KSCE Journal of Civil Engineering (0000) 00(0):1-13

DOI 10.1007/s12205-017-0535-8

Transportation Engineering

pISSN 1226-7988, eISSN 1976-3808
www.springer.com/12205

Short-term Travel-time Prediction on Highway: A Review on Model-based Approach

Simon Oh*, Young-Ji Byon, Kitae Jang***, and Hwasoo Yeo******

Received February 16, 2016/Revised January 21, 2017/Accepted January 28, 2017/Published Online May 5, 2017

Abstract

Emerging technologies provide a venue on which on-line traffic controls and management systems can be implemented. For such applications, having access to accurate predictions on travel-times are mandatory for their successful operations. Transportation engineers have developed numerous approaches including model-based approaches. The model-based approaches consider underlying traffic mechanisms and behaviors in developing the prediction procedures and they are logically intuitive unlike data-driven approaches. Because of this explanation power, the model-based approaches have been developed for the on-line control purposes. For departments of transportation (DOTs), it is still a challenge to choose a specific approach that meets their requirements. In efforts to develop a unique guideline for transportation engineers and decision makers when considering for implementing model-based approaches for highways, this paper reviews model-based travel-time prediction approaches by classifying them into four categories according to the level of details involved in the model: Macroscopic, Mesoscopic, CA-based, and Microscopic. Then each method is evaluated from five main perspectives: Prediction range, Accuracy, Efficiency, Applicability, and Robustness. Finally, this paper concludes with evaluations of model-based approaches in general and discusses them in relation to data-driven approaches along with future research directions.

Keywords: *highway travel-time prediction, model-based approach, traffic simulation, Traffic Management System (TMS), Intelligent Transportation System (ITS), On-line simulation*

1. Introduction

There are various types of travel-time prediction approaches that can be categorized from different perspectives. Some researchers have categorized them according to its prognosis horizon as short, medium, and long-term. Lint (2004) defines the short-term as from 0 to 60 min time horizon, and long-term as longer than one-day horizon. Shen (2008) finds that making predictions with appropriate time horizon plays a significant role in implementing a successful travel-time prediction system. Another perspective is whether the road network predictions are made for are signalized (arterial roads) or not (highways). Making predictions on the urban arterial is known to be more complicated due to additional factors including different signal cycles from multiple intersections that are connected to each other. The complications tend to require additional data dependent techniques in order to overcome the challenge and this paper focuses on analytic (also known as model-based) approaches for highways that are more suitable for on-line applications. A spatial scope of predictions can also be used to categorize different prediction models depending on whether relatively small section of roads or large-scale network is being considered. For the large-scale network, including highway networks, it is important to keep computational complexity arising from large size to minimum while delivering sufficient accuracies.

Furthermore, another perspective in categorizing travel-time prediction models that stands out is whether the models are data-driven or model-based. The types of approach influence prediction accuracy and efficiency. The data-driven approach assesses the traffic state (or travel-time) against historical traffic patterns. This approach assumes that the current traffic state would remain with similar patterns to the traffic states in historical databases. Different types of parametric and nonparametric (statistical) methods have been applied, including linear regression (e.g., Kwon *et al.*, 2000; Zhang and Rice, 2003; Sun *et al.*, 2003), ARIMA (e.g., Williams, 2001; Chen *et al*., 2001; D'Angelo *et*

*Research Specialist, Future Strategy & Convergence Research Institute, Korea Institute of Civil Engineering and Building Technology, Goyang-Si 10223, Korea (E-mail: simonoh.phd@gmail.com)

**Assistant Professor, Dept. of Civil Infrastructure and Environmental Engineering, Khalifa University P.O. Box: 127788, Abu Dhabi, UAE (E-mail: youngji.byon@kustar.ac.ae)

***Member, Associate Professor, Graduate School of Green Transportation, CCS Graduate School for Green Transportation, Korea Advanced Institute of Science and Technology, Daejeon 34141, Korea (E-mail: kitae.jang@kaist.ac.kr)

****Associate Professor, Dept. of Civil and Environmental Engineering, Korea Advanced Institute of Science and Technology, Daejeon 34141, Korea (Corresponding Author, E-mail: hwasoo@kaist.ac.kr)

al., 1999; Ishak and Al-Deek, 2002), Kalman filter (e.g., Chen and Chien, 2001), Artificial Intelligence (AI) (e.g., Dougherty and Cobbett, 1997; Smith and Demetsky, 1997; Innamaa, 2005; Dia, 2001; Lint, 2006), and Pattern searching (e.g., Davis and Nihan, 1991; Smith *et al.*, 2000). The model-based approach is known to be more robust since it is relatively simple to deal with future variances (e.g., network expansions and unexpected events of incidents) and it can incorporate traffic dynamics as model variables in the traffic model. By updating the necessary parameters adapting for unexpected situations, the model-based approach can forecast traffic states without searching historical traffic patterns from large databases. This is the main reason why many researchers emphasize to increase the performance of model-based approach for real-time on-line traffic management systems. On-line travel-time prediction is relatively new that arose from the development of information technology and recent progress of computational power capable of dealing with complex computation problems. This enables applications of theoretical models for on-line traffic control systems.

This paper presents an extensive review on reported applications of the model-based prediction approach. The simulation approach is mainly initiated in efforts to improve the Transportation Management Systems (TMS) by means of evaluating different strategies including ramp-metering, variable massage sign, and variable speed limits (SUMO (Behrisch *et al*., 2011)) and different Mobility-on-Demand services (SimMobility (Azevedo *et al*., 2016; 2017)). Also, applications have been implemented in real-life that are on-line and real-time by different research groups (e.g. VISUM On-line, SBOTTP, OLSIM in Section 3). High accuracy would be expected from the incorporated model as an inherent property, and the data quality also influences significantly. Furthermore, model-based approach is originally aims to real-time control traffic through on-line system. For this reason, sophisticated preprocessing of data filtering and efficient imputation methods are required.

2. Description of Model-based Approach

2.1 Procedure of Model-based Approach

Figure 1 illustrates general procedure of model-based approach. Similar to the data-driven approach, the model-based approach also can deliver comparable accuracies in its predictions as long as the acquired data quality and incorporated formulations are at or above certain threshold levels. The approach is intended for on-line and real-time applications and hence, sophisticated pre-processing/filtering of data and efficient computation methods are required. Different from the data-driven approach, the model-based approach describes traffic propagation on the network based on traffic flow models for predicting travel times with traffic forecasting methods. The traffic state is estimated from real-time traffic surveillance sensors (at fixed points (e.g., VDS) or limited ranges (e.g., Probe vehicles, DSRC)). By simulating this information, against the entire network with certain generalized assumptions, travel-times can be deduced for given origin-destination (OD) matrices. The procedure can gain significant advantages when the simulation is carried on-line rather than off-line/post-processed for real-time applications.

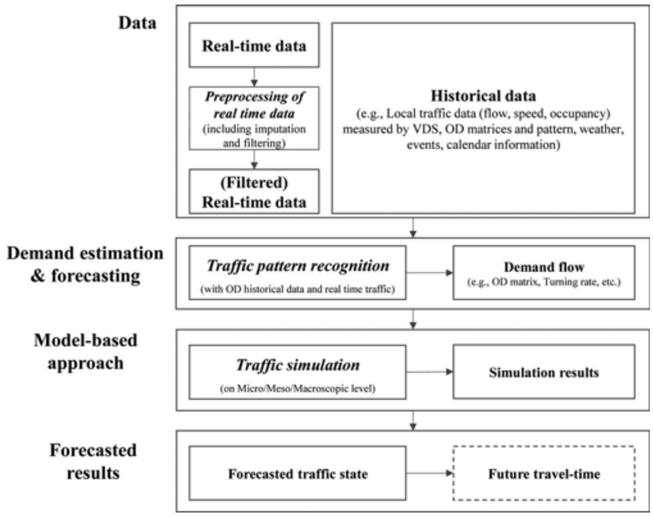

Fig. 1. General Procedure of Model-based Approach

2.2 Taxonomy of Model-based Approach

Many researchers in the field of traffic flow modeling have developed models that explain the traffic characteristics and movements of vehicles on the roads. The description power of the models have been increasing. The models explain intrinsic mechanisms with varying levels of detail and viewpoints, describing from individual vehicles' perspective (microscopic-level) to aggregation of vehicular flow (macroscopic-level). According to the varying level of detail, the model-based approaches are classified into four levels as in Fig. 2: macroscopic, mesoscopic, Cellular Automaton (CA) and microscopic approach.

Macroscopic approaches explain traffic dynamics in the network at an aggregated level, using macroscopic traffic variables including flow, density, and mean speed based on macroscopic models (e.g., LWR theory (Lighthill and Whitham, 1955; Richards, 1956) and three-phase traffic theory (Kerner, 1998)). Individual vehicle behaviors including lane-changing involving relaxation and anticipation to adjacent vehicle are not considered in this level. For this reason, macroscopic models are usually

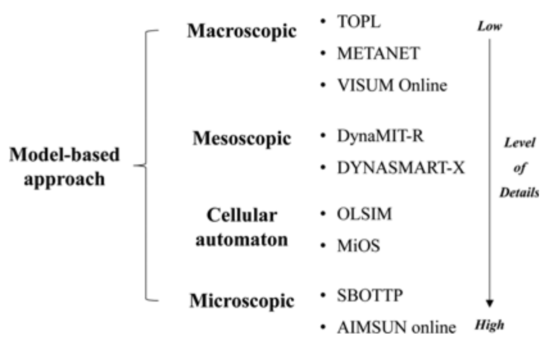

Fig. 2. Taxonomy of Model-based Approach to Travel-time Prediction

associated with lower computational complexity compared to microscopic approaches. Some examples are listed in Fig. 1: TOPL using CTM, METANET using second-order macroscopic model, and VISUM On-line using FOTO and ASDA (Kerner *et al.*, 1999). Mesoscopic approaches simulate traffic states by partially incorporating micro-level attributes into the macro-level simulations. There are two main differences in this approach from others. Interactions among individual drivers and the road networks are first generated from the model as in micro-level simulations. Then, in the following aggregation stage, traffic dynamics and characteristics are applied with a "supply simulator" on a macro level. Hence, the mesoscopic model is considered as a middle level approach. Generally, vehicles are grouped into an entity moving along the network together, and the properties are derived from speed-density relations of each link. Two most widely covered mesoscopic models are reviewed in this paper: DynaMIT-R and DYNASMART-X. CA-based models simulate traffic states based on the methodology proposed by the Nagel-Schreckenberg's model, which discretely explains movements of vehicles from its cell to another. CA-based traffic models are sometimes classified as a microscopic level approach (Hoogendoorn and Bovy, 2001; Chrobok *et al*., 2002; Miska, 2007). However, CA explains drivers' characteristics by discretizing space and time which roughly describes traffic flow compared with the conventional microscopic approaches that are represented in terms of car-following and lane-changing characteristics (e.g., Gipps-Model (Gipps, 1981), Wiedemann-Model (Leutzbach and Wiedemann, 1986)). In this paper, OLSIM and MiOS are selected as examples of the CA approach. Microscopic approaches view traffic dynamics from the perspective of individual drivers. Drivers' behaviors include car-following, lane-changing behaviors, and their preferences related to route-choice problems. An aggregation of individual performance measures in a network is interpreted as a traffic state, which researchers use for predicting future travel-times. Because the approach directly applies driving behaviors of individual drivers and simulates each vehicle as an active particle in the system, it is indeed computationally very complex in general. As of now, microscopic traffic simulation software such as CORSIM and AIMSUN, have been implemented in practice with on-line systems that predict future traffic in real-life.

A model-based approach predicts travel-times with physical traffic mechanisms over a network for a given time horizon. In other words, the approach does not involve a "black-box" process that is often adopted in data-driven approaches and makes more intuitive "sense". This aspect allows traffic engineers to evaluate various traffic control schemes including, ramp-metering, VMS, and VSL. It is also effective with networks with relatively small number of detectors for which data-driven approaches cannot provide reliable predictions due to the lack of data. (Shen, 2008). Moreover, the model-based approach is more robust with respect to changes in input factors (e.g., geometric change such as adding additional networks) compared with the data-driven approach which requires an extensive amount of historical data regarding the changes.

The efficiency varies according to the type of model. The simplicity of the macroscopic approach has its strength in large-scale networks, while the detailed description of the microscopic approach involves intensive computational complexities. For improving the accuracy, models needs a calibration process with real-data. For real-time applications, model-based approach predicts travel-time based on real-time data which are fed back to the model (e.g., capacity of link), and this input data determines the quality of prediction (Lint, 2004; Liu, 2004).

3. Review on Model-based Approach

3.1 Macroscopic Approach

Macroscopic models predict travel-times with aggregated traffic properties of networks, represented by flow, density, and space-mean speed. Using the first or second-order of macroscopic model (e.g., LWR model), this approach predicts the future travel-time indirectly, with forecasted traffic states. Examples of the approach include TOPL, METANET, and VISUM On-line. It is known that the ability to simulate large networks efficiently is the main advantage of macroscopic models. In the simulation, the virtual detectors collect the time-mean speed during unit-time for each fixed point for the visualization purpose, for example speed contours in GUI. However, generally lower level of description is expected due to the aggregated measures used in the model.

3.1.1 TOPL (CTM)

TOPL (Tools for Operations Planning) is a project initiated to implement Active Traffic Management (ATM) system for dynamic traffic management based on surveillance measurements. The ATM system predicts future traffic states with the Aurora macroscopic simulator that incorporates a macroscopic traffic model known as, Cell Transmission Model (CTM) (Daganzo, 1994, 1995). The CTM is based on the LWR model by discretizing the road network into cells. For each time-step, the model calculates the link density with the number of vehicles in a cell and sends vehicles over to their nearest cells. From the speed-density relationship, the traffic state can be derived for each cell (Fig. 3).

On- and off-ramp flows are important for the CTM simulation,

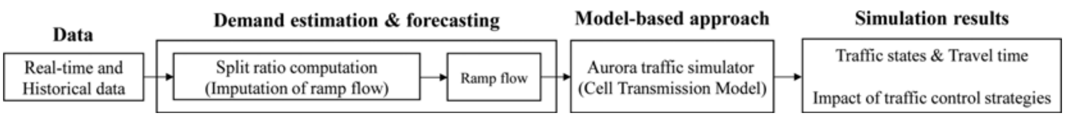

Fig. 3. Procedure of TOPL

Table 1. Mean Relative Error (%) of CTM

	Length (km) (On / Off ramp)	Density (%)	Flow (%)	VMT (%)	VHT (%)	Delay (%)
I-80E	31 km (25 / 23)	4.1	6.8	4.6	3.2	23.7
I-210W	42 km (32 / 26)	4.9	8.0	6.7	0.34	6.23

however, the data often contain missing values. In order to deal with the data-flaw, the researchers have initiated imputation in ramp flow through density and flow matching processes. The CTM model needs to calibrate its base-setting with real-data in terms of model boundaries regarding links and nodes that contain link length and lane information. Traffic dynamics are described based on the fundamental relationship with specified model boundaries including free-flow speed, wave speed, and link capacity. The model calibration of the fundamental diagram is implemented with real-data, PeMS. This model-based approach has been validated in terms of its accuracy from highway I-80E (31 km) and I-210W (42 km) in California. Real-traffic of 7 days are compared with the CTM simulation, and it was shown on average 4.1, 6.8, 4.6, 3.2, 23.7% of MRE for density, flow, VMT, VHT, and delay respectively from the I-80E site. In case of I-210W, the error ranges from 0.34 to 6.23% for each categories as in Table 1 (Chow *et al.*, 2008; Dervisoglu *et al.*, 2011).

3.1.2 BOSS (METANET)

The decision support system, BOSS, aims to provide future traffic states using current traffic state and other conditions on the potential control scenarios. In the BOSS system, the macroscopic traffic modeling tool METANET (Messner and Papageorgiou, 1990) is incorporated for prediction purposes. METANET simulates deterministically for describing traffic phenomena on motorway networks (Link-and-Node), considering five types of links and being fed with demands at its boundaries and origin-destination information.

Figure 4 briefly shows the procedure of METANET-based prediction. The demand for each link is estimated by using a turning fraction (e.g., splitting rates), which is the portion of traffic volumes from each node heading to destination (output) links. The traffic at nodes are calculated using the turning rate. Then the density of nodes are estimated for entering links. The similar strategy can be extended to simulations for traffic control through dynamic traffic assignment if necessary, for the case of ramp-metering and route guidance (destination-oriented mode). Basically, METANET explains traffic dynamics using the model for each link categorized into normal motorway links, origin links, store-and-forward links, destination links, and dummy links. Particularly, a second-order macroscopic model (Payne, 1971) is used for normal motorway links, describing traffic flows using the variables including traffic volume, density, and mean speed. The model is based on the flow conservation and the dynamic speed evolution as a function of density. The model can describe free-flow, critical and congested traffic conditions. For origin links, METANET incorporates a simple queue model to explain outflow from on-ramp to mainline, and the queue spillback is modeled in store-and-forward links with limited capacities. METANET has been validated using traffic networks in Amsterdam (Kotsialos *et al.*, 2002), which is a large-scale network that stretches around 143 km mainly including the A10 ring-road. The study site consists of 654-links (249 motorway links, 231 store-and-forward, and 174 dummy links), and the links are divided into segments of 491.4 m in length on average. The authors validate the METANET through two phases that are, quantitative-level (that determine model parameters by solving least square error problem) and qualitative-level (that calibrate parameters manually to capture traffic dynamics sufficiently). Hoogendoorn *et al.* (2003) evaluate the prediction results under normal circumstances (neither incident nor traffic control situation), and determine the importance of sub-networks by giving weights considering performance indicators such as total travel-time, total wait time, and total fuel consumption. Readers can refer more case studies regarding traffic control using METANET in Papageorgiou *et al.* (2010).

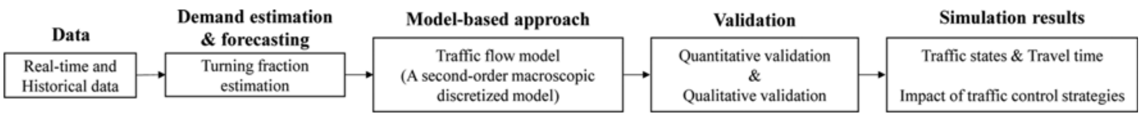

Fig. 4. Procedure of METANET

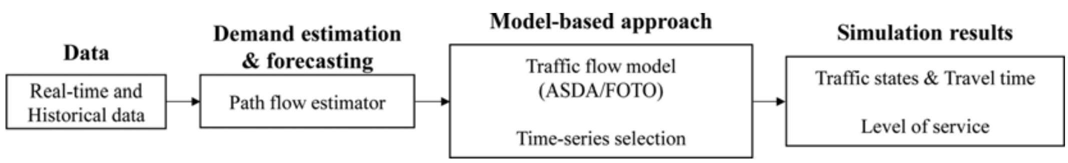

Fig. 5. Procedure of VISUM On-line

3.1.3 VISUM On-line

VISUM On-line developed by PTV, calculates traffic conditions of network based on static and dynamic data for intermodal routing and dynamic propagation.

With the path estimation (Bell, 1997), the demand matrices are generated with regards to the class of day. Real-time traffic data and pre-calibrated demand matrix are used to find the similar traffic patterns. VISUM On-line predicts traffic states of highway networks with the ASDA/FOTO (Kerner *et al*., 1999). ASDA/FOTO identifies traffic dynamics into three categories: free-flow, synchronized traffic, and wide moving jam, using VDS, floating-car (FCD), and mobile-data. The system makes local forecasts through the time-series selection by recognizing the similar traffic patterns of the day (see also VISUM On-line procedure in Fig. 5).

VISUM on-line has been applied in several cities, including Berlin traffic network where 400 VDSs had been installed. From the field test from Berlin for the whole day prediction, PTV reports that 80% of reported level of service from simulations match real-world data, while 14% are close to the data and 6% are determined as wrong prediction. For the prediction results, 73% are reported as correct prediction (Vortisch, 2001).

3.2 Mesoscopic Approach

Mesoscopic approach provides an individual route-choice model on a microscopic level and simulates traffic dynamics using macroscopic models (e.g., queuing model). It need traveler's behavioral models (represented as route-choice) for modelling individual driver's behavior, however, detailed information describing car-following and lane-changing behaviors are not considered in detail. DynaMIT and DYNASMART are the examples of validated applications of the approach. The approach can simulate large networks with relative ease yet its operations are not on fully described theoretical backgrounds.

3.2.1 DynaMIT-R

DynaMIT-R estimates current traffic conditions and predicts future traffic states using an incorporated assignment system. As in the Fig. 6, the state estimation component is composed of two modules: the supply and the demand simulators. The demand simulator estimates and forecasts the traffic demand (OD) based on a traveler's behavioral model (Route and departure time choice), and the supply simulator describes the traffic condition based on interactions between the demand and the network state. The feedback links between the demand and supply simulators' output allows assigning OD-flows until the convergence is achieved between the two simulators. The supply simulator groups drivers into cells that are travelling along the links with deterministic speed and estimated link density, at a mesoscopic level. The simulator is also capable of knitting the traffic dynamics from one to the other links. (e.g., formation of queues)

Assignment matrices as input to the demand estimation results in a traffic state from the supply simulator, showing the information regarding link flow, density, and mean speed. The demand simulator incorporating an auto-regressive process using a Kalman filtering technique predicts the demands, and the resulting demands are disaggregated into the network in the supply simulator. The supply simulator uses a microscopic representation of the traffic, where each individual vehicle is simulated, while macroscopic models are used to capture the traffic dynamics. A deterministic queuing model measures the queue dissipation with parameters including positions of the end of queue, output capacity, vehicle length, and number of vehicles in moving sections, while a speed model calculates the speed values using upstream and downstream speeds of segments with assumptions of constant upstream speed and linearly decreasing speed in deceleration zones (for more details, see Ben-Akiva *et al*., 2001; Balakrishna, 2006).

The DynaMIT-R generates prediction-based guidance for drivers, aiming to minimize travel-times. The researchers compare travel-time predictions of two vehicles with and without the DynaMIT-R application. For the validation purpose, Balakrishna (2006) compares the traffic counts from sensor data and simulated data with RMSN (Root Mean Square Normalized) error. The study-site is the highway and arterial networks in Los Angeles including major urban roads and highways of I-110 and I-10, that are installed with 203-VDS. The demands have been predicted with the AR-process spending 15 min for the 1hour prediction in September 2004. The author reports 0.065 to 0.124 of RMSN in terms of the traffic flow for a sample of VDS in the networks.

3.2.2 DYNASMART-X

The DYNASMART-X DTA (Dynamic Traffic Assignment) system provides a framework for estimating current and predicting future network traffic states, network demand patterns, and routing information. The system consists of several modules including OD-estimation, OD-prediction, and real-time network state simulation.

With historical demand information and real-time traffic surveillance data, DYNASMART-X estimates time-varying demand patterns with Kalman filters which uses a polynomial trend model to estimate the deviation from the historical demand (a priori estimate of regular demand pattern). Regular demand

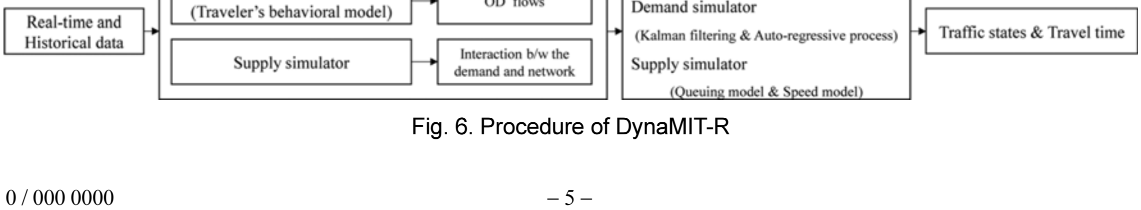

Fig. 6. Procedure of DynaMIT-R

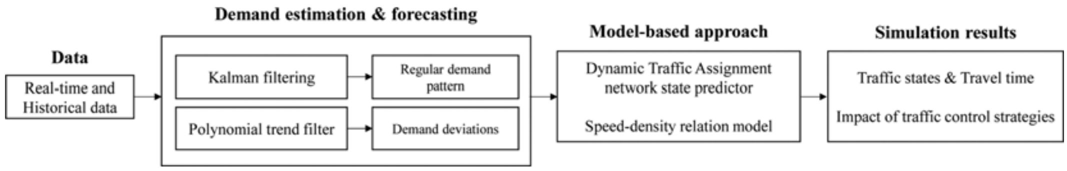

Fig. 7. Procedure of DYNASMART-X

pattern information are important in making real-time demand predictions, since DYNASMART-X aims to predict the true demand with regular patterns as a priori estimate, then its flexibility is achieved by using structural deviations and random disturbances (following Gaussian distribution with zero mean). The predicted demand takes role as an input for simulator of dynamic traffic assignment network state predictor. With respect to the network with link-nodes in DYNASMART-X, the speed of individual vehicles on a link is calculated by speed-density functions. The traffic state (represented by a link speed) is derived from the density and flow, which is then used to deduce travel-times (Fig, 7). In this context, validation of prediction output of link density, speed, and flow is important.

Mahmassani *et al.* (2005) evaluate DYNASMART-X from the CHART study area (including I-95, I-295 and other main arterials covered with 18 VDS), and compare observations and predictions reporting RMSE as 3~5 and 200~225veh/hr/lane in density and flow respectively. The result also shows that the short-term prediction (4^{th} prediction) in the present time step returns more reliable predictions, and the authors ascribe this to the dependency on recent information of the simulator. Additionally, the researchers compare RMSEs for each scenario with varying detector locations, and estimate with better accuracies (in terms of RMSE of density) as the number of detectors on highways increases. In addition, from the networks including highways (I-5, I-405, and Highway 133) and other main arterials in Orange County, Mahmassani and Zhou (2005) simulate and predict densities and compare with observations on a link (link 212 in Irvine network), and conclude that the simulator captures the time dependent trend with acceptable prediction accuracies.

3.3 Cellular Automata (CA) Based Approach

Recently, CA-based approaches have been used for traffic simulations, on a semi-microscopic level. CA approach defines local rules that explain the interaction of the cell itself with its adjacent cells considering a cell as a vehicle unit. Inherently, CA models treat individual vehicles' behavior with less detail than conventional microscopic models. OLSIM and MiOS have been developed as CA-based on-line prediction system. From the literatures, the approach has been shown to be applicable in the largest-scale networks with feasible computational time constraints.

3.3.1 OLSIM

OLSIM is an on-line traffic simulator that forecasts traffic demands using the cellular automaton traffic flow model, which is effective for a large-scale network mainly due to its discretization of the network (Esser and Schreckenberg, 1997; Nagel *et al.*, 2000). OLSIM has been implemented and applied on the real freeway network of North Rhine-Westphalia, and the on-line simulation provides travel-time information and the current traffic state via internet (http://www.autobahn.nrw.de).

In the procedure of OLSIM (Fig. 8), a smoothing-averaged traffic flow of last recent minutes ($J_c(t_0)$) are used for 30 min forecasting, while a 14-day classification and categorization of historical data are used for 60 min forecasting. This heuristic approach considers daily and seasonal differences and contributes to reducing computation times and increasing accuracies. After the process, the long-term averages of the last 20-days of each class of traffic patterns are calculated. Daily features include i) repeated morning and afternoon peak during weekdays, ii) similar traffic flow patterns on Tuesdays, Wednesdays, and Thursdays, and iii) low-flow on Saturdays, Sundays and holidays. Seasonal differences refer to the fluctuations caused by holiday seasons including the Christmas and year-end periods. Predicted traffic demand ($J_{pred}(t_p)$ at time t_p) is predicted based on the sum of the average demand ($J_{dem}(t_p)$: estimated according to prediction horizon ($\Delta\tau$) of 30 and 60 min) and the weighted difference of $J_c(t_0)$.

Advanced cellular automaton traffic flow model aims to simulate accurate traffic states over the networks. Which particular discretization method has been applied on the network is a key factor contributing to how efficient the implementation is with large-scale networks. The smaller cell size (1.5 m) compared with the 7.5 m in Nagel-Schreckenberg's model (1992) enables to describe realistic traffic behavior in terms of acceleration values. Moreover, extensions of the original model with a slow to start rules, anticipation, and brake lights reproduce diverse traffic states including free-flow, spontaneous breakdown, synchronized traffic, and meta-stability. Additionally, two classes of vehicles

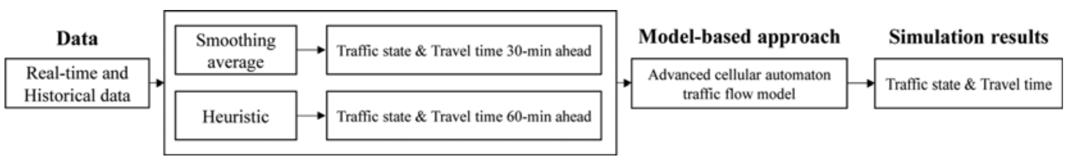

Fig. 8. Procedure of OLSIM

(passenger cars and trucks) having different characteristics (free-flow speed, acceleration capability, and lane-changing rules) are discriminately incorporated in advanced CA methods. Even though OLSIM delivers efficient and realistic simulations, OLSIM requires continuity correction processes, for CA-based discretization. Especially, its speed randomization processes based on the synchronized flow theory need to be verified (Hafstein *et al*., 2004; Chrobok, 2005).

The simulation approach has been implemented in an on-line environment, and the exchange of vehicles between the links, speed and position of vehicles are updated with the CA every 1 min. The predicted traffic states are derived with the combination of current demand and classified historical demand. Based on the prediction, OLSIM provides current and future traffic states along with fastest routes using a dynamic route guidance system. Chrobok *et al.* (2004) validate the simulation model by comparing the simulated traffic state with empirical evidences from a location of A40. The simulation reproduces various traffic states including free-flow, synchronized traffic and wide moving jams that are observable in real traffic data. However, none of the studies with OLSIM have reported specific statistical measures.

3.3.2 MiOS (Microscopic On-line simulator)

MiOS (Miska, 2007) has been developed incorporating 6 modules of on-line data interface, traffic simulator, driving behavior model, route-choice model, OD estimation prediction tool, and postprocessor. MiOS is an extended version of cellular automaton traffic model of Nagel-Schreckenberg's model that can deal with multiple traffic vehicle classes by adjusting cell sizes.

MiOS determines vehicles' position and traffic dynamics through the CA method. Time and space are discretized to 0.1sec and 5 m respectively (Note that the conventional traffic cellular automata model is designed with 1sec and 7.5 m of unit time and space.), and able to describe multiple vehicle classes in the system. And drivers react according to his traffic environment with the assumed reaction time of 0.7 to 1.4sec. The drivers perceive the actual traffic situation with a belief network to calculate the actual belief state considering drivers' car-following and lane-changing behaviors. For the route-choice model in MiOS, the Floyd-Warshall algorithm finds shortest route by incorporating the Dijkstra algorithm. As an OD estimation and prediction tool, a dynamic OD-matrix characterizes static matrices with the times of the day by using the factor vectors. By determining the differences between the calculated demand and real-traffic demand of the most recent 15 min, the prediction factor for the future traffic demand is found (Fig. 9).

MiOS has been validated at the A13 motorway in Delft for four days that show different traffic patterns during peak hours. Travel-times estimated by the PLSB (Piecewise linear speed-based trajectory algorithm (Lint, 2004)) are compared with predicted travel-times of MiOS. During the peak hours, larger errors are observed for the days with larger fluctuations in measurements. However, MiOS accurately predicts the change points of travel-time tendency showing 5.20 to 12% of MAPE (0.651~1.340 min of RMSE).

3.4 Microscopic Approach

A microscopic model approach describes the traffic network performances from the perspectives of individual vehicles. The model is based on detailed interactions among vehicles including car-following, lane-changing, and route-choice behaviors.

Due to the specific and detailed descriptions involved in the approach, there are computational challenges and limitations when it is applied for large-scale networks. However, it is expected to result in relatively high accuracies in simulation for the cases of unexpected events and traffic controls. In this article, SBOTTP and AIMSUN On-line are reviewed.

3.4.1 SBOTTP (CORSIM)

For the purpose of predicting travel-times of the road network in Ocean-city, Maryland, which has relatively small number of detectors installed throughout the network, Liu *et al.* (2006)

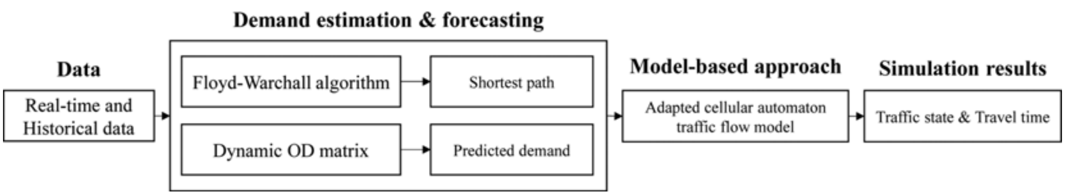

Fig. 9. Procedure of MiOS

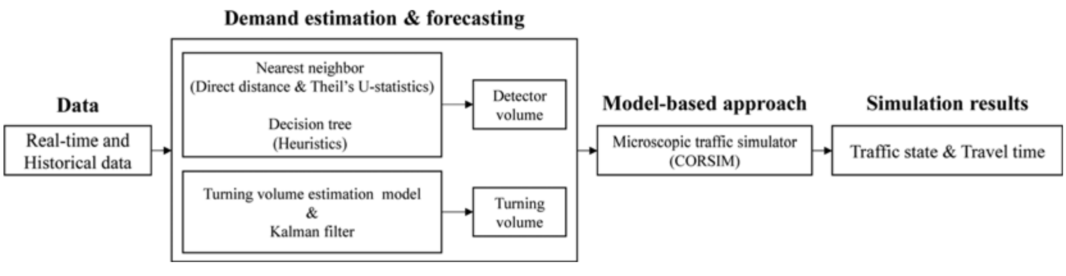

Fig. 10. Procedure of SBOTTP

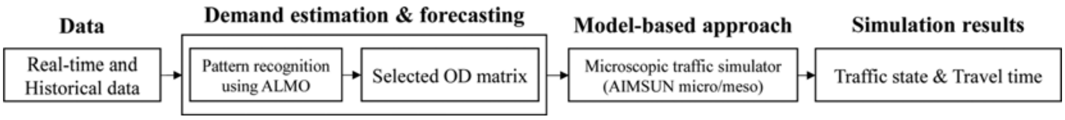

Fig. 11. Procedure of Traffic Management System at M-30

propose a simulation-based on-line travel-time prediction (SBOTTP) system using a microscopic traffic simulator, CORSIM. The on-line service is available from the website, http://oceancity.umd.edu.

Figure 10 illustrates the method of SBOTTP. Raw-data are refined through 3-steps, dealing with outliers and missing-data. Firstly the outliers are removed and the missing points are interpolated with adjacent points. Then the remaining points are smoothed with 5 min time sections. After the filtering process, SBOTTP uses the nearest neighbor (using direct-distance and Theil's U-statistics) method and a decision tree (using heuristic-method) to predict the future volume for associated loop detectors. The decision tree mainly consists of three main categories that are season, weekdays, and events including holidays and hurricane warning. Traffic volumes considering on- and off-ramps (Turning volume estimation) are estimated with a model which calculates the detected volume according to the type of network segment. The authors utilize Kalman filtering technique in order to overcome the challenge of having insufficient observations in the turning volume estimation phase. This volume takes a role as an input variable for the CORSIM-based on-line simulation. Finally, the simulation returns predicted travel-times directly.

The on-line simulation part of SBOTTP has been developed with CORSIM (One of the most widely used microscopic traffic simulator). SBOTTP incorporates a customized version of CORSIM into the on-line system, which results in efficient implementation in operation for a large-scale network (2 min of computation time for simulating vehicular traffic throughout the networks over a 2hour period). SBOTTP needs calibration process for the parameters (including driver population, vehicle composition, and microscopic driving behavior) embedded in the CORSIM simulator, and it is crucial for making reliable predictions.

The study network stretches about 48 km and consists of US-50 (two-lane arterial) and MD-90 (one-lane highway) connecting Salisbury and Ocean-city. The entire network is covered with only 10 VDSs, which is insufficient for implementing a data-driven approach for the travel-time prediction model. The authors compare the predicted traffic state with VDS-data from the location of VDS-02 and 08 over a 2hr prediction period (Differences are found to be less than about 16 km/hr. See Fig. 14~15 in Liu *et al.* (2006)). For the two routes, the authors compare travel-times from field survey and simulation. The differences are found on average as 3 min (0.8~5.7 min) and 2.8 min (1.2~7 min) for route-1 (route through US-50 and MD-90) and 2 (route through US-50 only) respectively.

3.4.2 Traffic Management System at M-30 (AIMSUN On-line)

For predicting the evolution in traffic networks, AIMSUN On-line provides real-time prediction capabilities by integrating ALMO (for OD generation) and AIMSUN micro/meso (for simulation). By determining current demands from real-time based data, corresponding OD matrices can be generated and fed into the simulation model (Fig. 11).

AIMSUN On-line determines the current pattern of demand with the real-time VDS-data as basic input by matching with historical patterns, then loading the corresponding historical OD-matrix into the simulation. For AM and PM peak hours, the OD-matrices are generated using EMME/2. In addition to the demand information determined from ALMO and EMME/2, traffic control strategies including lane-closure, rerouting (VMS), ramp-metering are incorporated into the simulation as input factors. Through the simulation, the indicators (which is characterized according to traffic management objectives) such as average travel-times would be generated as output and can be used for evaluating the control strategies.

AIMSUN On-line has been applied for a case study with the M-30 highway in Madrid (Torday *et al.*, 2010). The study shows generated OD matrices from the simulation is reasonable with acceptable R-square values from the comparison of simulated flows and VDS-flows (0.93~0.97). Then the study validates the quality of the model and shows the R-square value (0.87~0.93) from the comparison of the whole simulation and real-data. The evaluation for this forecasting system in Madrid is currently in progress.

In addition, a second case study has been conducted at I-15. A NPS (Network Prediction Subsystem) is incorporated in the ICMS (Integrated Corridor Management System), and predicts the network demand in 15min intervals (Casas *et al.*, 2013). The NPS analytically predicts the demands (OD-matrices) for the associated VDSs with real-time information, and the predicted demands are used as input for the simulation. For the forecasting purpose, RTSS (Real-Time Simulation Subsystem) simulates traffic dynamics based on information from the database (known as a Data Hub) including i) current traffic conditions, ii) current and future events, and iii) traffic control plan as input arguments. The project area (I-15, 32 km length) covers additional networks including 260 intersections. Monitoring and evaluation of management strategies have been proposed in their works. The system performance of NPS and RTSS are provided according to the network components (including intersections, sections, ramp, mainline lanes, public transit, and route). The evaluation for each component can be shown through indicators of macroscopic variables (speed, flow), travel-time, and total delay. The ICMS considers four prediction horizons of 15, 30, 45, and 60 min (producing predictions every 5 min interval), and it is found that less than 15% of the detectors show significant differences between the reality and predictions.

4. Conclusions

Traffic simulator has been developed for its own purposes: e.g., evaluation of traffic policies / infrastructure change - SUMO (Behrisch *et al*., 2011). One of the main purpose of traffic simulation is to evaluate control strategies, hence the model-based systems providing real-time management service have been highlighted from recent researches. In this paper, we compared with five pillars (prediction range, accuracy, efficiency, applicability, robustness), which are crucial for real-time services. As presented in section 2, various types of model-based approaches are developed. It is important to decide on pertinent method for a given experimental environment. When a large historical database is available, it would be best to apply pattern searching methods for higher accuracies. However, for a large-scale network with a small database, it would be better to opt for model-based approaches. Once the main approach has been decided, optimizing the model structure additionally improves each method before its actual implementation: data-driven (e.g., variable selection in regressions, input/output mapping in ANNs, and optimized k in k-NN) and model-based (e.g., boundaries in traffic models).

In this paper, each model-based approach is based on traffic models that are categorized into macroscopic, mesoscopic, CA, and microscopic-level, and they are investigated according to five main pillars (Prediction range, Accuracy, Efficiency, Applicability, and Robustness). The descriptions and performances of model-based approach are summarized in the appendix of this paper (see Table 2 and 3). For each domain, some findings are summarized below including comparisons of data-driven and model-based approaches:

a) Prediction range and Accuracy:

Previously, some researchers have suggested appropriate prediction horizons (e.g., Vythoulkas, 1993; Kirby *et al*., 1997; Abdulhai *et al*., 1999) for the data-driven approach, and have found the increasing prediction errors as the prediction horizon increases (Park and Riltett, 1999; Dia, 2001; Ishak and Al-Deek, 2002; Sun *et al*., 2003). However, none of the model-based researches have reported regarding this issue. Many data-driven studies have adopted about 5 to 25 min of prediction horizon, and this is shorter than typical horizon of model-based approaches. Model-based approaches reviewed in this paper do not have certain recommendations for a critical prediction range, however, the studies show acceptable accuracy for longer periods of 30 to even 120 min. In addition, as some data-driven approaches (Davis *et al*., 1990; Ohba *et al*., 2001; Rice and Zwet, 2004) have reported, congestions tend to adversely affect the prediction accuracies of model-based approaches as in the case of MiOS where the prediction errors have increased during the peak hours.

Prediction systems incorporating model-based approaches generally manage a large scope of area while maintaining relatively excellent computation efficiency. In the case of data-driven approaches, it is reported from some literatures that the accuracy of data-driven approaches are not significantly influenced by spatial ranges (Innamaa, 2005; Lint *et al*., 2005; Lint, 2006). It is also noted that researches based on data-driven methods generally have conducted studies on sites with smaller ranges than model-based approaches (varied from 32 km (AIMSUN On-line) to 2250 km (OLSIM)).

Due to different i) experimental environments and ii) statistical measures used in each research, directly comparing them on accuracy is a challenge. Some models report unstable accuracies (e.g., 3.2~23.7% of MRE in TOPL(CTM)), while some others report stable accuracies (e.g., 0.87~0.93 of R-squared in AIMSUN On-line): The reported accuracies fluctuate slightly, meaning that the systems are currently still being validated and calibrated due to their short research history.

b) Efficiency, Applicability, and Robustness:

Efficiency is as crucial as accuracy in practice and in implementing TMS. As the level of the detail increases, the model-based approach is expected to require more computational efforts. Macroscopic and CA-based approaches tend to require relatively shorter processing time (even for a large network) than microscopic approaches (e.g., SBOTTP and AIMSUN On-line also report acceptable computation efficiency, (presumably) due to the small spatial ranges (32~48 km).

It is noted that the efficiency of data-driven approaches in general are poor and not fit for real-time applications. Even though many researchers have proposed hybrid methods in efforts to increase the efficiency, three still are problems that need to be address in data-driven approaches: i) coefficient estimation in parametric regression approaches, ii) parameter decisions in neural network methods, and iii) efficient pattern searching in databases. Also, generally, data-driven approaches are significantly influenced by historical data, since the method is highly dependent on scale and integrity of the historical data. For model-based approaches, the integrity of real-time data is also a critical factor that determines the prediction accuracy, since many model-based systems deal with feeding data in real-time for on-line services. A well-defined preprocessing capability that corrects various type of data errors including missing data is mandatory for a reliable model-based system with acceptable accuracy and efficiency.

Relatively, basic principle of model-based approach is accordance with the objective of real-time TMS application (Traffic control and management). In this context, the prediction system is capable of incorporating control measures (e.g., ramp-metering, VMS for incident management, VSL, and alternative route guidance, and so on) by adjusting model variables. Furthermore, forecasting services for networks installed with small number of sensors are good candidates for which model-based approaches can be applied, since the approach is not highly dependent on historical sensor data as in the case of data-driven approach. (Shen, 2008).

Most of models with data-driven approaches are site-specific and their determined coefficients and parameters associated with their test-beds. Some of the generically-designed models (e.g., neural networks) are reported as applicable for different sites, without parameter modifications. However, generally, data-driven approaches tend to require parameter changes more due to the changes in geographic conditions from site to site. Contrarily, a model-based approach is theoretically expected to be relatively robust from changes in experimental circumstance (e.g., geometric change such as adding an additional network). However, inherently, the models pre-determines some boundaries (e.g., safety gap, capacity, jam density) which limit the prediction performance for the exceptional cases exceeding the boundaries.

Acknowledgements

This research was supported by the MSIP (Ministry of Science, ICT and Future Planning), Korea, under the ITRC (Information Technology Research Center) support program (IITP-2016-R2718-16-0011) supervised by the IITP (Institute for Information & communications Technology Promotion), and supported by a grant (17CTAP-C129888-01) from Technology Advancement Research Program (TARP) funded by Ministry of Land, Infrastructure, and Transport of Korean government.

References

Abdulhai, Baher; Porwal, Himanshu, and Recker, Will. (1999). *Short Term Freeway Traffic Flow Prediction Using Genetically-Optimized Time-Delay-Based Neural Networks*, California Partners for Advanced Transit and Highways (PATH). UC Berkeley: California Partners for Advanced Transportation Technology.

Azevedo, C, Oh, S., Deshmunk, N., Marimuthu, B., Marczuk, K., Soh, H., Basak, K., Toledo, T., Peh, L., Ben-Akiva, M. (2017). "SimMobility Short-term: An integrated microscopic mobility simulator." *In Transportation Research Board 96th Annual Meeting*, Nos. 17-06621.

Azevedo, C. L., Marczuk, K., Raveau, S., Soh, H., Adnan, M., Basak, K., and Ben-Akiva, M. (2016). "Microsimulation of demand and supply of autonomous mobility on demand." *Transportation Research Record: Journal of the Transportation Research Board*, (2564), pp. 21-30.

Balakrishna, R. (2006). Off-line calibration of dynamic traffic assignment models (Doctoral dissertation, Massachusetts Institute of Technology).

Behrisch, M., Bieker, L., Erdmann, J., and Krajzewicz, D. (2011). "SUMO–simulation of urban mobility: An overview. In Proceedings of SIMUL 2011." *The Third International Conference on Advances in System Simulation.* ThinkMind. (ISBN 978-1-61208-169-4).

Bell, M. G., Shield, C. M., Busch, F., and Kruse, G. (1997). "A stochastic user equilibrium path flow estimator." *Transportation Research Part C: Emerging Technologies*, Vol. 5, No. 3, pp. 197-210, DOI: 10.1016/S0968-090X(97)00009-0.

Ben-Akiva, M., Bierlaire, M., Burton, D., Koutsopoulos, H. N., and Mishalani, R. (2001). "Network state estimation and prediction for real-time traffic management." *Networks and Spatial Economics*, Vol. 1, Nos. 3-4, pp. 293-318, DOI: 10.1023/A:1012883811652.

Casas, J., Torday, A., Perarnau, J., Breen, M., and Ruiz de Villa, A. (2013, October). "Present and future methodology for the implementation of decision support systems for traffic management." *In Australasian Transport Research Forum (ATRF),* 36th, 2013, Brisbane, Queensland, Australia.

Chen, H., Grant-Muller, S., Mussone, L., and Montgomery, F. (2001). "A study of hybrid neural network approaches and the effects of missing data on traffic forecasting." *Neural Computing & Applications*, Vol. 10, No. 3, pp. 277-286, DOI: 10.1007/s521-001-8054-3.

Chen, M. and Chien, S. I. (2001). "Dynamic freeway travel-time prediction with probe vehicle data: Link based versus path based." *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1768, No. 1, pp. 157-161, DOI: 10.3141/1768-19.

Chow, A., Dadok, V., Dervisoglu, G., Gomes, G., Horowitz, R., Kurzhanskiy, A. A., Kwon, J., Lu, X.-Y., Muralidharan, A., Norman, S., Sánchez, R. O., and Varaiya, P. (2008, January). "Topl: Tools for operational planning of transportation networks." *In ASME 2008 Dynamic Systems and Control Conference*, pp. 1035-1042. American Society of Mechanical Engineers.

Chrobok, R. (2005). Theory and Application of Advanced Traffic Forecast Methods (Doctoral dissertation, Universitätsbibliothek Duisburg).

Chrobok, R., Hafstein, S. F., and Pottmeier, A. (2004). "Olsim: A new generation of traffic information systems." *Forschung und wissenschaftliches Rechnen*, Vol. 63, pp. 11-25, DOI: 10.1.1.90.8400.

Chrobok, R., Pottmeier, A., ur Marinosson, S., and Schreckenberg, M. (2002). "On-line simulation and traffic forecast: Applications and results." *Cell*, Vol. 3, No. 1, pp. 2-2.

D'Angelo, M. P., Al-Deek, H. M., and Wang, M. C. (1999). "Travel-time prediction for freeway corridors." *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1676, No. 1, pp. 184-191, DOI: 10.3141/1676-23.

Daganzo, C. F. (1994). "The cell transmission model: A dynamic representation of highway traffic consistent with the hydrodynamic theory." *Transportation Research Part B: Methodological*, Vol. 28, No. 4, pp. 269-287, DOI: 10.1016/0191-2615(94)90002-7.

Daganzo, C. F. (1995). "The cell transmission model, part II: Network traffic." *Transportation Research Part B: Methodologica*l, Vol. 29, No. 2, pp. 79-93, DOI: 10.1016/0191-2615(94)00022-R.

Davis, G. A. and Nihan, N. L. (1991). "Nonparametric regression and short-term freeway traffic forecasting." *Journal of Transportation Engineering*, Vol. 117, No. 2, pp. 178-188, DOI: 10.1061/(ASCE) 0733-947X(1991)117:2(178).

Davis, G. A., Nihan, N. L., Hamed, M. M., and Jacobson, L. N. (1990). "Adaptive forecasting of freeway traffic congestion." *Transportation Research Record,* Vol. 1287, DOI: 10.1016/S1874-1029(08)60062-2.

Dervisoglu, G. (2011). TOPL Project Review presentation material (source: http://path.berkeley.edu/topl).

Dia, H. (2001). "An object-oriented neural network approach to short-term traffic forecasting." *European Journal of Operational Research*, Vol. 131, No. 2, pp. 253-261, DOI: 10.1016/S0377-2217(00)00125-9.

Dougherty, M. S. and Cobbett, M. R. (1997). "Short-term inter-urban traffic forecasts using neural networks." *International Journal of Forecasting*, Vol. 13, No. 1, pp. 21-31, DOI: 10.1016/S0169-2070(96)00697-8.

Esser, J. and Schreckenberg, M. (1997). "Microscopic simulation of urban traffic based on cellular automata." *International Journal of Modern Physics C*, Vol. 8, No. 5, pp. 1025-1036, DOI: 10.1142/S0129183197000904.

Gipps, P. G. (1981). "A behavioural car-following model for computer simulation." *Transportation Research Part B: Methodological,* Vol. 15, No. 2, pp. 105-111, DOI: 10.1016/0191-2615(81)90037-0.

Hafstein, S., Chrobok, R., Pottmeier, A., Schreckenberg, M., and C

Mazur, F. (2004). “A high-resolution cellular automata traffic simulation model with application in a freeway traffic information system.” *Computer-Aided Civil and Infrastructure Engineering*, Vol. 19, No. 5, pp. 338-350, DOI: 10.1111/j.1467-8667.2004.00361.x.

Mahmassani, H. S., Fei, X., Eisenman, S., Zhou, X., and Qi, X. (2005). DYNASMART-X evaluation for real-time TMC application: CHART test bed. Maryland Transportation Initiative, University of Maryland, College Park, Maryland.

Hoogendoorn, S. P. and Bovy, P. H. (2001). “State-of-the-art of vehicular traffic flow modelling.” *Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering*, Vol. 215, No. 4, pp. 283-303, DOI: 10.1177/095965180121500402.

Hoogendoorn, S. P., Schuurman, H., and De Schutter, B. (2003, August). “Real-time traffic management scenario evaluation.” *In Proceedings of the 10th IFAC Symposium on Control in Transportation Systems (CTS 2003),* pp. 343-348.

Innamaa, S. (2005). “Short-term prediction of travel-time using neural networks on an interurban highway.” *Transportation*, Vol. 32, No. 6, pp. 649-669, DOI: 10.1007/s11116-005-0219-y.

Ishak, S. and Al-Deek, H. (2002). “Performance evaluation of short-term time-series traffic prediction model.” *Journal of Transportation Engineering*, Vol. 128, No. 6, pp. 490-498, DOI: 10.1061/(ASCE) 0733-947X(2002)128:6(490).

Kerner, B. S. (1998). “Experimental features of self-organization in traffic flow.” *Physical Review Letters*, Vol. 81, pp. 3797-3800, DOI: 10.1103/PhysRevLett.81.3797.

Kerner, B., Kirschfink, H., and Rehborn, H. (1999). U.S. Patent No. 5,861,820. Washington, DC: U.S. Patent and Trademark Office.

Kirby, H. R., Watson, S. M., and Dougherty, M. S. (1997). “Should we use neural networks or statistical models for short-term motorway traffic forecasting?.” *International Journal of Forecasting*, Vol. 13, No. 1, pp. 43-50, DOI: 10.1016/S0169-2070(96)00699-1.

Kotsialos, A., Papageorgiou, M., Diakaki, C., Pavlis, Y., and Middelham, F. (2002). “Traffic flow modeling of large-scale motorway networks using the macroscopic modeling tool METANET.” *Intelligent Transportation Systems, IEEE Transactions on*, Vol. 3, No. 4, pp. 282-292, DOI: 10.1109/TITS.2002.806804.

Kwon, J., Coifman, B., and Bickel, P. (2000). “Day-to-day travel-time trends and travel-time prediction from loop-detector data.” *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1717, No. 1, pp. 120-129, DOI: 10.3141/1717-15.

Leutzbach, W. and Wiedemann, R. (1986). “Development and applications of traffic simulation models at the Karlsruhe Institut für Verkehrswesen.” *Traffic Engineering & Control*, Vol. 27, No. 5, pp. 270-278.

Lighthill, M. J. and Whitham, G. B. (1955). “On kinematic waves. I: Flood movement in longrivers. II: A theory of traffic flow on long crowded roads.” *Proc. Royal Soc. London, Ser. A 229*, pp. 281-345.

Liu, X. (2004). *Development of dynamic recursive models for freeway travel time prediction*, Ph.D. thesis, New Jersey Institute of Technology.

Liu, Y., Lin, P. W., Lai, X., Chang, G. L., and Marquess, A. (2006). “Developments and applications of simulation-based online travel time prediction system: Traveling to Ocean City, Maryland.” *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1959, No. 1, pp. 92-104, DOI: 10.3141/1959-11.

Mahmassani, H. and Zhou, X. (2005). “Transportation system intelligence: Performance measurement and real-time traffic estimation and prediction in a day-to-day learning framework.” *In Advances in Control, Communication Networks, and Transportation Systems*, pp. 305-328, Birkhäuser Boston, DOI: 10.1007/0-8176-4409-1_16.

Messner, A. and Papageorgiou, M. (1990). “METANET: A macroscopic simulation program for motorway networks.” *Traffic Engineering & Control*, Vol. 31, Nos. 8-9, pp. 466-470, DOI: 10.1007/978-1-4419-6142-6_11.

Miska, M. P. (2007). *Microscopic online simulation for real time traffic management (No. Trail Thesis Series T2007/1).* Netherlands TRAIL Research School. (ISBN-13: 978-90-5584-082-3).

Nagel, K. and Schreckenberg, M. (1992). “A cellular automaton model for freeway traffic.” *Journal de Physique I*, Vol. 2, No. 12, pp. 2221-2229, DOI: 10.1051/jp1:1992277.

Nagel, K., Esser, J., and Rickert, M. (2000). “Large-scale traffic simulations for transportation planning.” *Annual Review of Computational Physics*, Vol. 7, pp. 151-202, DOI: 10.1.1.13.5188.

Ohba, Y., Ueno, H., and Kuwahara, M. (2001). “Travel time prediction method for expressway using toll collection system data.” *In Proceedings of the 7th World Congress on Intelligent Systems*, DOI: 10.1109/ITSC.1999.821103.

Papageorgiou, M., Papamichail, I., Messmer, A., and Wang, Y. (2010). “Traffic simulation with metanet.” *In Fundamentals of Traffic Simulation pp. 399-430*. Springer New York. Smulders et al., 1999, DOI: 10.1007/978-1-4419-6142-6_11.

Park, D. and Rilett, L. R. (1999). “Forecasting freeway link travel times with a multilayer feed forward neural network.” *Computer-Aided Civil and Infrastructure Engineering*, Vol. 14, No. 5, pp. 357-367, DOI: 10.1111/0885-9507.00154.

Payne, H. J. (1971). *Models of freeway traffic and control*, Mathematical models of public systems. (ISSN: 0037-5519)

Rice, J. and Van Zwet, E. (2004). “A simple and effective method for predicting travel times on freeways.” *Intelligent Transportation Systems, IEEE Transactions on*, Vol. 5, No. 3, pp. 200-207, DOI: 10.1109/TITS.2004.833765.

Richards, P. I. (1956). “Shock waves on the highway.” *Operations Research*, Vol. 4, No. 1, pp. 42-51, DOI: 10.1287/opre.4.1.42.

Shen, L. (2008). “Freeway travel-time estimation and prediction using dynamic neural networks.” January 1, 2008. *ProQuest ETD Collection for FIU.* Paper AAI3346733.

Smith, B. L. and Demetsky, M. J. (1997). “Traffic flow forecasting: comparison of modeling approaches.” *Journal of Transportation Engineering*, Vol. 123, No. 4, pp. 261-266, DOI: 10.1061/(ASCE) 0733-947X(1997)123:4(261).

Smith, B. L., Williams, B. M., and Oswald, R. K. (2000). *Parametric and nonparametric traffic volume forecasting,* In Transportation Research Board 79th Annual Meeting.

Sun, H., Liu, H. X., Xiao, H., He, R. R., and Ran, B. (2003, January). *Short term traffic forecasting using the local linear regression model*, In 82nd Annual Meeting of the Transportation Research Board, Washington, DC.

Torday, A. (2010). *Simulation-based Decision Support System for Real Time Traffic Management,* In Transportation Research Board 89th Annual Meeting (No. 10-2120).

van Lint, H. (2004). *Reliable travel-time prediction for freeways*, Netherlands TRAIL Research School, ISBN: 90-5584-054-8.

van Lint, J. W. (2006). “Reliable real-time framework for short-term freeway travel-time prediction.” *Journal of Transportation Engineering*, Vol. 132, No. 12, pp. 921-932, DOI: 10.1061/(ASCE)0733-947X (2006)132:12(921).

van Lint, J. W. C., Hoogendoorn, S. P., and van Zuylen, H. J. (2005). “Accurate freeway travel time prediction with state-space neural networks under missing data.” *Transportation Research Part C: Emerging Technologies*, Vol. 13, No. 5, pp. 347-369, DOI: 10.1016/

j.trc.2005.03.001.
Vortisch, P. (2001). *Use of PTV-Software in the traffic management centre (VMZ) Berlin*, In th PTV Vision User Group Meeting, Berlin, Germany.
Vythoulkas, P. C. (1993). *Alternative approaches to short term traffic forecasting for use in driver information systems*, In International Symposium on the Theory of Traffic Flow and Transportation (12th: 1993: Berkeley, Calif.). Transportation and traffic theory.
Williams, B. M. (2001). "Multivariate vehicular traffic flow prediction: Evaluation of ARIMAX modeling." *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1776, No. 1, 194-200, DOI: 10.3141/1776-25.
Zhang, X. and Rice, J. A. (2003). "Short-term travel-time prediction." *Transportation Research Part C: Emerging Technologies*, Vol. 11, No. 3, pp. 187-210, DOI: 10.1016/S0968-090X(03)00026-3.

Appendix – Descriptive and performance tables for model-based approaches

Table 2. Descriptive Table of Model-based Approach

Model level	Model	Input		Approach:	Representative outputs
		Data	Factor		
Macroscopic	TOPL (CTM)	– Historical & Real-time surveillance data: VDS-data	– Traffic controls – Incidents management	**Demand:** Imputation of ramp flow **Simulation:** CTM	– Speed contour – Hourly delays – Travel tune
	BOSS (METANET)	– Historical & Real-time surveillance data: VDS-data – Demand information	– Traffic controls – Incidents management	**Demand:** Turning fraction estimation **Simulation:** A second-order macroscopic discretized model	– Macroscopic variables – Total travel time – Total wait time – Total traveled distance – Total Fuel consumption
	VISUM On-line (FOTO and ASDA)	– Historical & Real-time surveillance data: VDS, FCD, mobile-data	– Traffic controls – Incident report – Others (e.g., Road works)	**Demand:** Path flow estimator **Simulation**: FOTO and ASDA Time-series selection	– Visualization through macroscopic variables (On-line) – Level of service – Route information (On-line)
Mesoscopic	DynaMIT-R	– Historical & Real-time surveillance data: VDS-data	– Incidents report	**Demand:** AR-process with Kalman filtering **Simulation:** Mesoscopic queuing and speed model	– Macroscopic variables – Vehicle travel time
	DYNASMART-X	– Historical & Real-time surveillance data: VDS-data – OD demand	NA	**Demand:** Kalman filtering using polynomial trend filter **Simulation:** DTA network state predictor Speed-density relation model	– Macroscopic variables – Time dependent shortest path and associated travel time
CA	OLSIM	– Historical & Real-time surveillance data: VDS-data	– Day information	**Demand:** **Short-term:** Smoothing average **Long-term:** Heuristics **Simulation:** Advanced CA	– Visualization through macroscopic variables (On-line) – Macroscopic variables – Travel time
	MiOS	– Historical & Real-time surveillance data: VDS-data	– Incidents information	**Demand:** Floyd-Warchall algorithm & Dynamic OD matrix **Simulation:** Adapted CA	– Macroscopic variables – Travel time
Microscopic	SBOTTP	– Historical & Real-time surveillance data: VDS-data – Incident monitor	– Geometric conditions – Speed limit – Signal control – Season information – Day information – Events (Holidays, Hurricane)	**Demand:** **Mainline:** Nearest neighbor & Decision tree **On/Off-ramp:** Turning volume estimation with Kalman filter **Simulation:** CORSIM	– Visualization through macroscopic variables (On-line) – Travel time
	Traffic Management System (AIMSUN On-line)	– Historical & Real-time surveillance data: VDS-data	– Traffic controls – Day information – Special events – Calendar information – Weather forecast	**Demand:** OD pattern recognition using ALMO **Simulation:** AIMSUN Micro/Meso	– Visualization through macroscopic variables (On-line) – Travel time – Delay time – Fuel consumption – Emissions – Number of stops

Table 3. Performance Table of Model-based Approach

Model level	Model	Prediction range		Accuracy	Efficiency (Computation complexity)	Applicability (Possible application)
		Prognosis horizon	Site (Spatial scope)			
Macroscopic	TOPL (CTM)	Given horizon	I80-E (31 km)	MRE: 3.2~23.7%	NA (Very quick)	– Ramp metering – Variable speed limits (VSL) – Incident management (VMS) – Lane specific control (HOV, Shoulder lane) – Lane closure
			I210-W (4 km)	MRE: 0.34~6.23%		

Table 3. Performance Table of Model-based Approach

Macroscopic	BOSS (METANET)	1 hr	A10 (143km)	Quantitatively NA	Simulation step: typically 5~20sec Output time interval: typically 1 min	– Ramp metering – Variable speed limits (VSL) – Queuing management (VMS) – Lane specific control (Shoulder lane) – Lane closure
	VISUM On-line (FOTO and ASDA)	1 hr (Short) 1 day (Long)	Berlin (400 VDS)	Current traffic: 80% correct Future traffic: 73% correct	Calculation update: 5~15 min cycles Forecasts every 15 min	– Ramp metering – Variable speed limits (VSL) – Alternative routing
Mesoscopic	DynaMIT-R	1 hr	LA (203 VDS)	RMSN: 0.065 to 0.124	15 min estimation	– Traffic information – Route guidance
	DYNASMART-X	20 min	CHART study area (18 VDS)	RMSE: 3~5 (Density) 200~225 vphpl (Flow)	OD Estimation: 15 min OD Prediction: 45 min	– Ramp metering – Traffic controls – Incident management (VMS) – Pre-trip & en-route travel information
			Orange County (NA)	NA	NA	
CA	OLSIM (Advanced CA)	30 min (Short) 60 min (Long)	NRW (2250 km, 4000 VDS)	NA	Update step: 1min	– Dynamic route guidance system – Travel time (w@ke up system)
	MiOS	30 min	A13 (NA)	RMSE: 0.651~1.340 min Bias: -0.569 ~ -0.204 min RRE: 0.603 ~ 1.213 min MAPE: 5.20~12.00%	Fast implementation and easy understanding Simulation time step: 0.1sec	NA
Microscopic	SBOTTP (CORSIM)	2 hr	US-50 & MD-90 (48 km, 10 VDS)	Difference: less than 16.1 km/hr Travel-time difference: 0.8~5.7 min (Route-1) 1.2~7 min (Route-2)	Simulation-time: 2 min Update-step: 5 min	– Incident management (VMS)
	Traffic control system (AIM-SUN On-line)	30 min	M30 (NA)	R-square: 0.87~0.93	3 min reaction time	– Lane closure – Rerouting with VMS – Speed limit variation – Ramp metering
		15 min	I-25 (32 km)	Difference: Less than 15%	Producing every 5 min interval	
		30 min				
		45 min				
		60 min				