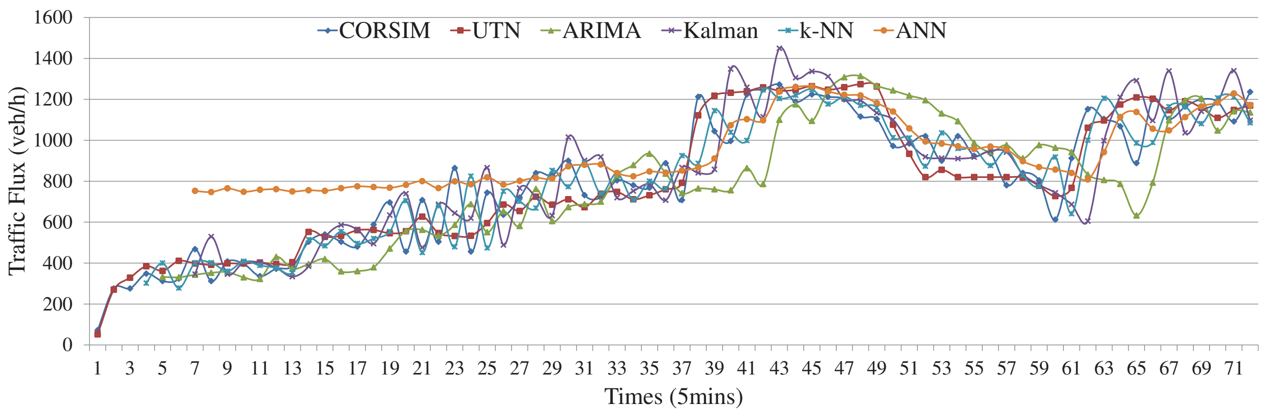

Fig. 6. Prediction of average traffic flux for link 2

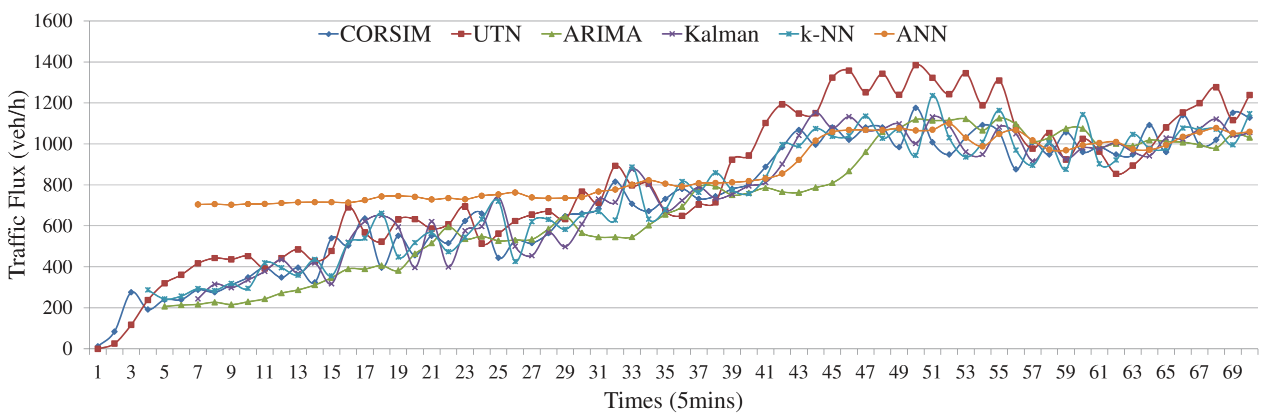

Fig. 7. Prediction of average traffic flux for link 3

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