An Integrated Method for Short-Term Prediction of Road Traffic Conditions for Intelligent Transportation Systems Applications

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Abstract – The paper deals with the short-term prediction of road traffic conditions within Intelligent Transportation Systems applications. First, the problem of traffic modeling and the potential of different traffic monitoring technologies are discussed. Then, an integrated method for short-term traffic prediction is presented, which integrates an Artificial Neural Network predictor that forecasts future traffic states in standard conditions, an anomaly detection module that exploits floating car data to individuate possible occurrences of anomalous traffic conditions, and a macroscopic traffic model that predicts speeds and queue progressions in case of anomalies. Results of offline applications on a primary Italian motorway are presented.

Key-Words: - Intelligent Transportation Systems, Short-term traffic predictions, Neural networks, Traffic flow model, Data fusion, Incident detection

1 Introduction

Intelligent Transportation Systems (ITS) are applications that integrate Information and Communication Technologies with transportation engineering in order to enhance the knowledge of users and operators on the transportation system state and, possibly, to enable them reacting promptly to changes of external conditions and keeping the system close to a desired state.

The general framework of ITS includes: a monitoring system composed by sensors that measure traffic and environment conditions; a traffic management system that applies dynamic suitable control strategies; a traveler information system that provides users with updated, reliable and predictive information; a decision support system, which processes available data to identify current traffic state and predict future conditions depending on management and information strategies.

Large deployment of locating technologies such GPS and Short Range Dedicated (SRD) detectors, combined with existing roadside traffic monitoring systems, make available a huge amount of data that need for new methods for data fusion and, more in general, integrated frameworks to better exploit real-time data, high performance computers, modeling capabilities. Success of ITS is indeed conditional to the ability of integrating all these potentials and provide quick and reliable predictions of short and medium term traffic conditions.

2 Problem Description

2.1 Road traffic network characteristics

Road traffic is a complex phenomenon resulting from the interaction between mobility demand, road network performances and external conditions. Both mobility demand and road network have space related structures, which are represented mathematically by an Origin-Destination (O-D) matrix and a directed graph, respectively.

Mobility demand varies in time both day-to-day and within-day, according to users' mobility needs. Demand patterns have a systematic component, which gives rise to time periodicity, and a random component, due to combination of many factors affected by uncertainty, due to users' behavior and environmental conditions.

Road networks performances, however, depend on physical and functional characteristics of the infrastructures. In standard conditions they are time-invariant. Nevertheless, they may be altered significantly by anomalous events, like accidents, road works, or bad weather. Network structure implies that changes of some elements may affect other elements in their neighborhood. This may occur, for example, when a queue spills back from one link to the upstream links.

Thus, road traffic is a time-dependent phenomenon characterized by periodicity, uncertainty, space correlation, and possible disruptions.

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2.2 Requirements for short-term traffic prediction model

In order to fit road traffic characteristics, a short-term prediction model should comply with the following requirements: exploit past observations to predict systematic patterns in the future; detect unexpected disruptions of the network; predict queue spreading and clearance across the network in case of over-saturation. In the general framework of Intelligent Transportation System, the prediction model supplies main inputs to Traveler Information System. Due to the interaction between users' choices and traffic performances, information provided to travelers can modify their choices and so change future traffic states. In order to avoid a bias between current information and actual future traffic conditions, the prediction model must forecast the effect the information provided produces on traffic performances. This is a fixed point problem, whose equilibrium solution is, under rather general assumptions, all drivers use their minimum individual travel time.

2.3 Traffic data

New traffic monitoring technologies supply Intelligent Transportation Systems with many sources of traffic data. Traditional traffic monitoring devices such as paired inductive loops, radar, infrared laser and video sensors based on virtual loops (see [1] for a review) count traffic flow and space average speed at a specific location; vehicle identification systems such as Radio Frequency Identification (RFID) and video sensors based on Optical Character Recognition (OCR) detect vehicle passing at consecutive monitoring sections and measure individual travel time; Floating Car Data (FCD) are collected by sampling fleets of vehicles equipped with GPS, which transmit their positions and speeds through cellular mobile communication. Each source of information has peculiar advantages and drawbacks. Data fusion techniques have been developed to combine such different data and apply them in a joint framework [2], often based on some version of Kalman filter ([3] and [4]), although other approaches are valuable, such as Bayesian networks [5], Shannon's information entropy [6], artificial neural networks [7] or a combination of them [8].

3 Problem Modeling

Many different classifications of short-term traffic prediction models have been proposed in technical literature. In the author's view, traffic prediction models can suitably divided into implicit and explicit models. The former are in their turn divided in parametric and non parametric.

- *Parametric models* estimate future values of a traffic variable as a mathematical function of its past observations, assuming they are affected by a random noise process; examples are: time series models, like autoregressive, moving average, ARMA and ARIMA; machine learning models, like artificial neural networks and support vector machines; different versions of Kalman filter [9].
- *Non parametric models* assume the process is characterized by some regularity, which allows estimating future values by find closest analogy with the past; examples of parametric models are clustering and pattern matching methods [10];
- *Explicit models* (in our specific case, *traffic network models*) derive future values of traffic performance variables through mathematical relationships that reproduce vehicular interaction on the network; examples of explicit models are dynamic traffic assignment models, which simulate the interaction between mobility demand and network performances by assuming some behavioral rule for drivers' route choice [11]; macroscopic traffic flow models, which neglect space characterization of mobility demand and assume that traffic stream is subject to hydrodynamic laws, so that future traffic values on some road elements can be predicted by taking entering flow traffic as input [12].

Time-series models, which infer forecasts directly from past data sequences, have a rather efficient mathematical structure, so that they can provide a very quick and robust output, if a sufficient set of past data are available and, very important, if no relevant change has occurred in the transport system. Similar performances are provided by non parametric models. However, if some unobserved anomaly –like an accident, road works or some demand concentration– has occurred in the meantime, past observations are no more a sound basis for future forecasts and implicit models become unreliable, until the time sequence comes to be regular or exhibits similarities with different previously observed patterns (non parametric model).

In such cases, given the modified input values of mobility demand or road traffic characteristics, network models can simulate the modified state of the network and so provide a more accurate prediction of queue spill back and clearance. Thus, a

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crucial issue is to promptly detect the anomaly, and estimate modifications of relevant input variables.

Different models have their peculiarities and so each of them has its own field of application. Parametric models can be effectively applied to predict relatively small variations of traffic variables, as typical of standard conditions. Automatic incident detection algorithms are necessary to recognize the occurrence of anomalous conditions, when explicit models can be applied to simulate future traffic patterns.

4 Integrated Framework for Traffic Prediction

Fig.1 illustrates the general modeling framework for traffic prediction. Input data are both travel times of a sample of vehicles along road segments and time average flows and speed detected at monitoring stations. Automatic Incident Detection Algorithm processes data to detect possible anomalies. If this is not the case, Artificial Neural Network estimates are applied for short-term prediction, while output of the traffic model supplies medium-term trend; otherwise, traffic model outputs are applied to estimate queue evolution even in the short term.

A rolling horizon procedure [11] combines medium-term and short-term predictions. It launches model simulations sequentially to achieve updated medium term predictions and superimposes newest short-term predictions supplied by neural network to them as soon as traffic monitoring measures are updated.

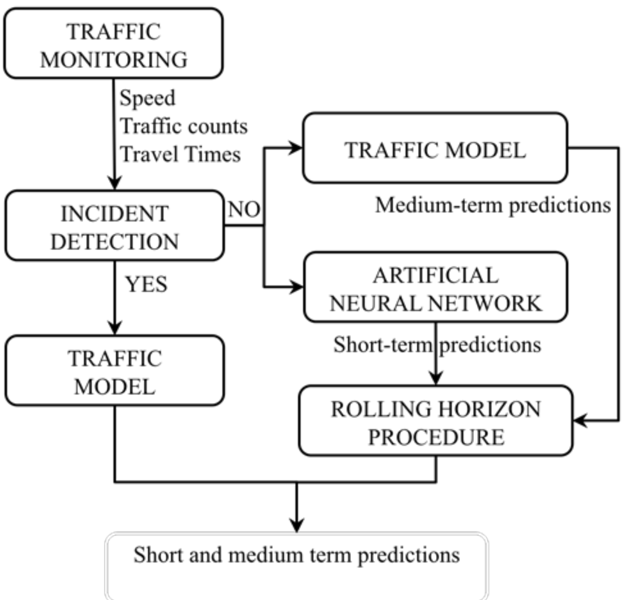

Fig.1. Integrated framework for traffic prediction in Intelligent Transportation Systems applications.

4.1 Artificial Neural Network model

Artificial Neural Networks (ANNs) are applied to perform short-term predictions in standard traffic conditions, when time and space correlation observed in far and near past are significant to determine, respectively, the structure and the next values of traffic variables.

In their general form, ANNs have a multi-input multi-output structure that provides future values of speed and flow as a non linear combination of recently observed data.

$\mathbf{y}=f(\mathbf{B}(g(\mathbf{A}\cdot\mathbf{x}))$

where:

$\mathbf{A}$, $\mathbf{B}$ are matrices of weights;

f and g are transfer functions;

$\mathbf{x}=\{x_P(t), x_P(t\text{-}1), x_P(t\text{-}2),\ldots x_P(t\text{-}m)\}$ are values of traffic variables detected at the set of locations P during consecutive time intervals t-m, …, t-1, t;

$\mathbf{y}=\{x_Q(t+1), x_Q(t+2), x_Q(t\text{-}2),\ldots x_Q(t\text{-}n)\}$ are traffic variables predicted for the future time intervals t+1, t+2, …, t+n.

Correlation between different time intervals seeks to capture the natural trend of traffic variables. Relating values of variables detected at different locations introduces space correlation in the model, which tries to capture the propagation of flows across the network implicitly. In such a way, ANN aims at anticipating future trend through the current or past trend at upstream locations.

A and **B** matrices are determined through a training (or learning) process, consisting in minimizing an error function that measures the capability of the model to reproduce an observed set of input and output values. While Error Back Propagation and Levenberg-Marquardt are the most usual, swarm algorithms revealed to be often more effective in the training process [13].

4.2 Automatic incident detection

Traditional incident detection algorithms like California, Payne or McMaster [14] are based on occupancy measures at fixed road sections and seek to recognize anomalous conditions by comparing upstream and downstream estimates of traffic density; that is, by observing the effects of incident on traffic flow. Monitoring techniques based on vehicle identification at consecutive road sections can be exploited to set up new algorithms based on observations of vehicle arrivals at two consecutive monitoring sections and checking if their delays exceed a given threshold. The detection rule is straightforward. At every time instant t, the algorithm:

1. updates the list of time stamps $\{t_n\}_i$ of vehicles $\{n\}_i$ passing each monitoring station i
2. computes their expected arrival times $\hat{t}_n$ at downstream station i+1
   $$\hat{t}_n^{(i+1)} = t_n^{(i)} + L/\hat{v}_n$$
   by assuming they should travel on the segment L at the standard speed $\hat{v}_n$ for the vehicle class which the vehicle belongs to
3. updates the estimated delays w_n of vehicles that have not yet passed the downstream section and resets them to zero as soon as the vehicle had passed it
   $$w_n = t - \hat{t}_n^{(i+1)} \text{ if } n \in \{n\}_i \cap n \notin \{n\}_{i+1}$$
   $w_n = 0$ otherwise
4. detects an incident if at least q vehicles among the last p vehicles have a delay larger than a given threshold z.

The detection method is quicker than traditional algorithms based on average measures of occupancy. In fact, the condition is applied with respect to expected arrival times and so does not require the vehicle arrive at downstream monitoring section to check each single condition. To avoid that vehicles stopped at an intermediate section can produce false alarms, the condition has to be checked repeatedly before an incident be recognized. To reduce the probability of false alarms, additional conditions can be introduced; for example, by requiring that the average delay of a set of vehicles be larger than a given threshold for a given number of consecutive observations.

4.3 Road traffic network model

Road traffic network model simulates physics of traffic, with suitable approximation. Traffic predictions on road network with many connections between their links require specific rules for assigning traffic accordingly to given assumptions on drivers' route choice. To reduce computational burden, a new quasi-dynamic traffic assignment model for road networks has been recently introduced that applies a probabilistic route choice behavior model and a macroscopic traffic performance model [15]. For sake of brevity, we limit our analysis here to expressway arterials. In fact, traffic predictions on expressway have only very simple route choice alternatives; however, they need for more advanced modeling of traffic phenomena to predict unstable conditions that can occur in case of severe congestion, when stop and go phenomena or traffic breakdown can take place.

The traffic model for expressway is the well-known second-order macroscopic traffic flow, which applies the following equations corresponding to conservation of flow and the gradient of speed

$$\frac{\partial k}{\partial t} + \frac{\partial q}{\partial x} = 0$$

$$\frac{\partial v}{\partial t} = -v\frac{\partial v}{\partial x} + \frac{1}{\tau}\left[V(\rho) - \rho - \frac{\mu}{\rho}\frac{\partial \rho}{\partial x}\right]$$

whose discrete form has taken from [16]:

$$v_i(k+1) = \begin{aligned} & v_i(k) + \\ & + \frac{T}{L_i} v_i(k)\left[v_{i-1}(k) - v_i(k)\right] + \\ & + \frac{T}{\tau}\left[v^e(\rho_i(k)) - v_i(k)\right] + \\ & - \frac{\mu T\left[\rho_{i+1}(k) - \rho_i(k)\right]}{\tau L_i\left[\rho_i(k) + \kappa\right]} + \\ & - \left(\frac{\delta T}{L_i \lambda_i}\right)\frac{r_i(k) v_i(k)}{\rho_i(k) + \kappa} \end{aligned}$$

where: k indicates the generic time period of length T, L_i is the length of the i road segment, r_i is the entering flow, $v^e(\rho)$ is the equilibrium speed for given value of density ρ, τ is a time constant, μ the anticipation constant, λ is the number of lanes of the expressway, κ and δ are tuning parameters.

Single elements of the second term of the equation are, respectively: the current speed on road segment i; a convection term, which takes into account that drivers do not adapt their speed instantaneously; a relaxation term, which describes the fact that drivers tend to reach their desired speed; an anticipation term, which assumes that drivers adjust their speed by looking ahead, so that they decelerate if traffic density ahead i+1 is higher than on segment i; an on-ramp flow term, which takes into account disturbances induced by merging traffic.

The traffic model takes the entering traffic at ramps as time dependent input and provides future speeds and flows as outputs. The numerous coefficients of the model need a careful calibration to provide a good estimate of the traffic dynamics.

In order to catch the effects of changes of the external environment, like bad weather, an on-line calibration can be performed. A swarm algorithm has been developed and applied in preliminary tests.

5 Implementation

The prediction model is being tested offline on real data collected on a 223km long stretch of "Autostrada del Sole", one of the most important motorways in Italy. The motorway is equipped with 7 inductive loop monitoring stations that provide flow and speed measures, and 16 couples of RFID detectors that provide a timestamp for each equipped vehicle when it passes through the detector. Twenty intersections are along the freeway stretch equipped with RFID detectors at entering toll barriers and on exiting ramps. Only offline counts are available for the total entering and exiting traffic flows, without discriminating between North-South or East-West directions. An offline O-D matrix estimation procedure is then applied that uses past counts for a priori estimates and corrects it by means of online detections of the sample of RFID equipped vehicles. Although this sample is very large (around 50% of total traffic), database is affected by some detection errors, which require application of filtering techniques.

Macroscopic simulation model, Artificial Neural Network and the incident detection algorithm were applied to the freeway stretch. The simulation model provided flow, density and speed on the whole freeway stretch for a simulation time horizon of several hours, with a granularity varying from 100m long segments and 2s simulation time step to 1000m and 20s, respectively. Processing time for simulations is on the order of several minutes on a standard PC.

Artificial Neural Networks (ANN) provided short-term predictions of either travel times between consecutive RFID detectors or traffic speed at loop speed detectors. Several ANN structures were tested by assuming aggregation of traffic data for 5 minutes. The most effective structure was a feed-forward ANN with 4 input neurons (corresponding to the last 4 traffic measures), 1 hidden layer of 10 neurons and 1 output layer, corresponding to the prediction for the next 5-minute interval.

Calibration of the both models was performed on the dataset from January 1st to 27th, 2012. Dataset from January 28th to 31st on a 8-km long segment were used for validation. It is worth mentioning that the dataset chosen for validation is very challenging, since it includes one day when a heavy snowfall affected traffic conditions. Coefficients of the traffic model such as maximum speed were recalibrated in snow conditions by applying a swarm algorithm that minimizes the total error function of speed and flows from loop detectors [17]. Both models catch the main trend of traffic performances and fit the relevant reduction of speed under snow conditions. Root mean square normalized errors (RMSNE) for the traffic model were 0.15 for flows estimations and 0.16 for speed estimations. RMSNE for ANN were as 0.10 for speed and 0.36 for travel times. Results of speed validation are shown in Fig.2 and 3 for the model and the ANN, respectively. It is worth mentioning that measures of effectiveness for model validation have a limited relevance, since they have to be considered in the general predicting framework. On this regard, the following remarks have to be noticed:

- the traffic model is used for medium-term traffic predictions, as it provides estimates over a 4 hours time interval with a roll updating period of 15 minutes: thus, its required capability is to catch the medium term trend in case of anomalies;
- ANN has to supply quick predictions holding for the short-term period, that is for the next 5 minutes: thus, its required capability is to catch the short term trend and to be sensitive even to rather small speed variations.
- Fig.2 clearly shows that the model fails to predict the day-night periodicity. Of course, calibration can be improved by varying free-flow speed with the time of day; however, this is not a crucial issue, since the traffic model is used as short-term predictor only in case of relevant anomalies.
- RMSNE values should be evaluated by considering that data used as input for ANN were not preprocessed to eliminate outliers, which were very numerous in RFID data and affected measures of effectiveness of travel time predictions by ANN.

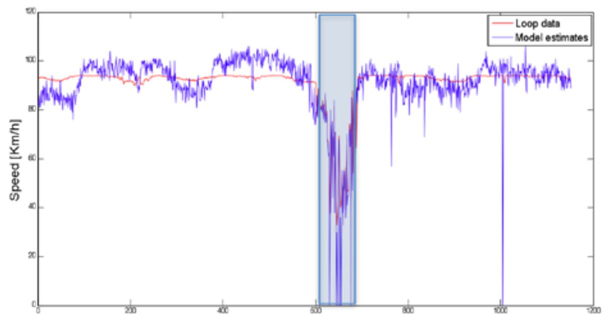

Fig.2. Traffic speed observed and simulated by the traffic model in the period January 28th-31st. Grey rectangle indicates the presence of snowfall [17].

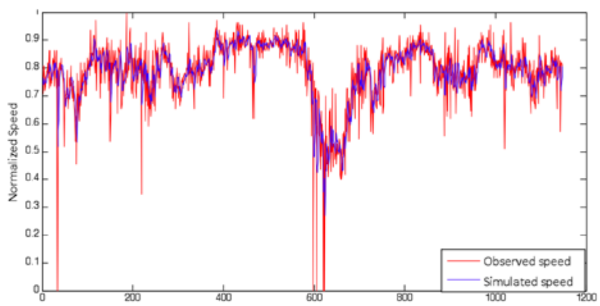

Fig.3. Traffic speed observed and predicted by ANN in the same period, January 28th-31st, of Fig.2 [17].

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Table 1. Results of speed validation for different data fusion techniques [17]

	M	F1	F2	F3	F4
RMSE (km/h)	18	14	10	11	7
RMSNE (–)	0,16	0,14	0,11	0,10	0,07
MAE (km/h)	3,0	1,6	1,8	1,3	0,9

Table 2. Results of travel time validation for different data fusion techniques [17]

	M	F1	F2	F3	F4
RMSE (s)	77	58	44	66	51
RMSNE (–)	0,20	0,13	0,09	0,16	0,13
MAE (s)	10,3	5,9	4,2	6,8	7,0

Several data fusion techniques based on Extended Kalman Filter were applied to improve traffic short-term predictions [17]. Speed provided by the traffic model (M) are taken as a priori estimate. Fusion techniques F1 and F2 correct model estimates by loop and RFID measures, respectively; F3 fuses both previous techniques in a state vector fusion framework; F4 applies the two corrections by loop measures and RFID measures sequentially. Results obtained for speed and travel time estimates are summarized in Table 1 and 2, respectively. Fusion techniques F3 and F4 that combine all traffic measures provide better performances for speed estimations, while travel times are estimated more effectively by applying only DSR measures.

6 Conclusion

The paper presented a general framework for short and medium term traffic predictions and highlighted the need of Intelligent Transportation Systems for quick, robust and reliable predictions.

Different prediction methods have to be used and integrated to combine promptness, robustness and reliability. Time-series models provide quick and sufficiently accurate short-term predictions when variations of traffic performances are mainly due to random disturbances. In case of accidents or other anomalous conditions, traffic simulation models are necessary to have reliable short and medium term forecasts. A new automatic incident detection algorithm has been introduced that checks delays of RFID equipped vehicles and so can detect incident even before vehicles arrive at downstream monitoring station. A cost-benefit method has been developed to determine optimal thresholds of the algorithms maximizing the difference between benefits from quick detection of an accident and costs from false alarm.

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