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Short-term Travel-time Prediction on Highway: A Review of the Data-driven Approach

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ABSTRACT *Near future travel-time information is one of the most critical factors that travellers consider before making trip decisions. In efforts to provide more reliable future travel-time estimations, transportation engineers have examined various techniques developed in the last three decades. However, there have not been sufficiently systematic and through reviews so far. In order to effectively support various transportation strategies and applications including Intelligent Transportation Systems (ITS), it is necessary to apply appropriate forecasting methods for matching circumstances in a timely manner. This paper conducts a comprehensive review study focusing on literatures, including modern techniques proposed recently, related to travel time and traffic condition predictions that are based on 'data-driven' approaches. Based on the underlying mechanisms and theoretical principles, different approaches are categorized as parametric (linear regression and time series) and non-parametric approaches (artificial intelligence and pattern searching). Then, the approaches are analysed for their strengths, potential weaknesses, and performances from five main perspectives that are prediction range, accuracy, efficiency, applicability, and robustness.*

1. Introduction of Data-driven Approach

Travel-time prediction is one of the most critical components in maintaining successful Intelligent Transportation Systems (ITS), particularly in Advanced Traveller Information Systems (ATIS). With accurate travel-time predictions, travellers can make informed decisions about their trips. Reliable travel-time forecasting methods enable establishing dynamic control strategies. As performance indicators, predicted travel times can also serve as tools for quantitatively comparing various proposed traffic management strategies. Accurate travel times can enhance traffic management systems (TMS) by giving them opportunities to react to the traffic proactively rather than passively. Many researchers have

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developed various travel-time prediction methods from different perspectives. In this paper, the prediction methods are classified as: linear regression and time-series models, artificial intelligence, and pattern searching methods, and evaluated based on five main perspectives: prediction range, accuracy, efficiency, robustness and applicability.

Prediction range is composed of two parts: prognosis horizon and spatial scope. The prognosis horizon represents the length of prediction time, while the spatial scope indicates the physical range of network the predictions are made for. It has been observed that a longer prognosis horizon generally results in larger prediction errors (e.g. Sun, Liu, Xiao, He, & Ran, 2003). Researchers suggest the appropriate prognosis horizon to be in the range of 5–30 min (e.g. Abdulhai, Porwal, & Recker, 1999; Kirby, Watson, & Dougherty, 1997; Vythoulkas, 1993). Smith and Demetsky (1997) and Vlahogianni, Golias, and Karlaftis (2004) recommend that more than a 15–30 min horizon is needed to take reactive operational activities corresponding to forecasted situations.

The accuracy is generally evaluated by the comparison between the predicted traffic conditions and empirically determined measures that are statistically post processed. In order to provide an acceptable level of accuracy, the model has to be well-established in terms of parameters and boundary conditions, and large historical data need to be secured typically containing more than one-year's data (Torday, 2010). The data can comprise mainly traffic data and other relevant information including incident events, road works, weather, and calendar. This multi-layered data structure influences the calculation efficiency as it helps to sort out the traffic pattern in prediction processes.

The efficiency refers to the computational efforts, typically reported in various forms (e.g. forecasting step, simulation time, and updating time). In general, the complexity of the model and the prediction range influence the efficiency. However, it is a challenge to adequately compare different researches due to different computational environments and different definitions used in various researches. Regardless of how different researches refer to the term, 'efficiency', an acceptable efficiency is a crucial factor and a mandatory requirement for real-time applications.

Prediction models can eventually be expanded to applications for real-time services via on-line channels. In the past, most of the applications in travel-time predictions have been relying heavily on model-based approaches. The applications have mainly focused on the traffic control and management field including topics such as the impact of ramp metering, variable speed limits, and incident management using variable message signs. Multiple researches have been initiated in the USA, Germany, the Netherlands and China, developing on-line real-time TMS with dynamic traffic control techniques. The techniques can be classified according to the level of details involved in the traffic model as: Macroscopic (e.g. TOPL (Chow et al., 2008), BOSS-METANET (Papageorgiou, Papamichail, Messmer, & Wang, 2010), Visum On-line (Vortisch, 2001)), Mesoscopic (DynaMIT (Ben-Akiva, Bierlaire, Burton, Koutsopoulos, & Mishalani, 2001), DynaSMART-X (Mahmassani, Fei, Eisenman, Zhou, & Qin, 2005)), Cellular-Automaton (OLSIM (Chrobok, Hafstein, & Pottmeier, 2004; Chrobok, Pottmeier, ur Marinosson, & Schreckenberg, 2002)), and Microscopic approach (SBOTTP (Liu, Lin, Lai, Chang, & Marquess, 2006), AIMSUN On-line (Casas, Torday, Perarnau, Breen, & Ruiz de Villa, 2013; Torday, 2010)). In the data-driven approach, particular efforts are devoted to implementing on-line real-time applications. Researchers present a straightforward and reliable framework integrating multiple modules including data collection, data processing, pattern identification, and prediction module (van Lint, 2006; van Lint, Hoogendoorn, & van Zuylen, 2005; Yu, Chang, Ho, & Liu, 2008). The data-driven prediction module yields an acceptable accuracy in dealing with the real-time traffic data. (Giving a few examples – Chien & Kuchipudi, 2003; Fei, Lu, & Liu, 2011; van Lint, 2006; Park, Rilett, & Han, 1999; Zhang & Rice, 2003). In Zhang and Rice (2003), the time-varying coefficient (TVC) linear model updates its coefficients at each time step. And Rice and van Zwet (2004) comment that linear regression is applicable if the model parameters are determined from the pre-estimation process offline. Later, van Hinsbergen and van Lint (2008) proposed a Bayesian combination framework to combine multiple linear models. Recently, Fei et al. (2011) have developed a Bayesian inference-based dynamic linear model (DLM) to robustly predict the exogenous factors (e.g. Accidents), and the authors emphasize that the Bayesian approach enables the efficient update of travel time prediction contributing to online practicability. In the case of neural networks, van Lint et al. (2005) have applied a state-space neural network (SSNN) in the Regiolab−Delft project (Zuylen & Muller, 2002) for a reliable online system by dealing with the incorrect input data with spatio-temporal interpolation. But still researchers are concerned about the real-time application of data-driven approaches, because of the data storage and computational limitation (e.g. large amount of training sets (van Lint & Schreuder, 2006)) as computational efficiency is one of the most critical issues in the context of practicality. As a solution to this problem, Chen and Grant-Muller (2001) incorporated the EKF (extended Kalman filter) in a sequential learning process to adapt the network parameter of RAN (Resource allocating network). van Lint (2008) introduced the delayed and censored EKF-based training method, enabling SSNN to adaptively train the parameters (i.e. weights) with the realized travel times.

A data-driven approach predicts the travel-time by finding the current traffic state from historical traffic patterns, without detailed descriptions of intrinsic network dynamics based on traffic flow mechanisms. With some types of data, researchers can predict travel-times directly or indirectly from various traffic sensors. Based on the license plate recognition technology, the Automatic Vehicle Identification (AVI) system collects travel-time of an individual vehicle directly. Similarly, the toll collection system (TCS) estimates individual travel-time through an RFID (Radio-frequency identification) receiver. The vehicle detector station (VDS) system is most widely used for indirect travel-time prediction, by providing macroscopic information including flow, occupancy, and time-mean speed. Traffic information from these heterogeneous sources often contains incorrect values because of missing or corrupt input data. In order to compensate for the incorrect values and reduce noises, researchers typically conduct pre-processing works based on imputation before the main prediction procedures are applied. With the filtered data, the model forecasts future travel-times with incorporated techniques either directly or indirectly.

There have been various efforts in classifying data-driven prediction methods as in the following:

(1) Parametric and Non-parametric models (van Lint, 2004)
(2) Historical profile, Regression, Time series, and Neural Networks (NNs) (Vanajakshi, 2004)

(3) Parametric regression (ARIMA, Kalman filter), Non-parametric regression (Nearest neighbourhood), and NNs (Chrobok, 2005)
(4) Naïve (Instantaneous, Historical averages, and Cluster analysis), Parametric (Traffic flow models (Model based), Linear regression, ARIMA, Kalman filtering), and Non-parametric models (NNs, k-NN, etc.) (van Hinsbergen, van Lint, & Sanders, 2007)
(5) Regression (Linear regression), Time series (ARIMA, Kalman filter), and NNs (Shen, 2008)
(6) Parametric (Regression models, Time series (ARIMA, Kalman Filter)) and Non-parametric (Artificial intelligence (ANN), Pattern search (k-NN)) approaches (Yu et al., 2008)
(7) Parametric (Linear regression, Time series, Kalman filter) and Non-parametric (NNs, Bayesian models, pattern recognition (k-NN)) methods (Fei et al., 2011)

In compliance with the previous researches' taxonomy on the data-driven approach, we propose a set of criteria for classifying and evaluating the data-driven approaches considering underlying mechanisms and theoretical principles. Figure 1 shows the taxonomy of data-driven approaches.

In the parametric approach the functional relationship between the explanatory and response variables is known, and some unknown parameters may be estimated from the training set. Selecting input variables and estimating coefficients minimizing errors are the key issues for this approach. The parametric statistical approaches are known to perform quite accurately despite their simple formulations provided that they have well-established theoretical and mathematical backgrounds and are validated by transportation engineers. The main drawback of this approach is that coefficients are site-specific and it is difficult to implement in large-scale networks.

NNs are non-parametric models that predict travel-times by training themselves with historical data which mimic the mechanisms of a human brain. The parameters (e.g. weights) have no physical meaning in regard to the problems to which they are applied. The main advantage of using NNs in transportation applications is that they can handle complex and non-linear properties that are inherently embedded in the nature of many transportation engineering problems. The method has been validated by many researchers with acceptable accuracy. Complex training with site-specific limitations and black-box procedures involved are the main demerits of artificial NNs (ANNs). Poor logical descriptions with regards to traffic mechanisms may be questioned by various audiences who

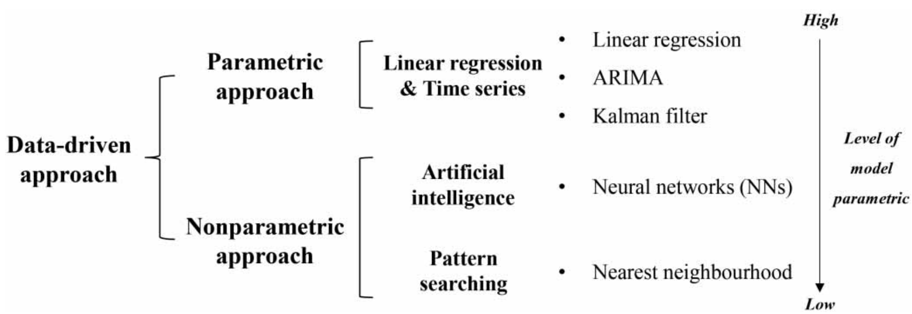

Figure 1. Taxonomy of a data-driven approach to travel-time prediction.

may demand intuitive rationales for their field applications regardless of their prediction performances.

Another non-parametric method that is widely used in literatures is the nearest neighbourhood method. This method matches similar historical patterns with the current one by searching archived databases. This non-parametric approach is expected to perform well with large data sets. However, this dependency inevitably requires the integrity of data and sufficient sizes of databases. The following sections present and describe various data-driven approaches with respect to their strengths, weaknesses, and performances.

2. Review of Data-driven Approaches

2.1. *The Linear Regression and Time Series Modelling Approach*

The parametric approach treats travel-time prediction problems with a pre-structured model by fitting the parameters using data, and there are both merits and demerits as discussed in previous sections. According to forecasting mechanisms and underlying rationales, the parametric models can be classified as linear regression, ARIMA, of which ARIMA is considered as a time series-based approach, and Kalman filter. The descriptions and performances of these approaches are listed in Tables 1 and 2, respectively.

2.1.1. *Linear Regression*. Prediction functions in linear regression basically assume a linear combination of covariates. Several researchers have conducted regression analyses for deriving future travel times from relevant variables. Due to their relatively simple structures, the researchers consistently confirm the high efficiency of the method in terms of computations.

Kwon, Coifman, and Bickel (2000) predict travel times using the linear regression with a stepwise method for covariates using a heterogeneous data set. The current traffic state is found to be the most influencing factor for short-term predictions, while the historical data are more useful in predictions for longer prognosis horizons. The regression model is fed with observed travel-times from probe-vehicles as a response variable and others are treated (VDS data, departure time, and day of week) as covariates. Then the model has been tested on I-880N&S. The observations show large variations in the metrics in the day-to-day scenario and their strong correlations with travel times, indicating the significant influence of the metrics on travel times. It is noted that the input explanatory variables have been filtered through the stepwise method which is unique in their works.

For different recurring and non-recurring congestion scenarios, the authors improve the explanatory power through the use of abnormality measures detecting outlying days from the normal days. The paper finds that the 20-min prediction time frame is beneficial, producing similar prediction errors for all four scenarios. On average, the resulting errors are found as 116.75 of root MSPE (95∼149 s) and 14.1% of MAPPE (11∼16.6%). Authors state that relatively short prediction horizons and small spatial ranges are the major limitations of the proposed model.

TVC, ATHENA, and Bayesian prediction. Zhang and Rice (2003), and Rice and van Zwet (2004) predict travel times using the method of simple linear regression

Table 1. Descriptive table of parametric approach

Researcher	Model	Input: Data	Input: Equipment	Input: Factor	Approach:
Kwon et al. (2000)	Linear regression	Flow, occupancy (30 s), and travel-time	VDS probe vehicle	The day of the week Departure time	Linear regression with step-wise variable selection
Zhang and Rice (2003)		Speed (30 s) and travel-time for I-880 N Flow and Occ (30 s) for I-405 N	VDS probe-vehicle	Departure time	Linear regression with TVC
Rice and van Zwet (2004)		Flow and Occ (30 s) – aggregated into 5 min	VDS	Departure time	
Sun et al. (2003)		Speed (5 min)		NA	Local linear regression
Wu et al. (2004)		Speed (3 min)		Distance of a section Number of sections	Linear regression with SVM
Fei et al. (2011)		Flow, occupancy, and Speed (1 min) – aggregated into 5 min		Unseen events (incidents, accidents, and bad weather)	ADLM
Oda (1990)	ARIMA	Flow and Occ (5 min)		Vehicle length	AR
Saito and Watanabe (1995)		Flow, occupancy, and Speed (NA min)		NA	
Ishak and Al-Deek (2002)		Speed (30 s)			Non-linear time series
Park and Rilett (1999)	Kalman filter	Travel-time – aggregated into 5 min	AVI		Kalman filter
Chien and Kuchipudi (2003)		Travel-time – aggregated into 5 min	AVI		Kalman filter (Path-based and Link-based)
Kuchipudi and Chien (2003)		Travel-time – aggregated into 5 min	AVI		Kalman filter (hybrid model)

Table 2. Performance table of parametric approach

Researcher	Model	Prediction range: Prognosis horizon	Prediction range: Site (Spatial scope)	Time	Accuracy		Efficiency
Kwon et al. (2000)	Linear regression	20 min	I-880N&S (10 km, 19 VDS)	Morning peak (05.00–10.00)	Root-MSPE	116.75 s (95∼149 s)	NA
				Evening peak (14.00–19.00)	MAPPE	14.1% (11∼16.6%).	
Zhang and Rice (2003)		30 min	I-880N (10 km, 18VDS)	Morning peak (05.00–10.00)	MAPEE	11%	Reported efficiency
		90 min	I-405N (32 km)	Morning peak (05.00–10.00)	MAPEE	14%	
Rice and van Zwet (2004)		60 min	I-10E (77 km, 116VDS)	All day (05.00–21:00) – collected 34 days	RMSE	Less than 10 min	
Sun et al. (2003)		25 min (five step)	US-290E (2.5 km)	Morning peak (06.00-10.00) – collected 32 days	RME	11.38%	NA
Wu et al. (2004)		10 min	Taipei-Chungli (45 km)	Morning peak (07.00∼10.00)	RME	3.91%	
			Taipei-Taichung (178 km)		RMSE	6.79%	
			Taipei-Kaohsiung (350 km)		RME	1.71%	
					RMSE	2.57%	
					RME	0.96%	
					RMSE	1.33%	
Fei et al. (2011)		5 min	I-66E (11.26 km, 17VDS)	Morning peak (5.00∼11.00)	MAE	0.13∼2.32 min	
				Evening peak (14.00∼20.00)	MAPE	2∼14%	Reported efficient in updating
				(Trained for March and April in 2009)	RMSE	0.17∼3.01 min	
Oda (1990)	ARIMA	P ($p >= 2$)	National Route 16 (7 km, 14VDS)	Morning peak (07.00–09.00)	Difference	5∼6 % (Morning)	NA

				Midday (12.00∼14.00)		Large (Midday and Evening)	
				Evening peak (17.00∼19.00)			
Saito and Watanabe (1995)		60 min	Arterial near Aomori (NA)	Peak hour	Average error	3 min	
Ishak and Al-Deek (2002)		5 min	I-4 (62.5 km, 70 VDS)	Morning and afternoon peak and off-peak (06.00–19.00)	Relative travel-time prediction error	0.059	5 min of prediction step
		10 min				0.061	
		15 min				0.069	
Park and Rilett (1999)	Kalman filter	5 min	US-290E (27.6 km, 7 AVI stations)	Morning-peak (06.00–10.00) (Trained for 131 weekdays in 1996)	MAPE	6.2%	NA
		10 min				12.1%	
		15 min				17.0%	
		20 min				20.8%	
		25 min				24.5%	
Chien and Kuchipudi (2003)		5 min	Eastbound NYST (17 km)	Morning and afternoon peak and off-peak (06.30–09.30) – collected 14 days	MARE	1.1∼7.3% (Path-based)	5 min of prediction step
Kuchipudi and Chien (2003)		5∼15 min (peak)	Eastbound NYST (17 km)	All day (24 h) – Collected from 12 Mar-		2.1∼9.2% (Link-based)	
		30 min (off-peak)			MARE	4.8∼11.73% (Hybrid)	5∼30 min of prediction step
						6.6∼17.5% (Path-based)	
						6.8∼14.7% (Link-based)	

with TVC according to the time of day. The authors show a linear relationship between the current traffic and future travel times for discrete time intervals. Zhang and Rice (2003) conduct the regression analysis with varying coefficients according to the departure time, and predict the future travel time with the current travel time predictor which is measured by the VDS speed. The method has been validated from two test sites: I-880N and I-405N. A smaller MAPEE is found using the model as 11% in the 30-min forecasting (I-880N), while Kwon et al. (2000) show 13% in the 20-min forecasting from the scenario for 5–10AM on I-880N. In the case of a larger spatial range on I-405N, the MAPEE is found to be 14% in the 90-min forecasting. Similar types of methods can also be found in Rice and van Zwet (2004), which is validated on I-10E. The speed values are estimated with flow and occupancy using the unique 'g-factor'. For the prediction period of 60 min, the RMSE is estimated to be less than 10 min. The RMSE is found to be large during the peak hour period, while the lower RMSE (5 min) is observed for non-peak hours. The results of the linear regression are compared with two alternative approaches: principal component analysis and nearest neighbour method. It is found that the regression-based estimations show the highest accuracies among them. Researchers claim that the acceptable accuracy can be achieved by having access to appropriate parameter estimations based on sufficiently large data sets and by incorporating time-varying traffic features. However, determining the parameters in real time for online applications does not seem feasible yet due to the time-consuming processes involved.

Sun et al. (2003) derive future travel times using a local linear regression model. The main difference from Rice's researches is that there is no assumption of linearity between the current information and the future estimations. From a 2.5-km segment on US-290E, the local linear predictor performs with an relative mean error (RME) of 8.46∼11.38% for each prediction steps 1∼5. The k-NN and (no-ridging) kernel smoothing methods yield larger RME of 10.27∼12.12% and 15.39∼17.8%, respectively. They conclude that the local linear method is the most reliable one because of its explicit use of current data while the other methods simply average the historical data for making predictions.

Other researchers combine linear models with non-parametric support vector machines (Vanajakshi, 2004; Wu, Ho, & Lee, 2004). Wu et al. (2004) apply the support vector regression for highways near Taipei during the morning peak, and report the accuracy measures in terms of RME and RMSE. The model is found to be outperforming other baseline predictors, showing relatively small errors. Danech-Pajouh and Aron (1991) take similar approaches and develop the ATHENA program. This layered approach predicts the future traffic with linear regression analyses separately applied on each cluster. The authors suggest that the proposed traffic classification method can significantly improve the prediction accuracy. ATHENA produces excellent numerical performances mainly due to its layered structures. It also has the main drawback of having practical difficulties for implementations due to its inherently complicated computational processes associated with 192 different clusters.

To increase practicality in the context of real-time application, van Hinsbergen and van Lint (2008) develop a Bayesian framework that combines two linear regression models (linear model and locally weighted model). Recently, Fei et al. (2011) proposed the adaptive dynamic linear model (ADLM) to increase real-time applicability dealing with diverse traffic situation including non-recurrent congestion. The Bayesian inference-based model considers travel time as a linear combination of the median historical travel times, the variations in travel times, and the model error. After training the prior information (in March and April, 2009), the authors test the proposed framework with VDS data collected from highway I-66 (11.26 km) for the typical weekdays (in May, 2009) and show that the ADLM outperforms the auto-regressive (AR) model particularly for the non-recurrent traffic.

2.1.2. *Auto-regressive Integrated Moving Average Model*. ARIMA is one of the most widely used time series models. Basically, the model regards traffic observations as statistical observations that are arranged in a stationary time series. Thus, the observations inherently contain real-life processes and data noises. The main objective of the method is minimizing the noises. ARIMA had originally been invented by combining the concepts of AR feature with moving average (MA) models, which also known as the Box-Jenkins model (see Box, Jenkins, & Reinsel, 2013)).

In the field of traffic engineering, researchers including Ahmed and Cook (1979), Levin and Tsao (1980), and Ahmed (1983) have introduced the ARIMA model in efforts to incorporate stochastic traffic mechanisms for making predictions. Later, Oda (1990) predicts the travel time with an AR model with the statistical presumption of vehicle lengths according to traffic conditions. For the highway section on Route-16, travel-times are predicted for the three time zones for four days with a lead time, p ($p>=2$). The predicted travel times are within the ranges of 5∼6% from the observed travel times for the morning peak, while larger errors have occurred for both midday and evening peaks. Saito and Watanabe (1995) predict travel times for the future 60-min time frame, using historical VDS data. The AR model is fed with the last 30-min observations for making predictions on the arterial roads near Aomori, Japan. They find that the average error is less than 3 min. The predicted travel times produced from the developed system have been relayed to users in real life via local VMS and radio stations.

Incorporating the Kalman filter to ARIMA. AR models are also presented in the work of Iwasaki and Shirao (1996) that utilizes pseudo traffic patterns. In their research, an extended Kalman filtering method is used for parameter identifications, which effectively eliminates the time lags in predictions. The results show less than 10% of RMEs.

The Kalman filtering method can also be adopted for the identification of parameters in the ARIMA models. For example, Iwasaki and Saito's AR model (1999) sequentially estimates parameters using Kalman filtering with historical patterns (with 3 years' data) for forecasting future speeds 10∼60-min ahead of time. From a test section on the Tomei highway, Japan, the authors find the lowest RMSE with the 10-min prognosis horizon (with the historical pattern weight factor of 0.1). For the 60-min horizon, the RMSE lowers as the weight increases.

Incorporating a self-organizing map to ARIMA. In efforts to improve the performance of the ARIMA method, van der Voort, Dougherty, and Watson (1996) propose a KARIMA (Kohonen-ARIMA) model that predicts future traffic conditions with a hybrid version of a self-organizing map (SOM) integrated with the ARIMA method. This approach adopts an advanced clustering technique that groups the data and assigns each cluster with its own time series. The authors recognize the limitations of the layered approach (ATHENA) in practical applications (complicated computations due to numerous clusters), and develop the KARIMA with different sub-components, reducing the number of clusters to a minimum level. Unlike the ARIMA model which uses all data points, the KARIMA model selects the data into groups according to a calendar property. For the four French highway sites, using the 30-min VDS flow and binary variables of calendar property, the authors reported $-15\sim+15\%$ of relative error observed from 90% of test examples in both 30- and 60-min forecasts. A similar combination approach is also found in Chen, Grant-Muller, Mussone, and Montgomery (2001). The authors classify a series of traffic patterns into several groups (free flow, transition, congestion, and capacity traffic) based on flow, occupancy, and speed from three VDSs (including up/downstream). From M25 in the UK, the MAPE of SOM/ARIMA is found as 11.4%, while the ARIMA has produced 14.6% of MAPE.

Adding additional parameters to ARIMA. Davis, Nihan, Hamed, and Jacobson (1990) recognize that the inherent problem that lies in the ARIMA is that it neglects the extremes (e.g. high points on during peak hours) in trend analyses, which induces difficulties for making predictions in some traffic situations such as the onset of congestions and bottleneck formations.

Compared with the historical average method, the ARIMA shows better performances in the work of Smith and Demetsky (1997) resulting in an MAE of 195 veh/hr and an average error of 9.03%. However, the ARIMA under predicts by more than 10~20% from the real traffic when compared with the historical average. In addition, it still shows lower performances in terms of accuracy and applicability when compared with the nearest neighbour methods and NNs. The authors suggest that the ARIMA model does not seem to be suitable in traffic forecasting.

Some years later, Williams (2001) improved the ARIMA by incorporating other exogenous inputs including the upstream data series, for predicting the downstream traffic flow time series (ARIMAX: ARIMA with explanatory variable (X)). Another attempt known as SARIMA which stands for Seasonal-ARIMA that incorporates parameters of normal and seasonal differences was reported by Williams and Hoel (2003). They compared the prediction performances of the SARIMA with others methods such as random walk and historical average-based approaches, from the section of M25 in the UK and I-75 in the US. They report the MAPE of 8.74~8.97% with the SARIMA predictions, while the other methods predict with larger prediction errors ranging from 9.54 to 12.85%. In addition, Clark, Chen, and Grant-Muller (1999) reported the prediction accuracies of SARIMA and KARIMA from the M25 study site. It is found that SARIMA is more accurate with 8.6% of MAPE than KARIMA with 11.5% of MAPE.

The SARIMA also outperforms the k-NN approach in Smith, Williams, and Oswald (2002). Using the two VDSs on M25 with the 15-min period, for the traffic flow forecasts, the SARIMA shows 8.8~8.83% of MAPE which is lower than 9.39~10.6% of MAPE using the k-NN approach.

Transformation of the ARIMA form into non-linear. D'Angelo, Al-Deek and Wang (1999) developed a non-linear time series for short-term predictions of traffic parameters on I-4 (18 km in length). For the morning peak, two types of traffic state predictions are made: prediction with a single variable (speed) and with multiple variables (speed, occupancy, and flow data). The authors conclude that the single variable approach outperforms for the 5-min travel-time predictions with acceptable errors. For the longer section on I-4 (62.5 km-length), Ishak and Al-Deek (2002) use a non-linear time series for predicting travel times by using future speed values forecasted with the local Hölder exponent. Depending on the traffic stability determined by local speeds, future speeds are calculated through a model called self-exciting threshold auto-regressive (SETAR), then travel times are derived. By varying the congestion index from severe congestions to a free flow, the authors observe relative errors increase as the congested level increases. The relative error is found to be increasing as the prediction horizon increases: 0.059, 0.061, and 0.069 of errors for 5, 10, and 15min of horizons, respectively. The study concludes that the prediction errors with congested conditions are significantly larger compared with the free flow state as the prediction horizon increases.

2.1.3. *Kalman Filter.* A Kalman filter is another parametric statistical technique, and it has been used for flow forecasting (e.g. Okutani and Stephanedes, 1984; Whittaker, Garside, and Lindveld, 1997) and travel time predictions (e.g. Chen and Grant-Muller, 2001; Chen and Chien, 2001; Chien and Kuchipudi, 2003; Chien, Liu, & Ozbay, 2003; Kuchipudi and Chien, 2003; Vythoulkas, 1993; Yang, 2005; Yasui, Ikenoue, & Takeuchi, 1995) by various researchers. This technique uses time series approaches predicting the future state by continuously updating the selected state variables. The technique assumes certain relations of state vectors with discrete time slots, and observation vectors with associated observation equations. Using the transition equation (first order Markov process), a selected state vector is created based on the past and current observations along with an optimal estimation state vector (Kalman, 1960).

Okutani and Stephanedes (1984) showed the applicability of Kalman filters in traffic flow forecasting. With the smoothed data collected from Nagoya, Japan, the authors report 0.0249∼0.0566 of MRE for prediction periods of 5∼45 min. The authors highlight the robust performance even in the case of the longest forecasting time period of 45 min. In travel time prediction, Park et al. (1999) predicted travel times using Kalman filters with AVI data from US-290, for the prediction range of 5∼25 min. The average accuracy of 16.1% is reported with varying prediction horizons. The Kalman filter outperforms other methods including historical profile based, real-time profile based, and exponential smoothing. However, ANN-based approaches (ANN, SNN) are found to perform better than Kalman filters. Chen and Chien (2001) showed more accurate prediction performance from path-based than link-based approach with AVI data in the recurrent traffic condition. Chien and Kuchipudi (2003) reported an accuracy of 1.1∼7.3% of MARE from path-based and 2.1∼9.2% from link-based prediction. To take the time-varying traffic conditions into account, Kuchipudi and Chien (2003) integrated the path-based and link-based models. The hybrid model yields better accuracy (4.8∼ 11.73% of MARE) compared with the result of path- and link-based models (6.6∼17.5% and 6.8∼14.7%, respectively). The authors also present the application of this algorithm for online application with time-varying prediction intervals.

Due to the limitations of accurately predicting future traffic patterns that encompasses various hidden and unknown underlying mechanisms, and inherent limitations of the Markov property (e.g. one step ahead prediction), some researchers use Kalman filters combined with other methods including ARIMA and NNs (e.g. parameter identification (Iwasaki & Saito, 1999), learning rule in training process for real-time application (Chen and Grant-Muller, 2001; van Lint, 2008; Vythoulkas, 1993), and data integration and traffic state estimation together with a macroscopic traffic flow model (van Hinsbergen, Schreiter, Zuurbier, van Lint, & van Zuylen, 2012; van Lint & Djukic, 2012; Nanthawichit, Nakatsuji, & Suzuki, 2003; Wang and Papageorgiou, 2005)).

2.2. *Artificial Intelligence Approach*

AI is a software approach that incorporates human-like intelligences, and an artificial neural network (ANN) is a representative AI that learns underlying patterns from the input/output relationship. An ANN computes outputs determined through internal transfer functions (i.e. sigmoidal transfer functions) using neurons that are linked with associated weights. The outputs of a neuron are inputs for other neurons, and the neurons are connected in forms of networks. The neurons are typically arranged with input layer, hidden layer, and output layer. And one of the main categories of ANNs is a feed-forward NN with the back-propagation properties (e.g. multi-layer perceptrons (MLPs), and radial basis networks (RBNs)), mapping sets of inputs onto a set of appropriate outputs allowing acyclic forms. In addition, some of the ANNs can further be categorized as recurrent NNs (RNNs) if they contain feedback mechanisms. The NNs from literatures are described in Table 3, and Table 4 investigated the performances of the NNs.

Traffic prediction problems are often associated with complex and non-linear properties and ANNs are capable of solving such problems with great performance and robustness. Reported accuracies outperform other approaches in many cases, and researchers have consistently validated NNs for traffic/travel-time forecasts. However, associated complex training and the 'black-box' nature of the method can be considered as non-intuitive. Model parameters including the number of hidden layers are typically optimized in efforts to enhance the performance of NNs which leads to NNs memorizing the training data and becoming site-specific as Byon, Abdulhai, and Shalaby (2009), Byon and Liang (2014) recognize.

2.2.1 *Feed-forward NNs: MLP.* MLP is a back-propagation method that aims to train multi-layered NNs by minimizing the errors between the actual and desired outputs. MLP contains multiple layers (input, output, and one or more hidden layers), containing transfer functions that enable the handling of the non-linearity between input and output data. It is a supervised learning technique that maps inputs with desired outputs during the training, generally requiring a large set of sample data. While monitoring the errors, ANNs update the connection weights iteratively until acceptable minimum values of errors from the input–output pairs are obtained.

Dougherty and Cobbett (1997) used the MLP using VDS data from highways near Hague, the Netherlands. Since the size of input is crucial for its implementation, the study develops stepwise reductions of the network size by performing elasticity tests on input selections. The authors use 40 inputs for the computational efficiency and acceptable prediction accuracies. In the case of 15-min prediction period, RMSEPs are reported as 0.22∼0.24 for the flow, 0.21∼0.23 for the occupancy, and 0.39∼0.41 for the speed. A similar level of performance is observed

Table 3. Descriptive table of AI approach

Researcher	Model	Input			Approach:
		Data	Equipment	Factor	
Dougherty and Cobbett (1997)	ANN	Flow, occupancy, and speed (1 min) – Aggregated into 5 min	VDS	NA	MLP – single hidden layer-
Huisken and van Berkum (2003)		Flow and speed (1 min) – Aggregated into 1 min			
Park and Rilett (1999)		Travel-time – Aggregated into 5 min	AVI		
Innamaa (2005)		Flow and speed (1 min) – Aggregated into 1 min	VDS		
		Travel-time	AVI		
Park et al. (1999)		Travel-time –Aggregated into 5 min	AVI		SNN – single hidden layer-
Dia (2001)		Flow and speed (20 s)	VDS		TLRN
Abdulhai et al. (1999)		Flow and density (30 s) – Aggregated into 5 min			Advanced TDNN-optimized model structure with GA-
van Lint et al. (2005)		Flow and speed (60 s)			SSNN-one hidden-layer and one context-layer-
van Lint (2006)					
van Lint (2008)		Flow and speed (60 s)			Delayed and censored EFK SSNN

for a longer prediction horizon of 30 min. The authors believe that slow vehicles during the low traffic flow state lower the performance of speed predictions.

Smith and Demetsky (1997) predicted travel times with back-propagation NNs. With 10 hidden processing elements on one hidden layer, the authors apply the developed NNs on Telegraph road in Virginia. For the traffic volume predictions, absolute error and average error are estimated as 167.3 veh/hr and 7.54%, respectively, which are more accurate than ARIMA and historical average approaches. In addition, Huisken and van Berkum (2003) compared MLPs with two naive methods dynamic travel time estimation (DTTE) and static travel time estimation (STTE). Using VDS flow and speed data from A13-highway, prediction performances of three systems are assessed with the estimated travel times. The MLP is trained with VDS data from 21 stations and time of day information (43-inputs). Among the 43 inputs, the authors reduced the size down to more significant 12 inputs for training in efforts to minimize the computational loads. The MLP is found to outperform DTTE and STTE giving smaller errors of -0.249%, 4.61%, -0.107s, and 35.1s of MRE, MARE, MTE, and MATE, respectively.

2.2.2. *MLP using AVI data*. There have been attempts at using MLPs for travel-time predictions with AVI data: Park and Rilett (1999), Park et al. (1999), and Rilett and Park (2001). Park and Rilett (1999) predicted link travel times with travel-time data collected from seven AVI stations installed on US-290. Among the 6 links (link-1$\sim$6) in US-290, link-4 is targeted for prediction. Then, four types of NNs (NN_M1$\sim$NN_M4) were developed and compared. NN_M1 uses

Table 4. Performance table of AI approach

Researcher	Model	Prediction range: Prognosis horizon	Prediction range: Site (Spatial scope)	Time	Accuracy					Efficiency
Dougherty and Cobbett (1997)	ANN	15 min	A3 and A13 (NA)	All day (06:00–19:30) for typical week days	RMSEP	0.22∼0.24 (flow)				NA
						0.21∼0.23 (occ)				
						0.39∼0.41 (speed)				
		30 min				0.26∼0.28 (flow)				
						0.25∼0.27 (occ)				
						0.35∼0.42 (speed)				
Huisken and van Berkum (2003)		NA	A13 (11.4 km, 21VDS)	NA (11 November 1996–23 February 1997)	MRE	−0.249%				
					MARE	4.61%				
					MTE	−0.107s				
					MATE	35.1 s				
Park and Rilett (1999)		–	US-290 (27.6 km, 7 AVI stations)	Morning peak 06:00–10:00-Trained for 131 weekdays in 1996	–	NN_M1	NN_M2	NN_M3	NN_M4	
		5 min			MAPE	7.4	8.3	10.2	9.4	
		10 min				10.3	10.8	12.3	11.5	
		15 min				13.1	12.8	14.2	13.7	
		20 min				16.2	14.5	15.8	15.5	
		25 min				17.9	16.1	17.2	16.9	
Innamaa (2005)		4 min	Road-4 (28 km)	All day (Collected 4 months)	Mean abs. value of error	1.1 min				30 min of maximum time b/w updates
					MRE	0.6%				
					MARE	6.0%				
Park et al. (1999)		5 min	US-290E (27.6 km, 7 AVI)	Morning peak (06:00–10:00) -Trained for 131 weekdays in 1996		7.2%				NA
		10 min				9.7%				
		15 min				12.2%				
		20 min				14.1%				
		25 min				15.7%				
Dia (2001)		20 s	Pacific highway (1.5 km, 4VDS)	Collected over a 5 h period on 2 days in April 1995	Average percent error	5%				

	1 min 2 min 4 min 5 min 10 min 15 min				6% 6% 7% 7% 7% 7%			
Abdulhai et al. (1999)	5 min 10 min 15 min	I-5 (8 km, 9VDS)	Evening peak (16:00–18:00) – trained 2 April 1997		4%(Flow), 6%(Density) 5%(Flow), 7%(Density) 6%(Flow), 8.5%(Density)			
van Lint et al. (2005)	NA	A13S (8.5 km, 13VDS)	NA	MRE	1.6%			6.5 hr of training time
				RMSEP	48 s			
van Lint (2006)	NA	A13S (13 km, 27VDS)	Evening peak (14:00∼19:45) – trained January–April 2003	MRE	0.64%			6 hr 7 min of training time
				RMSEP	13%			
van Lint (2008)	NA	A13S (7 km, 14VDS)	Evening peak (14:00∼20:00) – Trained January–April 2003	-	Delayed	Censored	SSNN	
				R^2	80.8%	82.4%	86.5	
				RMSE	117.8 s	112.4s	100 s	
				Bias	−13.5 s	−12.5s	−5.03s	
				PRE	116.8 s	111.6 s	100 s	

only the preceding travel times of link-4 as input, while all up/downstream links' travel times are used in NN_M2. Similarly, NN_M3 uses up/downstream links' travel time, with the exclusion of link-2 due to its low correlation. In NN_M4, the nearest downstream and upstream links' travel times are used. The number of inputs for each NN varies from 7 (NN_M1) to 25 (NN_M4). The authors found influences of traffic conditions and prediction horizon on prediction accuracies: (i) large MAPEs results from severe congestions (e.g. 6.6∼16.3% for minor congestions and 11.7∼25.9% for severe congestions from NN_M1) and (ii) increment of MAPEs in long prediction horizons (e.g. 7.4∼17.9% for 5∼25-min predictions in Table 4). The performances were found to be varying among proposed network models, and the authors highlight the importance of variable selections for higher accuracies when using the proposed ANN.

2.2.3. *MLP using both AVI data and VDS data*. In addition to AVI data, Innamaa (2005) incorporates VDS data into their research. From Road-4 in Finland, the authors collected travel-time data from four AVI stations and VDS data from two detectors. Through the correlation analysis between parameters and the predicted travel times, 36∼54 inputs were selected including travel times and average flows from different sub-sections and VDS locations. The study predicts travel times for each section varying in the range of 9.1∼28.1 km in length. It is shown that as the length of the section increases, the MAE increases from 0.3 to 1.1 min. However, MRE and MARE remain constant at around 0.5∼0.7 and 5.6∼6.0, respectively. Based on the findings from Park and Rilett (1999) and Innamaa (2005), combining heterogeneous data seems to be effective, especially when considering the limitations of single sensor-based AVI systems.

Even though MLPs produce acceptable accuracies, one of the major problems is that they require lengthy training times. Addressing the issue, researchers propose hybrid approaches combining various techniques incorporated in the model.

2.2.4. *Incorporating Self-organizing Map to MLP (SOM/MLP)*. Chen et al. (2001) present hybrid NNs using the SOM in the initial classification stage of traffic patterns (SOM/MLP). As mentioned in Section 2.1.2, SOM clusters traffic patterns according to traffic states into a 64 by 48 size output map. The SOM/MLP performs with 9.37% of MAPE, which is improved by 1.22% compared with the MLP network with 10.59%.

2.2.5. *Incorporating Pre-transformation of Input Features to MLP (SNN)*. As an example of combining advanced clustering techniques with a conventional ANN, Park and Rilett (1998) designed modular NNs (MNN) for link travel-time predictions. However, for solving the complex processes involved in the partitioning input feature in the MNN approach, Park et al. (1999) employed a spectral basis artificial neural network (SNN) conducting pre-transformation of input features based on sinusoidal functions, which obtains linearly separable input features. Adding an expanded transformation layer between input and hidden layers is expected to reduce classification errors. For the validation purposes, link travel times collected from AVI were used, similar to the work of Part and Riletett (1999). The authors compared the proposed SNN [7] (one hidden layer with seven expanded input nodes) with the conventional ANN. The SNN on average had a result of 11.8% of MAPE with its predictions made for 5 to 25-

min future, while conventional ANN yields 14%. The authors state that the performance gap between SNN and other models increase, as the prediction horizon increases. (e.g. 1.5% gap in the 5-min case and 2.6% gap in the 25-min case).

2.2.6. *Recurrent NNs: time-delayed neural network*. Unlike feed-forward NNs, a time-delayed neural network (TDNN) captures non-linear dynamics allowing feedbacks on current inputs with previous outputs, forming a directed cycle. Yun, Namkoong, Rho, Shin, & Choi (1998) compared the TDNN with other NNs. On the Seoul–Incheon Highway, South Korea, the time delayed recurrent model yielded 4.48% of MAPE, while the conventional back-propagation network yielded 5.76% of MAPE.

Dia (2001) developed a time-lag recurrent network (TLRN) for traffic state predictions that are made 20 s to 15-min ahead of time. The TLRN performs better than other methods (MLP, recurrent networks, and Hybrid networks), showing 84∼94% of accuracy for varying prediction horizons. The authors selected speed and flow from up/downstream VDSs, producing the optimized performance of 93∼95% of accuracy.

2.2.7. *Incorporating GA into TDNN*. Some researchers use the genetic algorithm (GA) for improving the performance of TDNN (Abdulhai et al. 1999; Lingras, Sharma, & Zhong, 2002). Abdulhai et al. (1999) presented a combined method of TDNN and GA to optimize key variables (e.g. prediction horizon and the data resolution). The TDNN's results are tested and validated with simulated data generated from Paramics, due to the absence of ramp data. With an additional spatial information layer, the prediction performance is evaluated with varying data resolutions. For flow and density forecasts, average percentage errors are found to increase as the prediction horizon increases. The comparison shows better accuracies in advanced TDNN than MLPs, which may indicate the significance of the spatial information used in the TDNN for higher accuracy.

2.2.8. *Incorporating State-space Function to TDNN*. Another interesting hybrid approach is the state-space neural network (SSNN) of van Lint, Hoogendoorn, and van Zuylen (2002). This model is based on a discrete state-space model, determining the link states with previous states and inputs. An SSNN contains a similar structure with the recurrent neural network, which calculates outputs through weighted functions of inputs using neurons in hidden and output layers with incorporated transfer functions. van Lint et al. (2005) used SSNN for travel-time predictions from A13. The SSNN yielded 1.6% and 48 s of MRE and root mean square error (RMSE), when compared with estimated travel times from the PLSB (Piecewise linear speed-based trajectory). For longer study sections, SSNN predicts travel times more accurately: 0.64% of MRE (van Lint, 2006). The main differences of van Lint et al. (2005) and previous researches can be ascribed to (i) different model design parameters (e.g. number of hidden neurons (12 and 24 for van Lint et al. (2005) and van Lint (2006), respectively), and (ii) longer spatial range (8 km and 13 km). Additionally, the author compares the SSNN's performance with other models, and concludes MARE of SSNN (5.4%) is significantly more accurate than the others. To increase online applicability, van Lint (2008) proposed the delayed and censored EFK SSNN algorithms that predict travel time based on updated weights. After training with 65 peak periods

(14:00∼20:00), the two algorithms yields 117∼118 s and 112∼113 s of RMSE, respectively. Both algorithms outperform other online methods; however, the conventional SSNN (offline) slightly outperformed the two methods in accuracy. The author evaluates that the two online approaches have merits in terms of model robustness and adaptivity.

2.3. *Pattern Searching Approach*

A pattern searching approach predicts travel times by searching traffic patterns based on similarities between current and historical traffic data. This method is also known as a non-parametric regression (Davis et al., 1990; Smith, Williams, & Oswald, 2000; Smith et al., 2002), because the approach is designed to process its inherent function without considering any set of parameters and no distributional assumptions placed on in/output variables. One of the most popular pattern searching approaches, the nearest neighbourhood method, determines closeness in a given space to find a matching historic pattern with the current traffic. This approach is feasible when high-quality data and large-scale database are secured. Tables describing pattern searching approaches from previous researchers are listed in Tables 5 and 6.

Davis and Nihan (1991) suggested the k-NN to predict traffic volume and occupancy at a fixed location on I-5. Using the WSDOT data for two consecutive weekdays, the study predicts the second day's traffic of morning peak (28 min) based on the first days' information. Using non-weighted Euclidean distances, they

Table 5. Descriptive table of pattern searching approach

		Input			
Researcher	Model	Data	Equipment	Factor	Approach:
Nair et al. (2001)	Nearest Neighbour	Flow, occupancy, and speed (20 s) – Aggregated into 5 min	VDS	NA	Phase Embedding based predictor algorithm
Ohba et al. (1999)		Travel-time	TCS	Weekdays, weekends, and holiday	Pattern matching
Sun et al. (2003)		Speed (5 min)	VDS	NA	k-NN
Clark (2003)		Flow, occupancy, and speed (10 min)			Multivariate k-NN
Bajwa et al. (2005)		Speed (5 min)			k-NN-Calibrated for optimal performance using GA-
Tak et al. (2014)		Flow (15 min), Occ, Speed (5 min)	VDS	Weekday, weekends, and holiday.	Multi-level k-NN
		Travel-time (5 min)	DSRC	Weather (snow, dry, rain).	
		TCS flow (1 h)	TCS		

Table 6. Performance table of pattern searching approach

Researcher	Model	Prediction range: Prognosis horizon	Prediction range: Site (Spatial scope)	Time	Accuracy		Efficiency
Nair et al. (2001)	Nearest Neighbour	5 min	San Antonio highway (11 km, 20VDS)	Morning peak (06:00–10:00) – Collected January-June 1999	Average mean square prediction error	0.00042	NA
Ohba et al. (1999)		120 min	Kan-Etsu (56 km)	All days (00:00–24:00) – Collected 18-days-	NA		
Sun et al. (2003)		25 min (Five-step)	US-290E (2.5 km)	Morning peak (06:00–10:00)	RME	12.12%	
Clark (2003)		10 min (One-step)	M25 (3 VDS)	Tested on one week (3–9 March 1998) – Collected 10 February ~ 2 March 1998	RMSE	Flow: 4.25~83.28 veh/hr	20 s for matching one week from three weeks' data base
						Speed: 6.06~7.22 km/hr	
						Occ: 2.62~3.56unit	
					MAPE	Flow: 0.39~11.51%	
						Speed:4.68~6.31%	
						Occ: 4.85~17.82%	
Bajwa et al. (2005)		NA	Shibuya (11.94 km)	Tested on (21–23 January 2004) – Collected in 2003	RMSE	10.1%	NA
			Shinjuku (13.50 km)			12.5%	
			Ikebukuro (21.44 km)			11.3%	
			Misato (9.52 km)			9.6%	
			Wangan (24.20 km)			3.3%	
Tak et al. (2014)		4 h	Daejeon-Seoul (125 km)	Tested on – Collected 1 January ~ 31 August 2013	Error	5 min (15 min during transition)	Reported efficiency

reported the performances with RMSE: 11.3, 13.8, and 12.3 min for 1, 5, and 10 neighbours. Relatively large errors were observed in the study, and the authors comment that large data sets are needed for improving the predictability.

Smith and Demetsky (1997), introduced in Section 2.1.2, reported prediction capabilities of ARIMA, MLP, and the nearest neighbourhood method for traffic forecasting. From the study, the k-NN shows better accuracies among others for two study sites. Particularly, on Telegraph Road, the k-NN shows 167.3 veh/hr and 7.54% of average absolute error and average error, while other methods yield 182.5∼195 veh/hr and 8.93∼9.03%. By comparing the k-NN with other parametric approaches, the authors recommend the k-NN method for forecasting.

A pattern matching with travel-time data collected from a toll collection system is conducted from Kan-Etsu highway, Japan, using calendar information for classification purposes (Ohba, Ueno, & Kuwahara, 1999). The authors find acceptable results for the 2-h predictions, while larger errors are yielded during the peak hours.

Larger prediction errors are reported in the nearest neighbour method when compared with other approaches from several researches. Lower accuracies of the MLP predictions are reported in Nair, Liu, Rilett and Gupta (2001). In the study, the phase embedding-based predictor (PEBP) searches for points in a state space within the optimum radius ($\epsilon = 0.004$). The study was conducted on highways in San Antonio for 6 months. The PSEP yielded 0.00042 of the average mean square error; however, MLP shows a better accuracy of 0.00009. The local linear regression (Section 2.1.1) also outperformed the k-NN in Sun et al. (2003). The study reports the accuracy of the k-NN: 12.12% of RME in 5-step predictions (25 min) with $k = 3$, while the local linear regression yielded 11.38%. Sun et al. (2003) emphasized larger databases would be needed in k-NN implementations. Rice and van Zwet (2004) also reported larger RMSEs for k-NNs when compared with time-varying linear regression models (Section 2.1.1). Even though generally a low level of accuracy results from the nearest neighbourhood methods was presented from previous researches, the merits of this non-parametric method keep motivating researchers to investigate this method further.

2.3.1. *Incorporating Heuristics*. Smith et al. (2002) forecast traffic 15-min ahead of time, calculating a hybrid state vector using current and historical traffic conditions, considering time of day and day of week. Among several calculations, the adjustments by the current flow led to the best performance of the k-NN when $k = 20$ yielding 9.39∼10.6% of MAPE, while SARIMA showed lower accuracy (MAPE: 8.82∼8.83 in Section 2.1.2). The authors state significant improvements in terms of the performance of the k-NN, due to the heuristic methods incorporated in the approach.

2.3.2. *Incorporating Multivariate Matching*. Clark (2003) adopted a k-NN with VDS data from three locations on M25 aggregating into 10-min time slots; the author predicted the traffic state one step ahead (10 min) using the 40-min matching. From the result, the multivariate matching outperformed the univariate case except for speed predictions. The prediction error varieed according to the combinations in multivariate matching. For example, speed and flow matching gave the best performance in case of flow predictions, while multivariate of three variables (including occupancy) yielded the best results for occupancy predictions. The author explains the varying errors according to objective variables with speed/flow/occupancy relationships (e.g. Same speed in different flow conditions).

Additional study in Clark (2003) assessing the effect of day of week classification shows generally less accuracies from the Classification/k-NN than the general k-NN. The author states the exclusion of a database in the Classification/k-NN may be related to the worse results when compared with the general k-NN which has the luxury of having access to the entire database.

2.3.3. *Incorporating Optimal Parametric Constants*. Many researchers developed advanced methods, for example, using the GA to optimize parameters of a model (Bajwa, Chung, & Kuwahara, 2004). Using the proposed method, Bajwa, Chung, & Kuwahara, (2005) calibrated models for optimal parametric constants in temporal sizes of patterns, weights, searching window sizes, and number of best matched patterns. From the five sites near Tokyo, Japan, the prediction yields 3.3∼12.5% of RMSE for each site. The method outperforms the instantaneous prediction method (3.2∼18.1%). Due to the calibration process and having access to one-year's amount of a large database, the prediction results are found to be highly accurate.

2.3.4. *Multi-level Search Strategy for Increasing Efficiency*. As the search process of nearest neighbours is a burdensome computation, Tak, Kim, Jang, & Yeo (2014) suggested multi-level k-NN decreasing the search space through the global and local matching. To reduce data error, the authors combined the heterogeneous data developing a fusion algorithm which is useful in study sites where the traffic information is limited due to the consecutive invalid detectors. For a 5-lane highway (125 km), the model searched the nearest neighbours from the 8 months of historical records. Overall, this algorithm yielded an error less than 5 min; however, the error is increased during the transition period. For more accurate k-NN-based predictions, the authors also emphasize the large size of historical data.

3. Conclusions

Data-driven approaches from literatures are reviewed in this paper. Based on the underlying mechanisms and theoretical differences, the approaches are classified as: parametric statistical model (Linear regression and time series (ARIMA and Kalman filter)), non-parametric statistical models including AI (ANN) and pattern searching (k-NN). There are strengths and potential weaknesses among these approaches, and it is important and a challenge to apply the appropriate method in matching circumstances.

The parametric models tend to perform predictions in a relatively quick manner with the well-defined theoretical background on a relation between variables. However, the method is known to have site-specific problems on the coefficients and limited performance on the wide-ranging network as demerits (Ishak and Al-Deek, 2002; Kwon et al., 2000; Williams, 2001; Zhang and Rice, 2003). AI (NNs) have been used for the prediction of complicated non-linear transportation problems, by learning the underlying mechanisms from the historical pattern. Although, sufficient level of accuracies are reported in many cases (Dougherty and Cobbett, 1997; Innamaa, 2005; van Lint, 2006; van Lint et al., 2005; Park & Rilett, 1999), neural networks are considered as non-intuitive because of the concealed nature of hidden layers and associated complex training processes. Finally, the nearest neighbourhood method has been recently receiving attention due to the substantial increase in data availability. This strategy relies on the historical data, which seems practicable if a sufficiently large database is available. However, a more advanced strategy is needed for the effective use of large-scale data because the applicability of a prediction module in ITS heavily relies on the efficiency of the searching method used.

The main findings can be summarized from the perspectives of performance (prediction range and accuracy) and feasibility (efficiency, applicability, and robustness) as follows:

(1) Prediction Range and Accuracy

Many researchers believe 15-min predictions are practical, based on the definitions of a 'stable traffic' in HCMs and the typical 5-min feeding rate from VDSs. The researchers set 15-min prediction horizon as standard for evaluating model performances. The majority of data-driven studies have used 5∼25-min for prediction horizons, which is shorter than the typical horizon of model-based approaches (e.g. TOPL (Gomes, Horowitz, Kurzhanskiy, Varaiya, & Kwon, 2008), BOSS-METANET (Kotsialos, Papageorgiou, Diakaki, Pavlis, & Middelham, 2002), Visum On-line (Vortisch, 2001), SBOTTP (Liu et al., 2006), OLSIM (Chrobok et al., 2004); AIMSUN On-line (Torday, 2010)). The prognosis horizon is found to influence prediction performances in the data-driven approaches. It is shown that the accuracy tends to decrease as the horizon increases regardless of the type of model: linear regression (Sun et al., 2003), ARIMA (Ishak and Al-Deek, 2002; Park and Rilett, 1999), AI (Abdulhai et al., 1999; Dia, 2001; Ishak, Kotha, & Alecsandru, 2003; Park & Rilett, 1999). Some researchers have observed increasing errors in peak hours indicating the negative impact of congested traffic on prediction accuracies: linear regression (Rice and van Zwet, 2004), ARIMA (Davis et al., 1990; Ishak & Al-Deek, 2002; Oda, 1990), AI (Park & Rilett, 1999), and the nearest neighbours method (Ohba et al., 1999). From the perspective of a spatial scope, most literatures conduct predictions based on link and path, while others make predictions at one or more fixed locations (e.g. Clark, 2003; Dia, 2001; Smith et al., 2002). Interestingly, some researches using NNs show constant accuracies even as the spatial range increases (Innamaa, 2005; van Lint, 2006; van Lint et al., 2005).

Researchers have transformed the models into more advanced forms in efforts to adapt the methods to given research circumstances (in terms of spatial scope and database scale). A simple linear regression results in high accuracies despite its simple form and relatively large-scale networks on which the method is applied. The successful prediction results with the linear regression approach seems to be ascribed to i) appropriate length of prediction horizon, ii) spatial scope which contains high quality of data, and iii) estimation of coefficients and parameters that give the required flexibility to the models. Meanwhile, in efforts to improve ARIMA family models' accuracies, researchers have developed combined ARIMA models (e.g. KARIMA (van der Voort et al., 1996), ARIMAX (Williams, 2001), SARIMA (Williams & Hoel, 2003)), and these models have validated their performances by comparing the results with other methods. The accurate performances seem to be due to (i) established theory regarding ARIMA and (ii) appropriate transformation approaches used. For dealing with complex and

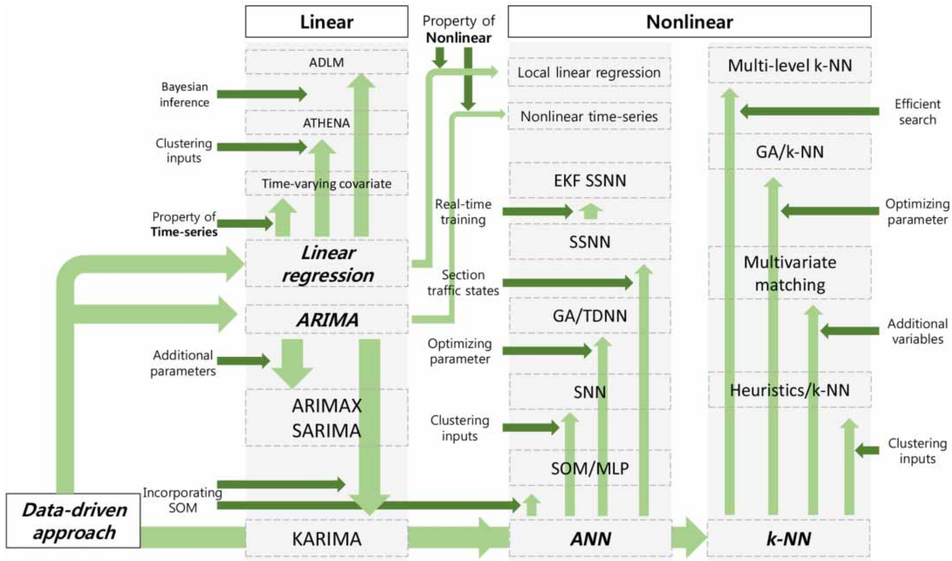

Figure 2. Endeavours of researchers on data-driven approach.

non-linear properties of prediction problems, Ishak and Al-Deek (2002) used a non-linear time series, and found that it can still produce accurate predictions even with large spatial networks. Similar to the research history of ARIMA models, researchers have developed combined methods including SOM/MLP (Chen et al., 2001) and SNN (Park et al., 1999) for feed-forward NNs, and TLRN (Dia, 2001), GA/TDNN (Abdulhai et al., 1999), and SSNN (van Lint, Hoogendoorn, & van Zuylen, 2002) for recurrent neural networks. Improvements of input/output matching processes (e.g. SOM/MLP) and optimizing parameters (e.g. GA/TDNN) have been successfully applied to ANNs, resulting in acceptably high accuracies. In addition, appropriate design parameters are found to improve the accuracies even for larger networks (van Lint, 2006). Recently, nearest neighbourhood methods have been widely used by researchers due to their potentially improved prediction performances. Larger prediction errors are observed from researches with small databases (e.g. Davis & Nihan, 1991) while more accurate predictions are reported from researches conducted with large databases (e.g. Bajwa et al., 2005) which seems intuitive. Nearest neighbourhood methods implemented in rather short time periods (maybe due to small database) still produce acceptable accuracies. However, the method can further be improved by securing large-databases as addressed in Davis and Nihan (1991) and Sun et al. (2003). The feasibility of securing the large databases are increasing as the promising 'Big-data' era is approaching. The endeavours to improve performances are illustrated in Figure 2, emphasizing the research trends of data-driven approaches.

(2) Efficiency , Applicability, and Robustness

Even though data-driven approaches can produce high accuracies with well-defined models, the efficiencies of the data-driven approaches are still critical issues for real-time applications. In addition, applications in TMS are generally carried out for large-scale networks, requiring efficient services. Data-driven approaches still generally involve time-consuming processes including (i) estimation of coefficients (in regression), (ii) decision of model parameters (in NNs) and (iii) pattern searching from databases (in nearest neighbours). Furthermore, as the TMS usually aims for real-time controls, the robustness that can deal with varying control measures is also mandatory. However, increasing applicability might still be challenging for the data-driven methods because of their high dependency on historical data. Efficient pre-processing with minimum data errors and efficient fusion of heterogeneous information sources are prerequisites for successful implementations of data-driven prediction methods.

Although the previous researches have shown the acceptable level of performances, the algorithms need to be improved. In general, a travel time prediction procedure contains two phases: Data processing and Prediction module part (e.g. Chen and Grant-Muller, 2001; Fei et al., 2011; van Lint et al., 2005), and future directions for both phases are discussed as follows.

(1) Data assimilation methodology

Conventionally, VDS data have been widely used because of the complete enumeration; however, the VDS data often contain a high proportion of deficient data. Recent developments of ICT provide promising alternatives (e.g. DSRC, Smartphone). With newly emerging sensing technologies, it seems feasible to fuse heterogeneous information for data imputation purposes. In addition, amalgamation of databases (e.g. traffic, weather, unexpected events) into an integrated database system is technologically becoming more flexible. Having access to such a seemingly luxurious database environment does not guarantee achieving a reliable travel time prediction system. It is important to note that the management of data quality and variable selection should carefully be considered throughout the maintenance of the system in order to avoid 'Data rich, information poor (DRIP)'.

(2) Sophisticated prediction algorithms

Diverse strategies can be developed to improve the conventional data-driven models. Parametric statistical models have apparent merits in terms of inferences, and are competitive in relation to other (non-parametric) non-linear methods in some researches. However, the models can be improved by replacing conventional least squares fitting methods with some alternatives (e.g. subset selection, shrinkage methods) to yield better prediction accuracy. Also, uncertainty of the predicted results also merits further study (e.g. Bayesian inference-based approach in linear regression and GARCH-based approach in ARIMA).

NN-based prediction can lead to improved results by optimizing experimental settings: (i) the optimal network (e.g. topology of layers) and (ii) updating strategy on model parameters (e.g. weights). Many successful efforts have been reported in this paper; however, the following items might be challenges to the researchers in this area: (i) dealing with invalid input data and abnormal traffic patterns (e.g. unseen bad weather) from input layer and (ii) a trade-off between accuracy and efficiency caused by the learning algorithms (e.g. Using particle filter instead of EKF).

The current k-NN type models have limitations in several aspects. To increase accuracy, researches dealing with (i) the structure of feature vector, (ii) the number of neighbours in k-NN, and (iii) the size of historical database would generate more similar posterior distributions. In addition, researches on optimal pattern search structure (e.g. sequential strategy) would contribute to increase applicability of the k-NN based prediction modules in ITS by minimizing search space. Also, a framework that responds to abnormal traffic conditions would be another direction (e.g. AQL (accident queue length) prediction module) as well.

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