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Short-term traffic forecasting: Where we are and where we're going

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A B S T R A C T

Since the early 1980s, short-term traffic forecasting has been an integral part of most Intelligent Transportation Systems (ITS) research and applications; most effort has gone into developing methodologies that can be used to model traffic characteristics and produce anticipated traffic conditions. Existing literature is voluminous, and has largely used single point data from motorways and has employed univariate mathematical models to predict traffic volumes or travel times. Recent developments in technology and the widespread use of powerful computers and mathematical models allow researchers an unprecedented opportunity to expand horizons and direct work in 10 challenging, yet relatively under researched, directions. It is these existing challenges that we review in this paper and offer suggestions for future work.

1. Introduction

Short term traffic forecasting has been a very important consideration in many areas of transportation research for more than 3 decades. This interest is the direct result of an increasing need for developing user friendly applications which can both provide accurate information to drivers and be used for signal optimization. The ability to provide such information is the result of phenomenal technological and computational advances that have enabled researchers to collect data and subsequently predict at very high temporal resolutions.

Both the technological aspects of this analysis (ITS Technology) and the analytical (data analysis), have been the focus of countless research papers over the past few years (Adeli, 2001; Vlahogianni et al. 2004; Van Lint and Van Hinsbergen, 2012). The combination of unprecedented data availability and the ability to rapidly process these data has brought on immense development and acceptance of ITS technologies. At the same time, a novel research area, based on data driven empirical algorithms, has been systematically growing in parallel to the well-founded mathematical models that are based on macroscopic and microscopic theories of traffic flow (Wang and Papageorgiou, 2005; Yuan et al., 2012; Treiber and Kesting, 2012; Fowe and Chan, 2013; Kerner et al., 2013). This significant leap from analytical to data driven modeling has been marked by an overwhelming increase of Computational Intelligence (CI) – Data Mining (DM) approaches to analyzing the data. Researchers have moved from what can be considered as a classical statistical perspective (the ARIMA Family of models), to Neural and evolutionary computational approaches (Karlaftis and Vlahogianni, 2011).

Short-term traffic forecasting based on data driven methods is one of the most dynamic and developing research arenas with enormous published literature. Interestingly, however, most of the research has concentrated on 'testing' alternative

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modeling approaches on short-term traffic data, possibly because of the data's ready availability and the relative ease of applying many of the available analytical approaches. This concentration leaves a number of important questions and challenges unaddressed or, relatively to the rest of the literature, under researched. In this paper we review existing research with an explicit focus on identifying, briefly discussing, and offering information on 10 areas where we believe that the technological and analytical challenges lie for the next generation of short term forecasting research.

2. Short term traffic forecasting: a brief overview

Since the early 1980s, short-term traffic forecasting has been an integral part of most Intelligent Transportation Systems (ITS) and related research. It concerns predictions made from few seconds to possibly few hours into the future based on current and past traffic information. Most of the interest has focused on developing methodologies that can be used to model traffic characteristics such as volume, density and speed, or travel times, and produce anticipated traffic conditions. The field of short-term traffic forecasting has a life of 35 years (Ahmed and Cook, 1979); in the first part of its development, most – if not all – of the research employed 'classical' statistical approaches to predicting traffic at a single point. Later, applications of data driven approaches were the focal point in the literature, where a rich variety of algorithmic specifications – most times creatively applied – were proposed. The weight placed recently on empirical computational intelligence-based approaches, including Neural and Bayesian Networks, Fuzzy and Evolutionary techniques, can be considered as inevitable, particularly as most classical approaches have been shown to be 'weak' or inadequate under unstable traffic conditions, complex road settings, as well as when faced with extensive datasets with both structured and unstructured data.

Existing literature has been studied in 3 papers; the first, by Vlahogianni et al. (2004) provided a critical review of the entire spectrum of the short-term traffic forecasting literature up to 2003, and underlined the complexities of several conceptual, design and methodological issues involved in developing forecasting applications. The second and third, by Adeli (2001) and van Lint and Van Hisbergen (2012), reviewed Neural Network and Artificial Intelligence (AI) applications to short-term traffic forecasting, collecting and analyzing the literature using such approaches. To avoid overlaps with already published work, in Tables 1–4 we summarize the available literature for the periods 2004–2006, 2007–2009, 2010–2011, 2012–2013 respectively, and categorize papers based on certain criteria that can give a good sense of where most research effort has concentrated over the past decade.

From the overview it becomes clear that most effort has gone into: i. using data from motorways and freeways, ii. employing univariate statistical models, iii. predicting traffic volume or travel time, and iv. using data collected from single point sources. Recent developments in technology and the widespread use of powerful computers and mathematical models allow researchers an unprecedented opportunity to expand horizons and direct work in 10 challenging directions. These are presented following a top-down approach; the first and second challenges refer to the system's characteristics (responsiveness and location of interest), that will integrate prediction models. The third challenge is dedicated to the problem of forecasting traffic and variable choice. Challenges 4 to 5 focus on data issues and the manner in which new technologies have altered the available prediction datasets. Next, Challenges 6 to 9 refer to the methodological and modeling issues that are involved with developing novel prediction algorithms. Finally, challenge 10 deals with the role of artificial intelligence models and on the manner of integrating such models into prediction schemes. These 10 challenges are reviewed and summarized in Table 5.

3. The challenges

3.1. Challenge 1. Developing responsive algorithms and prediction schemes

Transportation agencies require forecasts that are robust to short and longer term changes in traffic conditions. In cases where these changes are unexpected – accidents, and adverse weather conditions for example – traffic management systems should optimize management and advisory strategies. Responsive predictions are very important, yet difficult to construct, as the relationship between non recurrent (unexpected) events and short term traffic conditions is complex and several times unclear (even the effects of weather on short-term traffic flow remains elusive). Forecasting algorithms that can incorporate the effect of non-recurrent conditions and provide accurate predictions will enhance the decision making capabilities of traffic management systems, improve coordination between authorities, and help maintain a sustainable level of service.

Research on responsive traffic prediction schemes has focused on developing multi-regime models to account for the shifts of traffic between congested and uncongested conditions (Vlahogianni, 2009; Kamarianakis et al., 2010). These models have been also extended to incorporate the effect of accidents or adverse weather on predictions (van Lint and van Zuylen, 2005; Castro-Neto et al., 2009; Fei et al., 2011; Min and Wynter, 2011), yet with no straightforward results particularly with respect to the effects of weather. Li and Chen (2012) and Li and Rose (2011) reported that the inclusion of rainfall (5 min data) on the short-term travel time predictions may reduce forecasting inaccuracies and improve the model robustness. Innamaa (2009) reported similar prediction performance for 5 min data – based on average relative metrics – for both 'normal' and adverse weather and road conditions. Tsirigotis et al. (2012) emphasized the marginal effect of rainfall on short-term (10 min step) freeway speed predictability. Vlahogianni and Karlaftis (2012), using recurrence-based complexity measures,

Table 1
Literature for the period between 2004 and 2006.

Author(s) and Date[1]	Area	Traffic	Prediction		Data	Methodology							
		Parameter	Step (min)	Horizon (steps)	Collection	Approach	Problem[2]	Model[3]	Comparison	Inputs	State-Space	Optimization[4]	
Cetin and Comert (2006)	Motorway	Speed	1	1	Detectors	Univariate	TS	Statistical	■	Single	■		
Dion and Rakha (2006)	Motorway	Travel Time	1	2	AVI	Univariate	FA	Statistical		Single			
Innamaa (2006)	Motorway	Travel Time	1	1	Detectors	Univariate	FA	NN		Multiple	✓		
Lam et al. (2006)	Motorway	Volume	day	day	Detectors	Univariate	FA	Statistical	✓	Single			
Liu et al. (2006)	Arterial	Volume	1	1	Simulation	Univariate	FA	Statistical		Single			
Quek et al. (2006)	Motorway	Density	1	60	Detectors	Univariate	FA	NN	✓	Multiple		Fuzzy	M
Shekhar and Williams (2008)	Motorway	Volume	15	1	Detectors	Univariate	TS	Statistical	✓	Multiple			
Tsekeris and Stathopoulos (2010)	Arterial	Volume	3	1	Detectors	Univariate	TS	Statistical	✓	Single			
Turochy (2006)	Motorway	Volume	15	1	Detectors	Univariate	PR	Statistical		Single			
van Lint (2006)	Motorway	Travel Time	1	1	Detectors	Univariate	TS	NN	✓	Multiple	✓		
Wang et al. (2006a)	Motorway(U)	Travel Time	1	20	Simulation	Univariate	FA	Statistical	✓	Multiple	✓		
Xie and Zhang (2006)	Motorway(U)	Volume	5	1	Detectors	Univariate	PR	Hybrid**	✓	Multiple	✓	Wavelets	M
Zheng et al. (2006)	Motorway(U)	Volume	15	1	Detectors	Univariate	FA	Hybrid**/C	✓	Multiple		Bayesian	O
Innamaa (2005)	Motorway	Travel Time	1	1	Detectors	Univariate	FA	NN		Multiple	✓		
Jiang and Adeli (2005)	Motorway(U)	Volume	60	1	Detectors	Univariate	TS	Hybrid**		Multiple		Wavelets	M
Kamarianakis et al. (2005)	Arterial	State	7.5	1	Detectors	Univariate	TS	Statistical	✓	Single			
Kwon and Petty (2005)	Motorway(U)	Travel Time	15	1	Detectors	Univariate	FA	Statistical		Single			
Oh et al. (2005)	Motorway	Travel Time	1	1	Detectors	Univariate	TS	NN	✓	Single		Genetic	M
Shang et al. (2005)	Motorway	Speed	2	1	Detectors	Univariate	TS	Statistical		Multiple			
van Lint and van Zulen (2005)	Motorway	Travel Time	1	1	Detectors	Univariate	FA	NN		Multiple			
van Lint et al. (2005)	Motorway	Travel Time	1	1	Detectors	Univariate	TS	NN		Multiple	✓		
Vlahogianni et al. (2005)	Arterial	Volume	3	5	Detectors	Multivariate	FA	NN	✓	Multiple	✓	Genetic	I
Zhong et al. (2005)	Motorway	Volume	60	60	Detectors	Univariate	FA	NN	✓	Multiple		Genetic	I
Alecsandru and Ishak (2004)	Motorway(U)	Speed	5	4	Detectors	Univariate	FA	Hybrid**	✓	Multiple	✓	Genetic	I
Chrobok et al. (2004)	Arterial	Volume	1	60	Detectors	Univariate	PR	Statistical/C	✓	Single			
Ishak and Alecsandru (2004)	Motorway(U)	Speed	5	4	Detectors	Univariate	TS	Hybrid**	✓	Multiple	✓	Fuzzy	I
Lin et al. (2004)	Arterial	Travel Time	1	1	Simulation	Univariate	FA	Bayesian		Multiple			
Rice and van Zwet (2004)	Motorway	Speed	5	1	Detectors	Univariate	PR	Statistical		Single			
Wu et al. (2004)	Motorway	Travel Time	3	1	Detectors	Univariate	FA	Statistical	✓	Multiple			
Yang et al. (2004)	Motorway	Speed	5	10	Detectors	Univariate	TS	Statistical	✓	Single			
Zhong et al. (2004)	Motorway	Volume	60	60	Detectors	Univariate	FA	NN	✓	Multiple	■	Genetic	M

[1] U: urban.
[2] TS: time series, FA: function approximation, O: optimization, PR: pattern recognition, CL: clustering.
[3] NN: neural network, Hybrid*/**: statistical/computational intelligence model as the basis, /C: combined forecasts.
[4] Optimization of M: model parameters, I: input space, S: smoothing.

Table 2
Literature for the period between 2007 and 2009.

Author(s) and Date	Area[1]	Traffic	Prediction		Data	Methodology							
		Parameter	Step (min)	Horizon (steps)	Collection	Approach	Problem[2]	Model[3]	Comparison	Inputs	State-Space	Optimization[4]	
Castro-Neto et al. (2009)	Motorway(U)	Volume	5	1	Detectors	Univariate	FA	Statistical	✓	Single			
Chandra and Al-Deek (2009)	Motorway	Speed	5	1	Detectors	Multivariate	TS	Statistical	✓	Multiple	✓		
Ghosh et al. (2009)	Arterial	Volume	15	50	Detectors	Multivariate	TS	Statistical	✓	Multiple	✓		
Hamad et al. (2009)	Motorway	Speed	5	5	Detectors	Univariate	FA	NN		Multiple	✓	Spectral	I/S
Huang and Sadek (2009)	Arterial	Volume	5	1	Detectors	Univariate	PR	NN	✓	Single			
Innamaa (2009)	Motorway	Travel Time	5	4	Detectors	Multivariate	PR	NN		Multiple			
Jintanakul et al. (2009)	Motorway	Travel Time	5	1	Simulation	Univariate	FA	Bayesian		Single			
Karlaftis and Vlahogianni (2009)	Arterial	Volume/Occupancy	1.5	1	Detectors	Univariate	TS	Statistical	✓	Single			
Sheu et al. (2009)	Motorway	Volume	1	1	Detectors	Multivariate	TS	NN	✓	Multiple			
Srinivasan et al. (2009)	Arterial	Volume	15	1	Detectors	Univariate	FA	NN	✓	Multiple		Fuzzy	I
Szeto et al. (2009)	Arterial	Volume	15	1	Detectors	Univariate	TS	Statistical		Single			
Tan et al. (2009)	Motorway	Volume	60	3	Detectors	Univariate	FA	Hybrid*/C	✓	Multiple		NN	O
van Hinsbergen et al. (2009)	Motorway	Travel Time	5	3	Detectors	Univariate	TS	NN	✓	Multiple	✓	Bayesian	M
Vlahogianni (2009)	Arterial	Volume	1.5	1	Detectors	Univariate	TS	NN	✓	Multiple	✓	Genetic	M
Wang and Shi (2012)	Motorway	Travel Time	1	1	Detectors	Univariate	FA	Bayesian		Multiple			
Zou et al. (2009)	Motorway	Travel Time	5	1	Detectors	Univariate	FA	NN	✓	Multiple	✓		
Chandra and Al-Deek (2008)	Motorway	Speed	5	1	Detectors	Multivariate	TS	Statistical	✓	Multiple	✓		
Dimitriou et al. (2008)	Arterial	Volume	1.5	1	Detectors	Univariate	FA	Fuzzy/C	✓	Multiple	✓	Genetic	M
Guo et al. (2008)	Motorway(U)	Volume	1	1	Detectors	Univariate	TS	Statistical		Single			
Li (2008)	Motorway	Travel Time	5	1	Detectors/AVI	Univariate	FA	Bayesian		Multiple			
Stathopoulos et al. (2008)	Arterial	Volume	3	1	Detectors	Univariate	FA	Fuzzy/C	✓	Multiple			
van Lint (2008)	Motorway	Travel Time	1	1	Detectors	Univariate	TS	Hybrid**		Multiple	✓	Kalman	O
Vlahogianni (2008)	Arterial	State	1.5	1	Detectors	Multivariate	FA	NN	✓	Multiple			
Zhang and Ye (2008)	Motorway	Volume	15	1	Detectors	Univariate	FA	Hybrid**	✓	Single		Fuzzy	M
Ghosh et al. (2007)	Arterial	Volume	15	1	Detectors	Univariate	TS	Bayesian		Single			
Innamaa (2009)	Motorway	Travel Time	1	1	Detectors	Univariate	FA	NN		Multiple	✓		
Juri et al. (2007)	Motorway	Travel Time	1	1	Simulation	Univariate	TS	Statistical		Single			
Sun and Zhang (2007)	Network	Volume	15	1	Detectors	Univariate	FA	Statistical		Multiple	✓		
Vlahogianni (2007)	Arterial	State	1.5	1	Detectors	Univariate	FA	NN	✓	Multiple		Genetic	M
Vlahogianni et al. (2007)	Arterial	Volume	1.5	1	Detectors	Multivariate	TS	Hybrid**	✓	Multiple	✓	Genetic	I
Xie et al. (2007)	Motorway(U)	Volume	5	1	Detectors	Univariate	FA	Statistical	✓	Multiple	✓	Wavelets	M
Zhang and Xie (2007)	Motorway	Volume	15	1	Detectors	Univariate	FA	Statistical	✓	Single			

[1] U: urban.
[2] TS: time series, FA: function approximation, O: optimization, PR: pattern recognition, CL: clustering.
[3] NN: neural network, Hybrid*/**: statistical/computational intelligence model as the basis, /C: combined forecasts.
[4] Optimization of M: model parameters, I: input space, S: smoothing.

Table 3
Literature for the period between 2010 and 2011.

Author(s) and Date	Area[1]	Traffic Parameter	Prediction Step(min)	Prediction Horizon (Steps)	Data Collection	Methodology Approach	Problem[2]	Model[3]	Comparison	Inputs	State-Space	Optimization[4]	
Abu-Lebdeh and Singh (2011)	Arterial	Travel Time	5	1	Simulation	Multivariate	FA	Hybrid**		Multiple	✓	Bayesian	I
Bustillos and Chiu (2011)	Motorway	Travel Time	15	1	Simulation	Univariate	PR	Statistical	✓	Single			
Chang et al. (2011)	Arterial	Volume	5	1	Detectors	Univariate	TS	Statistical		Multiple			
Chen et al. (2011)	Arterial	Volume	0.1	1	Detectors	Univariate	PR	Hybrid*	✓	Single		Nature Inspired	M
Djuric et al. (2011)	Motorway	Speed	5	6	Detectors	Univariate	FA	Statistical	✓	Multiple	✓		
Fei et al. (2011)	Motorway(U)	Travel Time	1	1	Detectors	Univariate	TS	Bayesian	✓	Single			
Heilmann et al. (2011)	Motorway(U)	Speed	15	8	ETC.	Univariate	FA	Statistical		Single			
Hong (2011)	Arterial	Volume	60	1	Detectors	Univariate	TS	Hybrid**	✓	Single		Sim. Annealing	M
Hong et al. (2011a)	Arterial	Volume	60	1	Detectors	Univariate	FA	Hybrid*	✓	Single		Nature Inspired	M
Hong et al. (2011b)	Arterial	Volume	60	1	Detectors	Univariate	FA	Hybrid*	✓	Single		Genetic	M
Ishak et al. (2010)	Motorway	Speed	0.5	1	Detectors	Univariate	FA	Statistical		Single			O
Khosravi et al. (2011)	Motorway(U)	Travel Time	5	1	Detectors	Univariate	FA	Hybrid**	✓	Multiple	✓	Bayesian	M
Kuhn and Nicholson (2011)	Motorway	Volume	1	1	Detectors	Univariate	TS	Statistical	✓	Single			
Li and Rose (2011)	Motorway	Travel Time	10	6	AVI	Univariate	FA	NN		Multiple			
Min and Wynter (2011)	Motorway(U)	Volume/Speed	5	12	Detectors	Multivariate	TS	Statistical		Multiple	✓		
Myung et al. (2011)	Motorway	Travel Time	5	1	Detectors/ AVI	Univariate	PR	Statistical		Multiple	✓		
Oh and Park (2011)	Motorway	Travel Time	1	1	AVI	Univariate	TS	NN	✓	Single		Genetic / Wavelets	M/I/ S
Simroth and Zähle (2011)	Motorway	Travel Time	1	1	GPS	Univariate	FA	Statistical		Single			
Soriguera and Robusté (2011)	Motorway(U)	Travel Time	5	1	Detectors / AVI	Univariate	FA	Statistical/ C		Single			
Vlahogianni and Karlaftis (2011)	Arterial	Volume/Occupancy	1.5	1	Detectors	Univariate	TS	Statistical	✓	Single			
Wang et al. (2011)	Motorway	Speed	5	1	Detectors	Univariate	PR	Hybrid**	✓	Single		Bayesian	I
Xia et al. (2011)	Motorway	Travel Time	15	1	Detectors	Multivariate	TS	Statistical		Multiple		Kalman	O
Zhang et al. (2011a)	Motorway	Volume	5	1	Detectors	Univariate	FA	Statistical	✓	Single		Nature Inspired	M
Sun and Xu (2011)	Arterial	Volume	15	1	Detectors	Univariate	FA	Statistical	✓	Single			
Boto-Giralda et al. (2010)	Motorway	Volume	5	2	Detectors	Multivariate	PR	Hybrid**	✓	Multiple	✓	Fuzzy/wavelets	M/I/ S
Ghosh et al. (2010)	Arterial	Volume	5	1	Detectors	Univariate	TS	Hubrid**		Single		Wavelets	I/S
Guo and Williams (2010)	Motorway(U)	Speed	5	1	Detectors	Univariate	TS	Hybrid*		Single		Kalman	O
Kamarianakis et al. (2010)	Arterial	Volume/Speed/ Occupancy	1.5	1	Detectors	Univariate	TS	Statistical	✓	Single			
McCrea and Moutari (2010)	Motorway	Volume	15	1	Detectors	Univariate	FA	Hybrid**		Multiple	✓		
Stathopoulos et al. (2010)	Arterial	Volume	3	1	Detectors	Univariate	FA	Fuzzy/C	✓	Multiple			
Stathopoulos et al. (2010)	Arterial	volume	3	1	Detectors	Univariate	FA	Hybrid*/C		Single		Fuzzy	O
Thomas et al. (2008)	Arterial	Volume	5	2	Detectors	Univariate	TS	Statistical		Single			
Tsekeris and Stathopoulos (2010)	Arterial	Volume	3	1	Detectors	Multivariate	TS	Statistical	✓	Multiple			
Xie and Zhao (2010)	Motorway(U)	Volume	15	2	Detectors	Univariate	FA	Statistical	✓	Single			
Yang et al. (2010)	Motorway	Travel Time	15	1	AVI	Univariate	TS	Statistical		Single			
Zargari et al. (2010)	Motorway	Volume	5	1	Detectors	Univariate	FA	NN	✓	Single		Fuzzy/ Genetic	M/I

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[3] NN: neural network, Hybrid*/**: statistical/computational intelligence model as the basis, /C: combined forecasts.
[4] Optimization of M: model parameters, I: input space, S: smoothing.

Table 4
Literature for the period between 2012 and 2013.

Author(s) and Date	Area[1]	Traffic	Prediction		Data	Methodology							
		Parameter	Step(min)	Horizon (Steps)	Collection	Approach	Problem[2]	Model[3]	Comparison	Inputs	State-Space	Optimization[4]	
Celikoglu (2013)	Motorway(U)	Density	2	1	Detectors	Univariate	FA	Hybrid**		Multiple	✓		
Wang and Shi (2012)	Motorway(U)	Speed	5	1	Detectors	Univariate	FA	NN	✓	Single		Chaos/Wavelets	I/M
Mu et al. (2012)	Motorway	Travel Time	1	1	Simulation	Univariate	FA	Statistical		Single			
Chan et al. (2013)	Motorway(U)	Speed	1	5	Detectors	Univariate	FA	Hybrid**	✓	Multiple	✓	Nature Inspired	M
Guo et al. (2013)	Arterial	Volume	15	1	Detectors	Univariate	TS	Statistical	✓	Single		Singular Value Decomp.	S
Vlahogianni and Karlaftis (2013)	Motorway(U)	Speed	1	1	Detectors	Multivariate	TS	Hybrid**	✓	Multiple		Genetic	M
Abdi et al. (2012)	Motorway	Volume	1	1	Detectors	Univariate	TS	Hybrid**	✓	Multiple		Fuzzy/Wavelets	M/I/S
Chan et al. (2012a)	Motorway(U)	Speed	1	1	Detectors	Univariate	FA	Statistical	✓	Multiple	✓	Exponential	I/S
Chan et al. (2012b)	Motorway(U)	Speed	1	1	Detectors	Univariate	FA	NN	✓	Multiple	✓	n/a	
Chang et al. (2012a)	Motorway	Volume	15	4	Detectors	Univariate	PR	Hybrid*		Multiple		k-nearest neighbors	I
Chen et al. (2012)	Motorway(U)	Volume	3	1	Detectors	Univariate	FA	Statistical	✓	Single		Principal Comp.	I
Cheng et al. (2012)	Arterial	Volume	5	1	Detectors	Univariate	TS	Statistical		Multiple	✓		
Du et al. (2012)	Network	Travel Time	2	1	Simulation	Univariate	O	Statistical		Multiple	✓		
Dunne and Ghosh (2012)	Motorway	Volume/ Speed	1	1	Detectors	Multivariate	FA	NN	✓	Multiple			
Guo et al. (2012)	Motorway	Volume	15	1	Detectors	Univariate	TS	Statistical		Single			
Haworth and Cheng (2012)	Network	Travel Time	5	1	AVI	Univariate	FA	Statistical/ C	✓	Multiple	✓		
Hong (2012)	Arterial	Volume	60	1	Detectors	Univariate	FA	Statistical	✓	Single		Sim. Annealing	M
Kamarianakis et al. (2012)	Motorway(U)	Speed	5	5	Detectors	Univariate	TS	Statistical	✓	Multiple	✓	penalized estimation	M
Khan (2012)	Motorway	Travel Time	5	1	GPS	Univariate	FA	Bayesian		Single			
Li and Chen (2013)	Motorway	Travel Time	5	1	Detectors/ AVI	Univariate	FA	NN		Multiple			
Lu (2012)	Motorway	Travel Time	5	1	Detectors	Univariate	FA	Bayesian	✓	Single			
Ma et al. (2012)	Motorway	Travel Time	1	1	Simulation	Univariate	PR	Statistical	✓	Single			
Qiao et al. (2012)	Motorway	Travel Time	5	1	Bluetooth	Univariate	PR	Statistical	✓	Single			
Sun et al. (2012)	Network	Volume	15	1	Detectors	Multivariate	PR	NN	✓	Multiple	✓	penalized estimation	I
Tchrakian et al. (2012)	Motorway	Volume	15	5	Detectors	Univariate	TS	Statistical	✓	Multiple			
Tsirigotis et al. (2012)	Motorway(U)	Speed	10	1	Detectors	multivariate	TS	Statistical	✓	Multiple			
	Arterial	Volume	5	1	Detectors	Univariate	FA	Statistical		Single			
Xia et al. (2012)	Motorway	State	5	1	Detectors	Multivariate	CL	Statistical		Multiple			
Ye et al. (2012)	Motorway(U)	Speed	0.01	60	GPS	Univariate	FA	NN	✓	Multiple			
Zheng and Van Zuylen (2012)	Arterial	Travel Time	1	1	GPS	Univariate	FA	NN		Multiple	✓		

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[4] Optimization of M: model parameters, I: input space, S: smoothing.

showed that under rainfall, a dissimilar freeway speed temporal evolution is observed that should be incorporated into short-term traffic forecasting models.

Results reported so far indicate that both data and algorithmic specifications for responsive ITS applications are rather vague. Additionally, the development of responsive prediction schemes requires extensive datasets where multi-source data are fused, an often challenging task that can become rapidly obsolete (Khan, 2012). So far, the degree of modeling complexity and adaptability, as well as the data's spatio-temporal representations needed to support such schemes, have not been systematically assessed. Finally, a rather under researched issue in developing predicting schemes for ITS applications is to determine which technologies and methodologies are capable of adapting to information taken from forecasting models. The more complex the information on the anticipated traffic conditions, more robust structures of ITS applications – in both a conceptual and functional level – are needed.

3.2. Challenge 2. Freeway, arterial and network traffic predictions

Until recently, most short-term traffic forecasting algorithms were built to function at a freeway, arterial or corridor level. Short-term traffic forecasting at urban arterials forms a more complex problem than freeway predictions due to constraints such as signalization. Data driven (CI and DM) approaches provide a structurally flexible alternative to account for adaptive signalization's unpredictability and the complexity of traffic flow's self-organization, especially at areas where analytical approaches fail (Qiao et al., 2001). Predictions at a network level using data driven approaches remains a challenging task; the difficulty in covering a sufficient part of the road network by sensors, as well as the complex interactions in densely populated urban road networks, are among the most important obstacles faced in short-term traffic forecasting. Few short-term prediction applications have combined analytical modeling approaches such as cell transmission, with prediction models to both forecast traffic and replicate traffic dynamics (e.g. queue spillback), based on predicted traffic (Szeto et al., 2009; McCrea and Moutari, 2010). The problem of the number of sensors to be used and their placement in order to acquire the appropriate network for traffic flow monitoring and estimation has been reviewed in Gentili and Mirchandani (2012). Hu and Peeta (2009) and Ng (2012) have provided methods to determine the locations of vehicle sensors.

The ability of data driven approaches to develop spatio-temporal interrelations and predict traffic has been documented in recent literature; Chen et al. (2012) and Haworth and Cheng (2012) provide multivariate kernel regression models to predict travel time in a network. Kamarianakis et al. (2012) implemented classical time series approaches for short-term speed prediction in a network of motorways. Du et al. (2012) tested a data fusion and travel time prediction algorithm in a small scale simulated network. Finally, Sun et al. (2012) implemented more robust artificial intelligence algorithms for short-term traffic flow prediction in networks. However, research on incorporating network dynamics on short-term forecasting is still at an early stage.

3.3. Challenge 3. Short-term predictions: from volume to travel time

Over the past 10 years, travel time prediction has attracted increasing interest because of its importance as a network performance measure and its ease as a straightforward measure to inform road users on traffic conditions. Various univariate and multivariate methodologies to model average travel time have been proposed, with most using neural networks

Table 5
Existing challenges in short-term traffic forecasting and relevant literature.

Challenges	Relevant literature
1. Developing responsive algorithms and prediction schemes	van Lint and van Zuylen (2005), Castro-Neto et al. (2009), Innamaa (2009), Fei et al. (2011), Min and Wynter (2011), Li and Chen 2011, Li and Rose (2011), Kamarianakis et al. (2010), Khan (2012)
2. Freeway, arterial and network traffic predictions	Hu and Peeta (2009), Szeto et al. (2009), McCrea and Moutari (2010), Ng (2012), Chen et al. (2012), Haworth and Chen (2012), Kamarianakis et al. (2012), Du et al. (2012), Gentili and Mirchandani (2012), Sun et al. (2012)
3. Short-term predictions: from volume to travel time	van Lint (2008), Lu (2012), Fei et al. (2011), Zheng and van Zuylen (2012), Soriguera and Robusté (2011), Khan (2012)
4. Data resolution, aggregation and quality	van Lint et al. (2005); Wang et al. (2008), Qu et al. (2009), Ou et al. (2011), Chen et al. (2012), Haworth and Chen (2012), Dunne and Ghosh (2012), Tan et al. (2013)
5. using new technologies for collecting and fusing data	Oh et al. (2005), Jintanakul et al. (2009), Herrera et al. (2010), Van Lint and Hoogendoorn (2010), El Faouzi et al. (2011), Bhaskar et al. (2011), Dion et al. (2011a,b), Ma et al. (2012), Fries et al. (2012)
6. Temporal characteristics and spatial dependencies	Turochy (2006), Chandra and Al Deek (2009), Zou et al. (2009), Kamarianakis et al. (2010), Oh and Park (2011), Wang et al. (2011), Cheng et al. (2012)
7. Model selection and testing	Chandra and Al-Deek (2008, 2009), Chen et al. (2012)
8. Compare models or combine forecasts?	Chrobok et al. (2004), Zheng et al. (2006), Sun and Zhang (2007), Stathopoulos et al. (2008), Tan et al. (2009), Djuric et al. (2011)
9. Explanatory power, associations and causality	Zhang et al. (2011a,b), Karlaftis and Vlahogianni (2011), Chan et al. (2012a,b), Yang et al. (2010), Vlahogianni and Karlaftis (2013)
10. Realizing the full potential of artificial intelligence	Sadek (2007), Adeli (2001), Miles and Walker (2006), Chowdhury and Sadek (2012)

(Innamaa, 2009; Oh and Park, 2011; Li and Chen, 2013), Bayesian models (Fei et al., 2011; Khan, 2012; Lu, 2012), or hybrid approaches (van Lint, 2008; Abu-Lebdeha and Singh, 2011). Travel time predictions are usually associated with longer forecasting horizons (Wang et al., 2006a,b; Innamaa, 2005; van Hinsbergen et al., 2009; Li and Rose, 2011), while interactions between factors such as rainfall, heavy vehicles, speeds, type of day and travel time predictability have attracted some attention (Li and Chen 2013, Qiao et al., 2012).

The importance of predicting travel time variability as a mean for offering reliable traveler information has been systematically supported over the past decade (Kikuchi et al., 2005; Li and Rose, 2011). van Lint and van Zuylen (2005) proposed metrics for quantifying long term travel time (un)reliability based on observed variability. Bayesian methodologies have also been found to be appropriate – at least at a conceptual level – for quantifying travel time variability (Jintanakul et al., 2009; Khan, 2012; Fei et al., 2011; Lu, 2012).

The extensive literature dedicated to short-term travel time prediction has been possible because of the increasing use of new technologies in traffic data collection such as data Automatic Vehicle Identification systems (Dion and Rakha, 2006; Yang et al., 2010; Li and Rose, 2011; Haworth and Cheng, 2012), Electronic Toll Collection (ETC.) systems linked to detectors (Myung et al., 2011; Soriguera and Robusté, 2011), and Global Positioning Systems (GPS) (Simroth and Zähle, 2011; Khan, 2012; Ye et al., 2012; Zheng and Van Zuylen, 2012). Almost all of the above studies, with Haworth and Cheng (2012) as the sole exception, have used motorway data. Emerging probe vehicle data collection technologies have led to interesting applications in short-term travel time prediction, particularly when incorporating modules for fusing multi-source data for predicting travel time (Soriguera and Robusté, 2011). van Lint (2008) described the manner in which travel time prediction algorithms can be extended to network level information provision using multi-source data. However, there are still several issues that need to be addressed; for example, if and how these data may be associated to a macroscopic view of traffic conditions that is essential for most traffic management strategies. Further, the requirement for extended publicly available datasets has been recently discussed (Zheng and van Zuylen, 2012), as has been the need for larger data coverage (Lu, 2012; Fei et al., 2011), and the difficulties in fusing data from different sources in travel time prediction (Khan, 2012).

3.4. Challenge 4. Data resolution, aggregation and quality

The selection of the suitable forecasting interval (step) is critical and relates to the type of ITS application to which the algorithms are to be integrated. Data collection technologies provide the opportunity for acquiring traffic data at a variety of resolutions to match the needs for both traffic management and control applications. The higher the data resolution (e.g. 30 s data), the larger the portion of noise of the time series of the traffic variables and, consequently, the more tedious the traffic forecasting model development becomes (Qiao et al., 2003, 2004, Liu et al., 2011). Several approaches have been utilized for reducing noise from time series before proceeding with predictions; these range from simple smoothing, to wavelets and fuzzy algorithms (Jiang and Adeli, 2004; Boto-Giralda et al., 2010).

When dealing with data at high resolutions, a critical consideration is aggregation. Qiao et al. (2003) and Qiao et al. (2004) discussed the effect of aggregation on ITS data, while Abdulhai et al. (2002), Oh et al. (2005), Chen et al. (2012) and Dunne and Ghosh (2012) demonstrated the effect of data aggregation level on forecasting model performance. Aggregation has been found to have direct implications on the temporal structure of a time series because it eliminates variation in the data and

Table 6
Directions for further research in relation to the 10 challenges.

Challenges	Further research directions
1. Developing responsive algorithms and prediction schemes	Weather and incident responsive algorithms, enhancing the efficiency of online computations using artificial intelligence, standardizing the requirements with regard to the spatial and temporal data coverage
2. Freeway, arterial and network traffic predictions	Focus on network level predictions, Synergy with traffic flow theory and models
3. Short-term predictions: from volume to travel time	Producing existing or novel measures of traffic performance using data from multiple sources or using novel technologies for collecting and fusing data
4. Data resolution, aggregation and quality	Determining the optimal degree of aggregation in relation to the short-term forecasting application, Quality of probe data
5. Using new technologies for collecting and fusing data	Testing the efficiency of new technologies for collecting traffic data, Reliability under all types of traffic flow (constrained, unconstrained), market penetration, standardization, cost, privacy issues, Effectiveness of fusing strategies
6. Temporal characteristics and spatial dependencies	Focus on network level spatio-temporal approaches, fusing modeling and data-driven algorithms
7. Model selection and testing	Establishing synergies with statistics for estimating model specification and fit.
8. Compare models or combine forecasts?	Introducing combinations of forecasts for multiple steps ahead predictions, testing the reliability of combinations of forecasts over single model predictions
9. Explanatory power, associations and causality	Synergy with statistics and computationally intelligent algorithms to enhance the transparency of data-driven approaches
10. Realizing the full potential of artificial intelligence	Introducing intelligence to data collection and storage, traffic analysis, optimization modeling and decision making

alters most properties, including non-stationarity and nonlinearity, that exist at the disaggregated level (Vlahogianni and Karlaftis, 2011). However, there is no solid approach to select the appropriate aggregation level for ITS applications. Aggregation remains an indispensable step in most ITS systems and cannot be disregarded; but, since the consistency of statistical characteristics is a desirable property, further research is needed to determine the optimal aggregation level with respect to different modeling applications.

Data quality in short-term traffic forecasting mainly discusses the completeness of the available datasets. Haworth and Cheng (2012) underlined the uncertainty induced to short-term traffic forecasting attempts from missing data. Missing data need careful consideration in order to select the appropriate imputation strategy – online or offline – for efficiently dealing with them (Chen et al., 2012; Tan et al., 2013). Wang and Zou (2008) reviewed both single and multiple imputation strategies for real-time applications and assessed their effect on travel time prediction. However, the literature does not provide a clear cut result on the effectiveness of these strategies in terms of different algorithmic complexity levels (van Lint et al., 2005, Qu et al., 2009, Chen et al., 2012).

A novel problem faced in short-term traffic forecasting is the manner by which to assess the quality of probe vehicle datasets particularly at urban arterials where constraints such as signalization form a complex data collection setting. A recent report proposed vehicle probe sample size and standard deviation as well as the ratio of whether travel time or speed is produced from fusing data as quality indicators (MAG, 2011). Ou et al. (2011) emphasized that, when it comes to probe vehicle data, the higher the percentage of probe vehicles the greater the accuracy and reliability of fusing algorithms.

3.5. Challenge 5. Using new technologies for collecting and fusing data

Short-term traffic forecasting algorithms are usually data intensive approaches and, consequently, are directly dependent on the availability of systems and technologies for data collection. Several studies have systematically reviewed data collecting methodologies, particularly as it pertains to collecting section based data such as travel time (Zhang et al., 2011a,b). Departing for the classical loop detector data collection that is well-documented and researched, there are currently a variety of sources to collect traffic data such as video based technologies (Buch et al., 2011). Recently, wireless communication infrastructures and navigation technologies have revolutionized the manner by which we conceive data collection and data coverage. These technologies: (i) collect vehicle positions, (ii) infer relevant information concerning vehicular kinematic characteristics and congestion, and (iii) provide congestion information to drivers (Marfia et al., 2012). We note that research integrating new data collection technologies is still growing and the entire spectrum of new technologies has not yet been evaluated; as an example we note the mobility pattern information obtained from social media.

Among the challenges in dealing with multiple data sources is how to fuse them to construct ITS oriented datasets. As Van Lint and Hoogendoorn (2010) underlined, data to be fused encompass two dimensions: i. spatiotemporal semantics (data point or section measurements), and ii. aggregation level (single event or aggregated over a given period of time); these dimension impose certain complexities to the problem of data fusing from multiple sensors. El Faouzi et al. (2011) provided a review of data fusion approaches applied to traffic monitoring and forecasting.

Although there are no obvious barriers in making new technologies part of the data collection process, there are still several uncertainties that need to be carefully addressed due to the lack of maturity both from the technological and modeling aspects. A typical example is how to account for the bias induced by market penetration of such technologies. Oh et al. (2005) and Jintanakul et al. (2009) reported the difficulty in using probe vehicle technologies because of low market penetration. Herrera et al. (2010) suggested that a 2–3% penetration of cell phones in the driver population is enough to provide accurate traffic measurements. Ma et al. (2012) tested different penetration rates of vehicle infrastructure integration technologies for evaluating the effectiveness of travel-time predictions. Recently, Bhaskar et al. (2011) provided a methodology based on fused data from loop detectors and some probe vehicles for estimating travel time.

Critical consideration should be given to the effectiveness of such technologies with respect to different road settings. The question that arises is whether these technologies are directly applicable as well as equally efficient and reliable for all types of flow (constrained and unconstrained), and road network settings (freeways, motorways and urban networks). Dion et al. (2011a) emphasized the need to assess new technologies in a framework of actual systems that encompass multiple ITS applications. Later, Dion et al. (2011b) provided a virtual testbed to assess probe vehicle data generation by IntelliDrive vehicles, within a microscopic traffic-simulation environment. Issues such as cost and privacy, risks induced by multiple stakeholder involvement in data collection, lack of standardization, interactions with data fusion techniques and so on, must be addressed (Fries et al., 2012).

3.6. Challenge 6. Temporal characteristics and spatial dependencies

Identifying spatial and temporal flow patterns has been an important consideration in short-term traffic forecasting research. Several papers have supported the improvement of predictions due to the incorporation of upstream or downstream traffic information (Chandra and Al-Deek, 2009; Kamarianakis et al., 2010). Research attempts have also distinguished between freeways and urban arterials due to the constraints imposed by signalization and other control measures that alleviate traditional perception of periodicity (monthly, weekly, daily or even hourly periodicities) in traffic operations (Stathopoulos and Karlaftis, 2003; Vlahogianni et al., 2005, 2007). Nevertheless, even in the simpler case of freeway operations, accurately capturing spatial traffic features is still an open issue, as no generalized approach has been introduced. At a network level, limited effort has been put forth for incorporating traffic's spatiotemporal evolution in the prediction process (Cheng et al., 2012).

Spatiotemporal characteristics are usually introduced into the modeling phase through spatial and temporal correlations (Stathopoulos and Karlaftis, 2003). Several other approaches have been also implemented; Turochy (2006) incorporated a normalcy indicator to detect deviation from usual traffic patterns. A similar approach using k-nearest neighbors was followed by Zou et al. (2009), and Wang et al. (2011), to detect travel time pattern similarity. Vlahogianni et al. (2006, 2008) based the similarity on an analysis of the dynamics of traffic and the changing statistical characteristics of the traffic time series. Oh and Park (2011) introduced several entropy based measures to characterize travel time patterns and enhance predictions.

The accurate spatio-temporal representation in the framework of prediction schemes is of ultimate importance in fully integrating ITS applications. This may be done using either well established models that replicate traffic flow dynamics, or by attempting to integrate spatio-temporal information into the short-term prediction algorithms. Each approach has its own advantages and shortcomings; these should be considered when modeling short-term traffic flow. Nevertheless, the ability to fuse traffic flow models and data-driven short-term forecasting approaches may enable a much improved representation of the predictive information, and may enhance the decision making process particularly in cases of boundary traffic flow conditions.

3.7. Challenge 7. Model selection and testing

Short-term traffic forecasting is considered as an excellent field for developing and testing complex prediction algorithms because of the abundance of available data at very high time resolutions. Traffic forecasting has been viewed from different angles: as a time-series problem (Cheng et al., 2012), a regression and function approximation problem (Dunne and Ghosh, 2012), a clustering (Xia et al., 2012), or pattern recognition problem (Sun et al., 2012), or even combination of the above (Vlahogianni, 2009). The use of Bayesian inference as an alternative to classical statistical inference is one of the methodological advancements of the past 10 years (Ghosh et al., 2007), as is the implementation of multivariate (vector) time series models (Chandra and Al-Deek, 2008, 2009; Ma et al., 2012; Tsirigotis et al., 2012), using both classical statistical models and neural networks (Vlahogianni and Karlaftis, 2013).

Interest has concentrated on hybrid structures of Neural Networks (NNs) in short-term traffic flow prediction problems; these structures frequently outperform simple autoregressive models particularly for modeling multi-dimensional datasets and constructing models with various exogenous parameters (Van der Voort et al., 1996; Chen et al., 2001; Vlahogianni et al., 2007). Hybrid structures whose basic model is either a statistical (Chang et al., 2012a,b) or a computational intelligent model (Abdi et al., 2012), have been proposed. To optimize hybrid prediction structures, a vast range of optimization techniques have been implemented; these include Probabilistic Principal Component Analysis (PPCA) (Chen et al., 2012), adaptive absolute shrinkage and selection operator (LASSO) (Kamarianakis et al., 2012), fuzzy logic (Abdi et al., 2012), wavelets (Jiang and Adeli, 2005), genetic algorithms (Hong et al., 2011b), simulated annealing (Hong, 2012), Bayesian (Wang et al., 2011) and nature inspired algorithms (Hong et al., 2011a,b; Chen et al., 2011).

In this framework, two important modeling challenges must be considered. The first refers to model selection; the general approach followed in short-term traffic forecasting is to select the model that provides the most accurate predictions based on a collected dataset and regardless of the traffic's underlying statistical characteristics (e.g. non-stationarity, volatility, nonlinearity and so on), or whether certain modeling assumptions are violated or unrealistic (Chandra and Al-Deek, 2008, 2009). The selection of the proper modeling approach should be largely determined by the non-stationary and nonlinear features of the spatiotemporal evolution of traffic (Vlahogianni et al., 2006). Several classical or more advanced tests of non-stationarity and nonlinearity have been applied to traffic flow (Karlaftis and Vlahogianni, 2009 and Vlahogianni and Karlaftis, 2011, 2013). Recent evidence in disciplines such as econometrics and finance, has demonstrated the need to jointly consider non-stationarity and non-linearity in producing consistent short-term forecasting models.

The second challenge has to do with the selected model's performance. Most researchers place larger emphasis on discussing the findings and neglect the need to account for the quality of their model (in terms of the properties of the error), using even the most popular statistical diagnostics. This is of outmost importance in classical statistical modeling as a model of adequate structure should have white noise residuals (Washington et al., 2010). This implies that any "strong" properties in the error term – including serial correlation, volatility and so on – may indicate specification bias that can be attributed to omitted variables or misspecification of the functional form (inadequate complexity of the structure). In transportation time series applications, most artificial intelligence approaches (e.g. Neural Networks) rarely incorporate any testing of the properties of the error and the model specification. An exception is the work of Chen et al. (2012) that tested the properties of the errors of the autoregressive models developed for traffic flow forecasting. Vlahogianni and Karlaftis (2013) applied popular goodness-of-fit tests for serial dependence, normality, homoscedasticity and non-linearity on neural network time series models.

In general, a researcher's judgment of the accuracy or the error properties of a developed model is a difficult task; do we want smaller errors or more random-looking errors? Do we want both of those occurring at a fair degree? It is generally possible for a model to demonstrate good fit to the data but not necessarily as high prediction accuracy. This may be the effect of a variety of issues such as non-accounted patterns in data estimation or overtraining in NN. It is also common to have models that may predict accurately, but fail in some or all error specification tests (serial independence, neglected nonlinearity, and so on). This evidently shows that the errors produced are not random but have a systematic pattern that will make future predictions unreliable; such a model should be improved by possibly introducing a term to treat the variance along with the mean of the time series models (Karlaftis and Vlahogianni, 2011). In either case, the modeler should not disregard the importance of goodness-of-fit tests and should be able to apply them regardless of the modeling approach followed.

3.8. Challenge 8. Compare models or combine forecasts?

Comparing both modeling specifications and results are imperative to support the usefulness of a proposed forecasting scheme. Karlaftis and Vlahogianni (2011) discussed the usefulness and efficiency of current comparative studies in short-term traffic forecasting and suggested that most comparisons conducted are not always fair, particularly when comparing complex nonlinear to simple linear models. Further, there is a thin line between model accuracy, simplicity and suitability (Occam's razor). Kirby et al. (1997) suggested that accuracy is of great importance but should not be the only determinant in selecting the appropriate methodology when predicting. Other issues should be considered including time and effort required for model development, skills and expertise required, transferability of results, adaptability to changing temporal behavior and so on (Kirby et al., 1997; Smith and Demetsky, 1997; Vlahogianni et al., 2004).

Although selecting the "best" model among a set of baseline models through testing and comparisons is of outmost importance, a practical alternative is to provide a model or algorithm or heuristic approach to combine predictions. Combining should be useful in cases where the modeler may not result in a single well-specified model, a common case in complex data forecasting. This approach has been followed in a number of research efforts in traffic forecasting; Vlahogianni et al. (2006) provided a statistical and traffic criterion for dynamically shifting between models but did not provide combined forecasts. Zheng et al. (2006) combined forecasts from two neural networks using the Bayesian rule. Sun and Zhang (2007) combined predictions from different prediction models, while Stathopoulos et al. (2008) used fuzzy logic to combine forecasts. Tan et al. (2009) combined forecasts from three models using neural networks. Djuric et al. (2011) provided a probabilistic model for combining forecasts from a set of baseline prediction models. The positive effects of combining forecasts have been discussed in several papers; Chrobok et al. (2004) found improved prediction performance particularly for special events, Zheng et al. (2006) emphasized the increased system adaptability when combining forecasting approaches, and Djuric et al. (2011) discussed improvements in cases of sensor failures, a common problem in traffic monitoring systems.

Nevertheless, there are still issues that must be tackled; for example, in which cases should combined forecasts be used? Some researchers that it should be done in cases of multiple step ahead traffic predictions with increased uncertainty. Others may support the opposite, suggesting it is better to use in cases of very short-term predictions where we want to control and reduce the errors. Further, what baseline methods are more appropriate in combining forecasts? This is mainly related to the statistical characteristics of the data, the possible shifts and transitional behavior, as well as the complexities of the problem setting at hand. Moreover, which approach is most efficient for combining forecasts? Interdisciplinary literature has shown that averaging between different baseline predictions may form a simple and viable alternative (Clemen, 1989). However, it should be carefully used as it may fail in cases where one of the baseline prediction methods significantly outperforms the others. Finally, to what extent is the error reduced when combining forecasts? It is on the modeler to decide whether combining forecasts is worth the effort and whether it does not provide significant prediction improvements.

3.9. Challenge 9. Explanatory power, associations and causality

Until recently, it was adequate to provide forecasting algorithms with increased average accuracy (Zhang et al., 2011a,b; Chan et al., 2012a,b; Yang et al., 2004). However, as the need for a responsive traffic prediction scheme has emerged, there is demand for algorithms that can accurately predict as well as explain certain phenomena; the explanatory power of the models is imperative to make them adaptable and responsive to dynamic traffic and road environment changes. A typical example are weather responsive ITS applications. In such systems, weather is considered as an exogenous variable and the onset of adverse weather conditions as the emergence of a non-recurrent incident that critically disrupt typical traffic patterns. The ability to introduce exogenous information that explains – to some degree – traffic flow variability is imperative, but not a focal point of previous research. Approaches that claim to be the most accurate (in terms of prediction error), are based on advanced computational intelligence techniques which completely disregard the importance of developing synergies with classical statistics that will help increase model explanatory power (Karlaftis and Vlahogianni, 2011). Many statistical constructs and tests can be very effective in assessing input–output characteristic relationships and investigating causalities that are extremely useful in research (Vlahogianni and Karlaftis, 2013).

3.10. Challenge 10. Realizing the full potential of artificial intelligence

Artificial Intelligence (AI) is the key technology in many of today's transportation applications (Miles and Walker, 2006). The advantage of AI applications over other alternatives lies in their interdisciplinary nature and ability to straightforwardly combine forecasts, ease of modeling and computing, and relative associated autonomy (Karlaftis and Vlahogianni, 2011). However, the development of efficient AI transportation systems is complex; the challenge lies in creating mechanical intelligence and, at the same time, understanding the information basis of its human counterpart (Waltz, 1997).

There has been increased interest among both researchers and practitioners for exploring the feasibility of applying artificial intelligence (AI) paradigms in improving the efficiency, safety, and environmental-compatibility of transportation systems (Sadek, 2007). AI techniques have been used in various aspects of short-term traffic forecasting such as prediction algorithms, model fusing, and optimization techniques for analytical models. Until now, AI applications have been limited to specific modules of ITS applications, especially for data analysis and prediction. Such applications have not been developed as standalone systems that can cover the full range of processes involved in prediction schemes, including data collection and storage, analysis, prediction, decision making; this may limit their efficiency. Chowdhury and Sadek (2012) discuss the skepticism among transportation practitioners regarding the ability of AI to help solve some of the problems they face.

In the new conditions that are formed by the integration of novel technologies for gathering traffic data, there is a need for new modeling paradigms that are robust to data imperfections, are hypotheses free and are flexible to cope with the need for providing accurate and on time predictions. In this framework, AI is a strong candidate that may provide novel and easily deployable data mining tools.

4. Conclusions

In this paper we revisited much of the literature on short-term traffic forecasting and its advancements over the last decade. The literature was analyzed based on a set of ten challenges stemming from the changing needs of ITS applications. Findings support the shift of research interest towards: i. responsive forecasting schemes for non-recurrent conditions, ii. developing prediction systems with increased algorithmic complexity, iii. attempting to understand data coming from novel technologies and fuse multi-source traffic data to improve predictions, and iv. the applicability of AI methodologies to the short-term traffic prediction problem. The analysis of the literature with relation to the 10 challenging issues has shown that, although much work has been conducted in short-term traffic forecasting, there are still important research directions that will attract the interest of researcher in the following years (Table 6).

The literature on short-term traffic forecasting has covered and used an impressive amount of models and data specifications. Nevertheless, researchers seem to be unprepared to answer two important questions: are we confident that our models are better, in terms of accuracy, than models developed 30 years ago? And, what have we learnt about prediction that has significantly changed our perception for traffic operations and management? The above imply that both research and practice in short-term traffic forecasting are now entering a maturity phase, where models and methods must be critically assessed to produce solid knowledge on the concepts and processes involved with short-term traffic forecasting.

Towards this direction, decisive steps into the future are necessary to confirm the usefulness and merits of recent findings. The first step is towards enhancing the performance and explanatory power of the prediction models through *synergies* with classical statistics. Statistics and artificial intelligence should act complementarily to improve i. core model development and goodness of fit, ii. analysis of large data sets and iii. causality investigation. Regarding methodological issues, researchers should exchange knowledge between classical statistics and advanced artificial intelligence approaches to assure model performance and explanatory power. Researchers should also respond to modeling advances for efficiently treating complexities stemming for large datasets. Synergies may also be extended to the use of nature inspired algorithms and meta-heuristics. Several methodological aspects of short-term traffic forecasting – particularly concerning computational intelligent methods – involve tedious optimization requirements; in such cases, nature inspired optimization techniques (simulated annealing, genetic algorithms ant colony optimization and others) may assist to overcome drawbacks of traditional optimization (Teodorović, 2008).

The second step is to develop and use testbeds and test data for testing and comparing algorithms. As new sensors, electronics, communications, and information processing technologies continue to advance at phenomenal rates, the field of transportation management and operations increasingly looks to new technologies to solve problems such as congestion. This leads to an increasing rate of developed forecasting algorithms that need to be tested and evaluated with respect to older approaches on a common data set. Interestingly, although there are large traffic data sets publicly available that may serve as testbeds (a typical example may be the Mobile Century Data) (Herrera et al., 2010), these have not attracted significant interest from the traffic forecasting research community. Test beds of varying size and complexity are a critical tool for evaluating ongoing research and may serve as a proof-of-concept tool.

Finally, the third step refers to advanced computing and Internet of Things (IoT). Most short-term traffic forecasting applications have a rather reactive role. Placing weight on integrating the technological advances for storing and computing may enable a more efficient and proactive role for short-term traffic prediction systems. Concepts such as cloud (computation, software, data access, and storage services) that do not require end-user knowledge of the physical location and configuration of the system that delivers the services, and parallel computing (clusters of computers), can enable the implementation of complex network level short-term traffic forecasting algorithms. Moreover, as most vehicles are now equipped with high end technologies and modules, and many road users may send information through mobile phones (Wi-Fi, Bluetooth, GPS), the field of traffic predictions is changing. In this framework, communication protocols that will enable vehicles to continuously gather and transfer information on the road environment as well as their unique kinematic characteristics may revolutionize the way we think about short-term traffic forecasting. Further, integrating information sourcing from social networks and peoples' voluntary contribution to transportation systems (e.g. tweets on extreme conditions occurrence) may significantly improve the adaptability of short-term traffic forecasting algorithms.

In the future, where every moving subject (both humans and machines) may have a unique identity and operate in smart social and environmental settings, the future of short-term traffic forecasting seems intuitively challenging. In this framework researchers are deemed to excel not only in the traffic engineering arena, but also in the interdisciplinary field of data analyses for the realization and evaluation of advanced ideas. Short-term traffic forecasting may enjoy a prolific future in the ITS field only if researchers can cautiously adopt a unified perspective of modeling, computing, testing and explaining traffic phenomena.

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