Short Term Traffic Prediction Models

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Short Term Traffic Prediction Models

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ABSTRACT

Short-term prediction of traffic conditions is one of the central topics in contemporary ITS research and practice. However, it is hard to select the most appropriate traffic prediction method for one particular application. In this paper we aim to provide taxonomy of all different approaches reported in literature as a practical reference for ITS professionals and researchers. It is concluded that apart from traffic simulation models only few methods are used for network wide predictions, while this is necessary for most practical applications (e.g. in-car navigation). Second, there appears to be no single best method. It is suggested that instead of developing more methods future research should focus on *combining* models into one network wide application.

KEYWORDS

Travel Time Forecast, Traveler Information Services

INTRODUCTION

It is widely acknowledged that traffic information has the potential of increasing the reliability in road networks and in alleviating congestion and its negative environmental and societal side effects. However, for these beneficial collective effects to occur, *reliable* and *accurate* traffic information is a prerequisite [1, 2]. This implies that the capacity to provide accurate short-term *predictions* of traffic conditions (e.g. travel time) to travelers must be viewed as a critical requirement for advanced traffic information systems (ATIS). Since road traffic is the “visible” result of the complex interplay between traffic demand (the amount of travelers making a trip at a particular place and time) and traffic supply characteristics (e.g. capacity or maximum speed at a particular place and time), predicting travel time for ATIS is a complex nonlinear task, which has been the subject of many research efforts in the past few decades.

In the international literature a vast amount of studies have been focusing on short term traffic prediction, where short-term usually reflects a prediction horizon of up to one or two hours. Given the complexity of the traffic prediction problem and the amount of research that has been published on the subject it is a far from trivial task to select the most appropriate traffic prediction method for one particular application. In this paper we aim to provide taxonomy of the many different approaches reported in literature to tackle the traffic prediction problem, providing a practical reference for ITS professionals and researchers involved in travel time prediction.

The paper is divided into the following parts. First, an extensive and structured description of the state of the art in traffic prediction is presented, which is followed by an overview table. After this overview, there is a discussion, followed by a conclusion.

STATE OF THE ART IN TRAFFIC PREDICTION

This is not the first study that investigates different methods to predict traffic, see for example [3-11]. However, none of these studies cover all prediction methods that can be found in literature. This study aims to include all models that have been developed to predict traffic.

The studies have been scrutinized to compare the following: (1) the *prediction method*, (2) the *prediction horizon*, (3) the *scale of prediction* (a fixed location, a route or a whole network), (4) the *environment* (urban or freeway), (5) the *computational effort* and (6) the *accuracy of the predictions*.

In the studies different variables are predicted, the most important being (1) *flow* (vehicles/hour), also known as *intensity*, (2) *density*, (vehicles/km), or *occupancy* (percent of time a detector is occupied by vehicles), (3) *travel time* (min) on a link or on an entire route and (4) *mean speed* (km/h) of all vehicles that have passed during a certain time interval. Usually, the accuracy of a prediction is measured by a statistic, RMSE (Root Mean Square Error) and MAPE (Mean Absolute Percentage Error) the most widely used. RMSE expresses the expected value of the error and has the same unit as the data which makes the size of a “typical” error visible. MAPE has the advantage of expressing the error in percentages, which makes it more understandable for interpretation.

Below, all the models that have been found in literature are described. They are subdivided into three main categories: naïve methods, parametric models and non-parametric models, and further subdivided after that. See Figure 1 for a visual taxonomy that is used in this study.

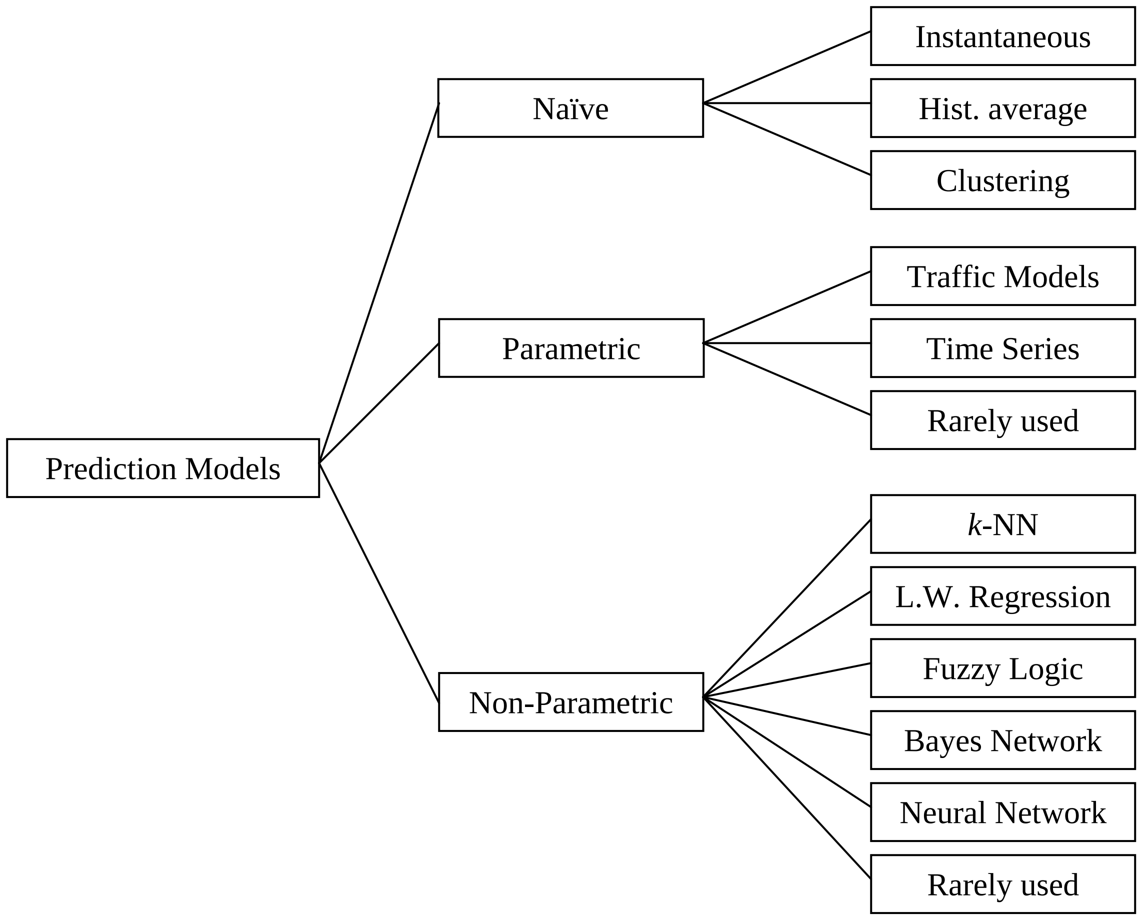

Figure 1 Taxonomy of prediction models

NAIVE METHODS

The term ‘naïve’ is rather subjective, but can be interpreted as ‘without any model assumption’. Naïve methods are widely applied in practice because of their low computational effort and easy implementation. The accuracy however is usually very low. Generally any parametric or non-parametric method was found to have a higher accuracy than these methods.

Instantaneous
When Instantaneous Travel Times (ITTs) are used as ‘predictor’, it is assumed that traffic will remain constant indefinitely. Although this method is very fast, as no calculation at all is required, its predictive performance is very bad because traffic is far from constant [7, 12-19].

Historical averages
Averaging past traffic data will produce the historical average of a certain traffic variable [7, 16-20]. Compared to more advanced techniques the historical average never comes out best, although sometimes it can outperform some prediction techniques on longer horizons. Sometimes, the historical averages are divided into time bins [21] to improve performance.

Combinations of instantaneous and historical average *[22-24]* all combine the last known measurement and the historical average in some way. These methods do not have high prediction accuracy.

Clustering
Clustering methods average traffic variables within a specific group of days based on similar traffic patterns. Applied algorithms are for example the Small Large Ratio and Ward's Clustering [25-27]. Sometimes, clustering is used for preprocessing input data [28]. These clustering techniques are shown to outperform historical average and in one occasion a linear regression, but are crude and therefore not often used.

PARAMETRIC MODELS

The term 'parametric' indicates that only the parameters of the model need to be found using data; the *structure* of the model is predetermined. Knowledge on the traffic processes can be implemented in these structures, especially in *traffic simulation models*, which can aid in understanding traffic processes. Also, 'unseen' cases such as incidents can be modeled. This is very useful for DTM purposes. Another advantage of these methods is that usually less data is needed compared to non-parametric models. Some parametric models have shown good performance, in accuracy as well as computational effort.

Traffic Simulation Models
The fundamentals of these models are laid as early as 1956 by Beckmann, McGuire and Winsten [29, 30]. Traffic is assigned from an Origin-Destiation (OD) matrix using the concept of Network Equilibrium ("Wardrop's First Principle"). The problem of predicting traffic using a traffic model usually comes down to predicting OD-matrices. This is a topic on its own that is not included in this research. For reference, see for example [31, 32]. Unfortunately, the predictions made by traffic models are never compared to any other model making their predictive quality hard to value.

Macroscopic In macroscopic simulation models, only global variables of a road network are considered, such as the densities, mean speeds and flows [33]. There are two types of assigning traffic to the network: (1) static assignment and (2) dynamic assignment. In a *static model*, variations in departure time are not considered; only an equilibrium using the *entire OD-flows* is found. This method is fast but has its drawbacks, as spillback of traffic on a network is not taken into account and effects of varying departure time on traffic flow are disregarded. Therefore, in the international literature, no reference of such a system applied for prediction purposes could be found. However, many of these models are still used in practice, because of their simplicity and fast calculations. *Dynamic models* take variations of demand through time into account. Using formulas stemming mainly from hydrodynamics, the development of flows and densities in time can be modeled [34-38].

Microscopic In a micro simulation model individual cars are simulated through a network, as well as interactions between individual cars. One typical approach is to use Cellular Automata (CA) [39] where a road is defined as a one-dimensional array of cells. A cell can be either empty or occupied by a single car. [40-42] use OD-matrices for predictions; [43-45] use *turn fractions*. In a *multi-agent system* [46] each driver is modeled as an *agent* who has an individual mental state. In an agent's 'mind', there is information of the trip, 'happiness' about his current state, a set of plans of for example when to leave, and so on. These models have been combined with OD-matrix predictions to come up with network wide traffic predictions [47].

Mesoscopic A mesoscopic model is a combination of macroscopic and microscopic modeling. First, traffic is assigned using macroscopic theory, after which individual cars are moved through the network based on the calculated macroscopic traffic variables. The big advantage of this approach is that queuing of cars can be modeled this way. A typical example of a mesoscopic simulation tool is DynaMIT [48], where historical and real-time information are combined to estimate the OD-matrix, after which the mesoscopic modeling is used to predict traffic.

Three Phase Traffic Theory Based on Boris Kerner's three phase traffic theory [49], the ASDA and FOTO models were developed. Kerner distinguishes three phases in traffic: (1) free flow, (2) synchronized flow, a congestion phase which is usually at a fixed location and (3) wide moving jams, a congestion phase that moves upstream the traffic with a constant speed. ASDA and FOTO can track and predict the characteristics of these phases. Reported results show that calculation times are lower than with microscopic simulation and that accuracy is satisfactory.

Time Series

Time series prediction involves modeling a variable as a function of its past observation and an error term. Time series modeling requires the process to be *stationary*. As traffic processes are not stationary, usually *seasonality* needs to be modeled. Instead of using traffic theory statistical functions are used. Compared to other methods some of these methods have shown a high accuracy and a low computational effort, making some of them usable for short term predictions.

Linear regression In linear regression the prediction function is assumed to be a linear combination of its covariates, where parameters indicate how much one covariate contributes to the outcome [7, 28, 50-56]. Although the model is simple, in some cases it is shown to produce quite good results, as well as very fast predictions due to its simple form.

ARIMA An ARIMA model, also called a Box-Jenkins model, is a common statistical technique that can be used for prediction. ARIMA is considered a more standard time series model in traffic prediction [20, 24, 57-61]. Results of applying ARIMA are mixed; some studies report good results, some report the contrary. Many variations on ARIMA have been proposed in literature, such as SARIMA [62, 63], subset ARIMA [59], Kohonen ARIMA [64], ARIMAX [65], VARMA and STARMA [20] and Exponential Smoothing [28, 66] in order to improve results. Some of these variations are indeed shown to improve prediction accuracy.

Kalman filtering A Kalman filter estimates the *future state* from only the estimated state in the previous time step and the current measurement [34, 60, 67-73]. Results are varying: the Kalman filters outperform some methods but sometimes the same models outperform Kalman filters.

ATHENA In this model, developed by the French traffic and safety research institute INRETS, traffic is modeled as a linear combination of historical and current states. For each type of traffic a non-linear transformation is applied [74]. This model outperformed several other models [58].

SETAR The Self-Exciting Threshold Auto Regressive (SETAR) model uses a linear combination of the current measurement and one past measurement to predict the future state [75-77]. The current measurement is weighted more heavily. Although this model is fast, the accuracy is low.

Gaussian Maximum Likelihood A Gaussian Maximum Likelihood is based on the following two principles: (1) the prediction deviates as little as possible from the historical average, and (2) the predicted increment deviates as little as possible from the historical increment. Predictive performance is better than several other methods [78].

Other time series models In the early work of [79], traffic flows are predicted using a *spectral analysis*. Results showed that this approach can lead to satisfactory predictions. A *Taylor series* has also been applied to describe the traffic process but this results in poor predictions [66]. A *state space model* [80, 81] can be described by (1) an observation equation and (2) a state equation. This model is outperformed by several other methods.

Rarely used methods
In *Grey Systems* the interaction between cases of partly clear and partly unclear information can be evaluated. The results of a study by [82] are not well reported, so the model's applicability remains to be determined. The *Pheromone Model [83]* describe a model based on an analogy with ant pheromones. Results are not too clearly reported, so conclusions on its applicability are hard to draw.

NON-PARAMETRIC MODELS

The term non-parametric is not meant to imply that these models completely lack parameters but that the number and nature of the parameters are flexible and not fixed in advance [84]. Model structure *as well as* model parameters need to be determined from data. Therefore, usually more data is required than for parametric models. The advantage of these models is that the difficult, dynamic and non-linear processes found in traffic can be modeled. No knowledge on the underlying processes is required. Unseen cases such as incidents pose a problem as the model structure is derived from data. What is striking is that only one of these methods has been applied network wide; all other studies focus on predictions on one single location or one route due to lack of data on all roads. For DTM purposes, this is a major drawback.

***k*-Nearest Neighbor**
With the *k*-Nearest Neighbor method, a historical database is searched every time for the *k* events which are *nearest* to the current traffic situation. The outcomes of the nearest events are averaged or weighed to their distance to the current situation [24, 53, 85-94]. All studies show that it is a fast method that can outperform naïve prediction methods, but none finds it more accurate than more advanced methods.

Locally Weighted Regression
Locally Weighted Regression uses local regression models. The prediction residual of each data point is then weighted proportionally to its proximity to the current measurement. Very good results are reported [7, 56], in prediction accuracy as well as computation time.

Fuzzy Logic
With fuzzy logic a rule base (a set of IF-THEN rules) is created, manually or automatically. A current situation corresponds to one or more rules. Based on the *then* and sometimes the degree of correspondence, a prediction is made. [95, 96] find promising results but do not compare their methods with others. [97] finds that BPNN and RBFNN produced better predictions.

Bayesian networks
In Bayesian networks, also known as causal models, the data from adjacent links are considered informative to the current link under investigation [98]. A Bayesian network is simply a directed graphical model for representing conditional independencies between a set of random variables. Comparisons with other methods are not made. However, this method is applied in real life by Inrix [99], a Microsoft spin-off company.

Neural Networks
Neural networks are the most widely applied models to the traffic prediction problem, because they are capable of modeling non-linear and dynamic processes well. Many extensions on the basic concept have been implemented to improve prediction accuracy and/or reduce computational effort. These extensions can be subdivided by the type of variation: (1) a different training procedure, (2) different internal structures or mathematics, (3) preprocessing input data and (4) include spatial and/or temporal patterns explicitly into the models. Before these extensions are dealt with, first the “standard” neural network is described.

The “Standard” Neural Network The Back Propagation Neural Network (BPNN) is more or less the “standard” neural network approach, and when a variation on it is applied, usually the models are compared to the BPNN. The BPNN consists of an input layer, one or more hidden layers and an output layer. Training with *back propagation* means that there are two steps: (1) input is fed to the hidden layer; one or more outputs are produced as the response of the network; (2) this response is then compared with the desired output, and the difference (the error) is propagated *backwards* through the network. During this phase, the weights of the connectors are adjusted. This process is repeated until weights stop being adjusted and the errors remain constant. Many studies use BPNNs to predict traffic data, e.g. [12, 23, 66, 100-110]. Results are good, although almost all extensions, which will be treated next, improve results even more.

Different training procedures The *Conjugate Gradient Algorithm* uses another way of adjusting weights when back propagating errors through the neural network. The most widely known CGA is the Fletcher-Reeves update [111, 112]. Results are comparable to the standard BPNN. *Evolutionary Learning* is inspired by the theory of evolution. Neural network “individuals” can reproduce and/or compete with other individuals. Strong individuals with good predictions survive longer and/or reproduce more. The “fittest” individual will be chosen as the predictor [52, 56, 113-116]. These Evolutionary Neural Networks (ENNs) show very positive results. Compared to the standard BPNN training is much faster and prediction accuracy is higher.

Different internals A *Modular Neural Network* (MNN) is based on a ‘divide-and-conquer’ strategy [104]. The input is processed in several subnetworks, each specialized in a certain task. MNNs are faster to train and can improve results [100, 106, 117, 118]. *Radial Basis Frequency Networks* (RBFNN) use the Euclidean distance between the hidden neuron center and the input vector [66, 97, 119, 120]. Results show a slightly positive preference of RBFNN over BPNN.

Inside the hidden layer of a *Neuro-Fuzzy Network* (NFNN), Fuzzy Rules are defined automatically [95, 121, 122]. Results are comparable to or better than those of the BPNN. In a *Counter Propagation Network* (CPNN) at each iteration the inputs are *assigned* to one node using a distance measure [123]. Training time is dramatically decreased and performance is slightly improved. A *Resource Allocating Network* (RANN) is much like the RBFNN [67], except that hidden units are created automatically. A comparison of RANN with existing methods lacks.

Preprocessing input data Wavelet transformation is generally used for de-noising data [124]. A *Wavelet Neural Network* (WNN) uses wavelet functions instead of the standard sigmoid function used in BPNN [120]. Improvements in prediction accuracy as well as computational effort are found [125, 126]. The *Spectral basis Network* (SNN) employs a Fourier expansion of the input vector to obtain linearly separable input features [17, 18]. This new input vector is fed to a standard BPNN model. Improvements in prediction accuracy are found, especially on longer prediction horizons. The *Generalized Network* (GNN) also uses a Fourier expansion of the input vector. The hidden neurons however are replaced with *intelligent neurons* which have an increased storage capability [127]. In convergence and in accuracy, the GNN is found to be better than the BPNN. A *Kohonen Self Organizing Feature Map Network* can be used to cluster input data before feeding it to a standard BPNN [16]. The Kohonen SOFM is itself a neural network, containing only input nodes and output nodes and no hidden layer. The Kohonen SOFM BPNN is found to outperform a standard BPNN, but is in its turn outperformed by a *Fuzzy c-means Clustering Network* (FCNN) [16]. The FCNN clusters the input data before feeding it to a standard BPNN. The FCNN outperformed a number of other neural network applications and other techniques. In a *Principal Component Analysis Neural Network* (PCANN), the input vector data is “compressed”, reducing the number of inputs and therefore improving the BPNN performance [100, 104]. *CoActive Neuro-Fuzzy Inference Systems* (CANFIS) combine features of the RBFNN and the FCNN and outperforms several other neural networks [104].

Include temporal/spatial patterns The Jordan/Elman network or *Simple Recurrent Network* (SRNN) contains *memory units* that are used to store the hidden-layer output signals at the previous time step, providing a mechanism to recognize recurring patterns [100, 128]. Results are similar to other improved neural network topologies. The *Partially Recurrent Network* (PRNN) is a simplified version of the Jordan/Elman network [100, 128, 129] and shows equal performance to other neural networks. The *State Space Neural Network* is a special version of the Partially Recurrent Elman network [13, 14]. The neurons in the hidden layer all represent a certain link of an entire route. The weights of a hidden neuron can be interpreted as the link travel times. The SSNN outperforms naïve methods drastically [15] but is not compared to other neural network types. In contrast to the BPNN, in the *Finite Impulse Response Network* (FIRNN) the static weights are replaced by linear filters which have tapped delay lines in it, so to capture the internal dynamics of the traffic processes [130]. The FIRNN outperforms BPNN, but is outperformed by a *Time Delay Recurrent Network* (TDRNN) where the previous output values are fed back into the input values [130, 131]. TDRNN has outperformed BPNN and FIRNN. The *Time Delay Feedforward Network* (TDFNN) has memory only at the input layer. It is composed of feed forward arrangement of memory and nonlinear processing elements. Results are good [100, 128], but the Locally Weighted Regression model performed better [56].

Rarely used methods
Decision tree learning method have been used for predictions [50]. The decision trees were outperformed by linear regression on short horizons and on longer horizons the effect was vice versa. *Regression trees*, similar to decision trees but capable of predicting continuous variables rather than discrete ones, perform bad compared to other methods [7]. *Support Vector Regression* (SVR) is a machine learning method where the goal is to find a function that has at most a certain threshold deviation from the actually obtained targets for all the training data and at the same time is as flat as possible [132]. The SVR method can outperform naïve methods [19].

OVERVIEW

In Table 1 there is an overview of the prediction methods, categorized in the same manner as above. First, the number of studies that have applied this method is mentioned, as well as the maximum prediction horizon (in minutes). Then, there is the scale of the predictions, either "Point" (one location), "Route" (a traffic variable, generally travel time, is predicted along a route) or "Network" (predictions are made for all roads in an entire network based on measurements on some of the link). Also, the environment in which the studies took place is mentioned, either "Urban" or "Freeway". Predicting traffic in these two environments is different, as in urban environments usually crossings and traffic lights influence the traffic streams. The "Speed" of prediction, the inverse of the computational effort, is mentioned, and finally the "Accuracy" of the prediction method.

DISCUSSION

As can be seen from the overview of prediction methods, none of the methods stick out. Under some conditions the linear regression, the Locally Weighted Regression model, and Evolutionary Neural Networks have shown good performance in comparison to other methods in prediction accuracy and in computational effort.

What is striking is the small number of methods that have been applied *network wide* and in both urban and freeway environments. After all, for most practical applications, such as trip planning for transport companies, route advice in consumer products and large scale Dynamic Traffic Management, network wide predictions in all environments are a necessity. This has only been done with historical averages, traffic simulation models, linear regression and Bayesian network. The vast majority of studies however have focused on predicting traffic on a single location or fixed routes on freeways. In order for the methods to be used in practice they should be able to predict traffic on a much larger scale and in both urban and freeway environments. This can be done either by interpolating traffic on non-measured links or by collecting data on all links. Now that *floating car data* is becoming more widely available worldwide, the barrier of lack of data is being removed and the latter may become possible.

	Method		Studies	Max hor.	Point	Route	Network	Urban	Freeway	Speed	Accuracy
Naive	**ITT**		9	-	x	x			x	++	--
	Hist. Avg		8	-	x	x	x		x	++	--
	ITT+Hist. Avg		3	-		x			x	++	--
	Clustering		4	-		x			x	++	-
Parametric	**Traffic models**										
	Macroscopic		6	60			x	x	x	-	0
	Mesoscopic		2	60			x	x	x	-	0
	Microscopic		10	60			x	x	x	--	0
	Three Phase Theory		1	60		x			x	0	0
	Time Series										
	Linear Regression		9	60	x	x	x		x	+	+
	ARIMA		13	80	x				x	0	+
	Kalman filtering		9	45		x		x	x	0	+
	SETAR		4	15		x			x	+	-
	ATHENA		1	60	x				x	0	+
	Gaussian Max Likelihood		1	5?		x			x	+	0
	Other		4	15	x			x	x	0	-
	Rarely used		2	5	x			x	x	0	0
Non-parametric	***k*-Nearest Neighbor**		12	40	x	x			x	+	-
	LWR		2	120		x			x	+	+
	Bayesian network		3	15			x		x	0	+
	Fuzzy Logic		3	50		x			x	++	-
	Neural Network										
	BPNN		30	60	x	x		x	x	-	0
	Learning proc	CGA	2	5		x			x	-	0
		GA/ENN	6	60	x	x			x	+	+
	Internal Structure	MNN	5	25	x	x		x	x	0	+
		RBFNN	4	15	x	x			x	0	0
		NFNN	3	50		x		x	x	0	+
		CPNN	1	30		x			x	+	0
		RANN	1	30		x			x	0	0
	Preprocess data	WNN	4	60	x			x	x	0	+
		SNN	2	25	x				x	0	+
		GNN	1	5	x				x	0	+
		Kohonen	1	25		x			x	-	+
		FCNN	1	25		x			x	-	+
		PCANN	2	20	x				x	0	0
		CANFIS	1	20	x				x	0	+
	Temporal/spatial	SRNN	2	20		x			x	0	0
		PRNN	3	60		x			x	0	0
		SSNN	3	40		x			x	-	+
		FIRNN	1	60				x	x	0	0
		TDFNN	3	20		x			x	0	0
		TDRNN	2	60	x			x	x	0	+
	Rarely used		2	180+		x			x	0	0

Table 1. Overview of traffic prediction methods.

Traffic simulation models seem to be an isolated research topic. In no study a comparison is made between a traffic simulation model and any other method. This can be due to the difference in scale as mentioned before. Nevertheless it would be very interesting to see how time series or non-parametric approaches would perform in comparison to traffic simulation models, on certain links *or* on a network wide scale.

An overwhelming amount of different methods have been developed by researchers from all over the world. Some can predict traffic accurately, but still not one of the methods can be considered the *best method* in any situation, let alone under all possible situations. Indeed, one can question if there is such thing as best method. Further research on traffic prediction could focus on either developing new methods which outperform the present state of the art presented above, or focus on methods which help to *select* or *combine* the appropriate model for a given situation. With the large amount of methods already at hand, the second option will be very worthwhile and can be expected to produce at least interesting results. For example, the average or a linear combination of predictions of multiple methods could be used for this. Also Bayesian theory could be used as suggested in [133]. This approach was already chosen by [118], but this study combined only neural networks. Other suggestions are to use Fuzzy Logic, decision trees, the *k*-NN method or input clustering to select one or more appropriate models under certain conditions.

CONCLUDING REMARKS

This paper has contributed in (1) providing an extensive structured overview of available short term traffic prediction methods and (2) suggesting a way forward with so many valuable prediction methods already at hand. With the knowledge on what methods can be applied to predict traffic conditions the real challenge now lies in trying to use these methods in practice. Therefore, network wide applications need to be made and tested, using the right prediction method(s) at the right time.

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