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Traffic Estimation And Prediction Based On Real Time Floating Car Data

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Abstract— **The knowledge of the actual current state of the road traffic and its short-term evolution for the entire road network is a basic component of ATIS (Advanced Traveler Information Systems) and ATMS (Advanced Traffic Management System) applications.**

In this view the use of real-time Floating-Car Data (FCD), based on traces of GPS positions, is emerging as a reliable and cost-effective way to gather accurate travel times/speeds in a road network and to improve short-term predictions of travel conditions.

The purpose of this paper is to present a large-scale working application of FCD-system, developed and operated by OCTOTelematics, delivering real-time traffic speed information throughout the Italian motorway network and along some important arterial streets located in major Italian metropolitan areas. Traffic speed estimates are deduced at an interval of 3 minutes from GPS traces transmitted in real-time from a large number (and still growing) of privately owned cars (about 600.000) equipped with a specific device covering a range of insurance-related applications.

This paper also proposes two algorithms, respectively based on Artificial Neural Networks and Pattern-Matching, designed to on-line perform short-term (15 to 30 minutes) predictions of link travel speeds by using current and near-past link average speeds estimated by the OCTOTelematics FCD system. The Rome ring road (GRA-Grande Raccordo Anulare) was used for testing the feasibility of the two algorithms. Testing results showed that the proposed approaches for short-term predictions are very promising and effective.

I. Introduction

The successful wide scale deployment of Advanced Traveler Information Systems (ATIS) and Advanced Traffic Management Systems (ATMS) relies significantly on the capability to perform accurate estimates of the current traffic status and reliable predictions of its short-term evolution (less than one hour in the future) on the entire road network.

In this view the use of real-time Floating-Car Data (FCD), based on traces of GPS positions, is emerging as a reliable and cost-effective way to gather accurate traffic data for a wide-area road network and to improve short-term predictions of travel conditions.

Unlike other traffic data collection techniques (Automated Vehicle Identification systems, video cameras, inductive loops, radar based sensors, etc.), floating cars, using GPS receiver and GSM/GPRS transmitter, act as moving sensors traveling in a traffic stream and do not require instrumentation to be set up on the roadway.

Besides increasing the understanding of individual travel behavior, floating car technique can easily provide near real-time traffic performance data on any part of large networks and offers a viable way to complement fixed-point traffic sensors, such as cameras and loop detectors, involving high installation and maintenance cost.

The FCD technique is based on the exchange of information between a fleet of floating cars traveling on a road network and a central data system. The floating cars periodically send the recent accumulated data on their positions (latitude, longitude and altitude) and, optionally, instantaneous speed, whereas the central data system tracks the received floating car data along the traveled routes by matching the related trajectories data to the road network. The frequency of sending/reporting is usually determined by the resolution of data required and the method of communication.

The most common and useful information that FCD technique provides is average travel times and speeds along road links or paths [8], [13], [14]. So far, various approaches have been proposed to deploy FCD in order to predict short-term travel conditions, to automatically detect incident or critical situations [6], [7], [10] and finally to determine Origin-Destination traffic flow patterns [12].

The reliability of travel time estimates based on FCD highly depends on the percentage of floating cars participating in the traffic flow [3], [5], [11]; other factors affecting the reliability of travel time estimates, mainly for lower penetration of floating cars, are traffic conditions and road link capacities. As a rule, a lower percentage of floating cars is required in more congested traffic condition while a higher percentage of floating cars is needed in low flow conditions.

The purpose of this paper is to present an evolution of an operating FCD system, integrating short term traffic forecasting based on current and historical FCD.

Unlike previously proposed FCD techniques (mostly using data from taxi or bus fleets), this system exploits data from a large number of privately owned cars, to deliver real-time

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traffic speed information throughout the Italian motorway network and along some important arterial streets located in major Italian metropolitan areas. Real-time traffic speed estimates are deduced from GPS traces wirelessly transmitted from a large number (and still growing) of privately owned cars (about 600.000) equipped with a specific device covering a range of insurance-related applications. Average traffic speed estimates are regularly updated at intervals of 3 minutes 24 hours a day and delivered to Infomobility service providers and motorway/roadway operators.

The paper is organized as follows. Section II provides a brief overview of the FCD system operated by OCTOTelematics. Section III shows how average travel speeds are deduced from GPS traces. Section IV provides a summary of the results obtained from the preliminary analysis of the estimated link travel speeds on the Rome ring road. Section V presents two algorithms, respectively based on Pattern Matching and Artificial Neural Networks, designed to on-line perform short-term (15 to 30 minutes) travel speed predictions for a specific road link by directly using current and near-past average FCD travel speeds. The Rome ring road (GRA-Grande Raccordo Anulare) was used for testing the feasibility of the two proposed approaches. Section VI concludes this paper.

II. THE OCTOTELEMATICS FLOATING-CAR DATA SYSTEM

OCTOTelematics (www.octotelematics.com) is the European leader for development and deployment of Telematics for Insurance application, with approximately 600.000 On Board Units (OBU) installed and provides complete solutions from in-vehicle On Board Units up to Data Processing Center for Pay As You Drive, Pay How You Drive, Pay Per Use insurance.

OCTOTelematics is part of METASYSTEM Group, an European leader in Electronics and Telematic Equipments. The group has more than 1.000 employees and a turnover of € 250 million.

Currently, OCTOTelematics is providing services to 32 insurance companies in Europe such as Unipol, Generali, Axa, Uniqa, Sara Assicurazioni, Lloyd Adriatico (Allianz Group), Reale Mutua, Linear, Norwich Union Insurance, Mapfre, Uniqa.

The system operated by OCTOTelematics is able to collect statistics on driver behavior, mileage, accident detection and reconstruction, traffic detection and estimation, road user charging data and remote automotive diagnostics as well as performing the “conventional” telematic functions as antitheft satellite tracking and fleet management.

OCTOTelematics’ system plays an important role in road safety reducing the number of accidents in compliance with European eCall regulation.

At present OCTOTelematics has about 600.000 on board units, mostly installed in Italian private cars, with an average increase of about 30.000 units per month and a projected installed base of 1.000.000 units by mid-2009 (see Fig. 1).

In Italy there are about 35 million cars (2006 official data), resulting in a market penetration of approximately 1.7% and a projected 3% in 2009.

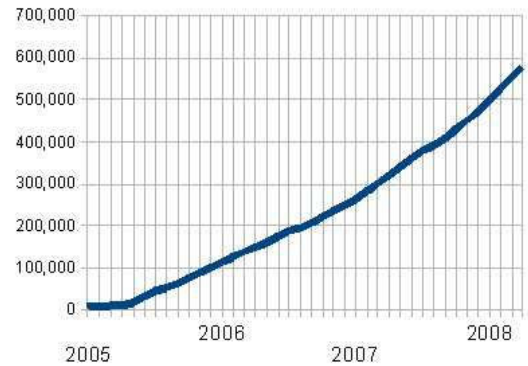

Fig. 1. Growth of equipped private cars in Italy

The system is also rapidly increasing in several other countries (Austria, Spain, UK, Slovakia, Russia, Mexico, Brazil, Malaysia, ...) and is expected to reach hundreds of thousands of units in several countries in the next years.

The target of the system is basically insurance profiling, therefore the telematic on board unit design and operation is utterly different from other telematic devices devised for anti-theft or fleet management services. One of the basic differences consists of the larger amount of data needed for a correct profiling: as a result at the time of writing there are over 20 million new records per day.

The OBU consists of a GPS receiver, a GPRS transmitter, a 3-axis accelerometer sensor, a battery pack, a mass memory, processor and RAM. The OBU has a dimension of 13.5 x 8.5 x 3 cm.

The OBU stores GPS measurements (position, heading, speed, quality) and periodically transmits (on request or automatically) the recent accumulated measurements to the central data system. Transmission occurs every 100 Km traveled or every 12 minutes when the equipped car is running along predefined motorways or crossing city centers.

Due to the large amount of real time data received for insurance profiling purpose and due to the high market penetration (giving the data a statistical consistency), several ITS application can be and have been developed by OCTOTelematics, as the Large Scale Floating Car Data System (**LSFCD**), a new and improved method of defining the Origin/Destination matrix, electronic road or zone charging, congestion and flow detection, and real time pollution estimation.

The most successful ITS application is the Italian’s Large Scale Floating Car System: the Central Data System tracks the received data along the traveled routes by matching the related trajectories data to the road/street network in order to estimate link travel speeds and then, freely disseminates them through WEB pages where data are presented in 6 speed categories (http://traffico.octotelematics.it/index.html), updated every 3 minutes, 24 hours a day, 7 days a week.

As an example, Fig. 2 presents the Web page for the Rome ring road whose links are color-coded according to the current FCD travel speed categories.

Fig. 2. The OCTOtelematics Web page for the Rome Ring Road

Likewise, estimated speeds (in km/h) are delivered real-time to Infomobility service providers, motorway/roadway operators and radio stations for real time traffic information.

III. Traffic Speed Estimation

In 2006 OCTOTelematics began developing the Large Scale Floating Car Data System (or LSFCD System) aimed at providing current link travel speeds along defined motorways.

Currently the system monitors the entire Italian motorway network (more than 6.000 Km) and some important arterial streets located in major Italian metropolitan areas.

By utilizing car tracking data related to the last hour as a data source, link travel speeds are derived from the map-matched trajectory data.

The proprietary LSFCD algorithm is divided in three steps:

a) map matching (using Latitude, Longitude and Heading from the GPS) for each positions.

b) routing (between subsequent positions) to determine the average speed along the tracks.

c) then the link travel speed is estimated base on the GPS position's speed and the track average speed weighted exponentially with the GPS time 'distance' for all cars passing the links.

Extensive field tests done in cooperation with Autostrade per l'Italia Spa (the leading Italian concessionaire for toll motorway, currently managing 2.854 km of motorways) and ANAS (Road and Motorways Authority of Italy) allowed a fine tuning of the LSFCD system and the development of the proprietary algorithms.

The actual accuracy of the OCTOTelematics LSFCD system is over 90% on the entire network, compared with measures coming from AVI (Automatic Vehicle Identification) and will obviously improve with the increase of the number of installed OBU.

IV. Preliminary Analysis of the Estimated Link Speeds: The Rome Ring Road Case Study

A preliminary analysis of the historical time series estimates of link travel speed from the OCTOTelematics LSFCD system was undertaken to select the appropriate prediction model and to identify the candidate input variables. Particularly, an investigation of their dynamic evolution on a given link and an examination of the interaction between neighboring links were carried out.

The FCD travel speeds, aggregated at 3-minute periods (480 values per link and per day), refer to the Rome ring road and cover the whole period ranging from January to April 2008. Currently, the penetration level of equipped private cars in Rome (about 2,4%) is significantly higher than the national average.

The GRA is a toll-free motorway (68,2km in circumference) that encircles Rome, as shown in Fig. 3. As of April 2008 97% of the GRA is 6 lanes (3 lanes per direction) with final sections expected to open by late 2008.

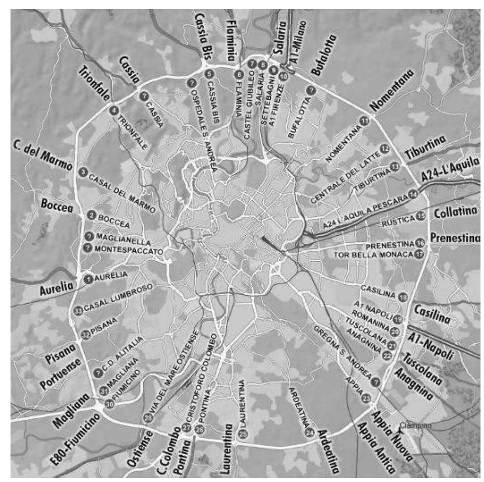

Fig. 3. The Rome Ring Road.

The GRA has 33 numbered entry / exit junctions (starting from "Aurelia" junction and proceeding in the clockwise direction) and is a major city traffic artery distributing traffic on radial routes and handling circumferential traffic in the city. Traffic on the GRA is heavy for most of the day and frequent delays and traffic-jams are experienced in part, due to accidents or queue spillbacks from the exit ramps or the adjacent radial arterial streets leading into the city centre. The most severely congested links are in the south-east quadrant specifically from junction 13 "Tiburtina" to junction 26 "Pontina" (from km 29,9 to km 54,6).

In a working day, about 15.000 floating cars pass through the GRA. The average distances traveled by a floating car on the GRA is about 10 km. During the peak period, an average of more than 2000 floating cars per hour travel on the GRA.

Fig. 4 shows a five-day (on March 3rd to 7th, 2008) time series of FCD travel speeds, grouped into 6 classes, for each of the 24 links used to represent the GRA in the clockwise direction (an aggregation of minor links reduced the number from 33 to 24). The X-axis is the 3-minute time slot for the whole five days and the Y-axis is the label of the link starting from the link between the junctions “Aurelia” and “Boccea”. The label assigned to each link corresponds to the label of the upstream junction.

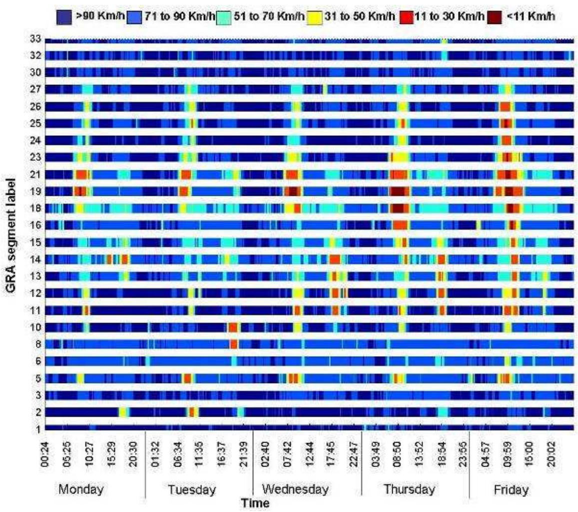

Fig. 4. Spatio-temporal travel speed estimates of GRA

Using this visualization, spatio-temporal traffic patterns can be easily observed such as the morning peak hour shown as the “red” regions, and the occurrence, propagation, and dissipation of traffic congestion.

The observable relationship among the FCD link travel speeds of neighboring links was further investigated with the aim to examine the potential for including values of neighboring links in the prediction model of the target link.

The cross-correlation coefficient function ρ_k, as defined in equation (1) and measuring the degree of linear relationship between random variables at various time lags (corresponding to multiples of 3-minute periods), was used to determine the relationship between travel speed time series of neighboring links:

$$\rho_{(XY)k} = \frac{E[(X_t - \mu_X)(Y_{t+k} - \mu_Y)]}{\sqrt{E[(X_t - \mu_X)^2]E[(Y_t - \mu_Y)^2]}} \qquad (1)$$

The cross-correlations between each GRA link and the neighboring links were calculated taking into consideration FCD link travel speeds from 7:00 am to 8:00 pm of working days over a two-month period.

As an example, Fig. 5 depicts, in both negative and positive directions, the calculated cross-correlation values between the links “19” and the neighboring links.

Fig. 5 indicates that link “19” has a relatively high correlation with the immediate upstream (link “18”) and downstream links (link “21”) and the second downstream link (link “23”).

Analogous ranges of correlation coefficients were found for the other links except in a few links where even a substantial lower correlation with the adjacent links was obtained.

The analysis also confirmed that the correlation between neighboring links decreases as the physical distances increase and the number of time lags grows. However the highest correlation between neighboring links does not necessarily occurs during the same time period (time-lag=0) since shock wave propagation between links may take place when the traffic conditions change.

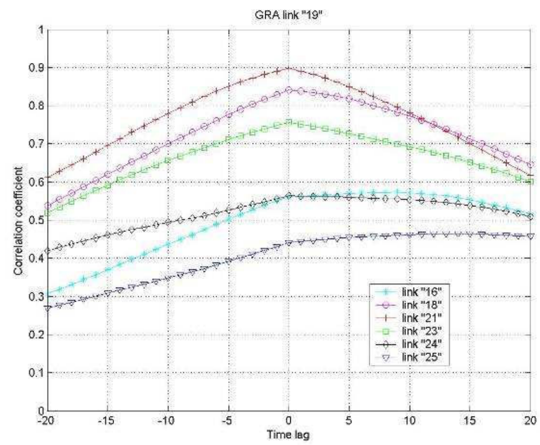

Fig. 5. Cross-correlation of LSFCD travel speeds between link “19” and neighboring links

V. Approaches for short-term travel speed predictions

In this section two algorithms, designed to on-line perform short-term (15 to 30 minutes) predictions of link travel speeds from FCD are presented. The proposed algorithms, based on Pattern Matching and Artificial Neural Networks, have been developed to directly use current and near-past average link speeds estimated for the target link and the correlated upstream/downstream links.

The two algorithms have been chosen because they have the ability to take into account spatial and temporal average speed information simultaneously. The underlying reasoning behind this choice is that knowing what has happened in the preceding time period could be useful for predicting what will happen in the near future for a given link; additionally knowing what has happened upstream and downstream of a given link could also be useful for predicting near future conditions. That is, an increase in congestion on an upstream/downstream links may be a useful indicator of a travel speed change in the near future on the target link.

A Pattern Matching model was applied to predict the future link travel speeds when base data is already classified into categories, whereas a multilayer feedforward neural network combined with a backpropagation algorithm was selected for predicting the link travel speeds when base data is expressed in km/h.

A. *Pattern matching based approach*

The pattern matching approach here proposed as a first method can be assumed when only categorical data (like

"Free", "Congested", etc..) are available to describe the traffic speed. The presented approach can be also seen as an application of the so-called lazy learning modelling [2], this last implying that past examples are considered the only representation of the system being modelled and that available historical database is searched for examples that, according to some measure of distance, are considered most similar to the actual one and extracted to fulfil the prediction requirement generally by means of local techniques.

The method looks at speed data as a categorical time series, that is when speed data are offered over a regular time sequence as quantized into interval data (quantitative situations are often described or measured only in this form). In the specific case we had 4 levels: "Free" for link speed > 90 km/h, "Conditioned" for 50 km/h < speed $\leq$ 90 km/h, "Slowed" for 30 < speed $\leq$ 50 km/h, "Congested" for speed $\leq$ 30 km/h). The method holds advantages and drawbacks that will be traced later, but as a matter of principle short-term prediction in terms of categorical speed data can be in every respect successfully deployed in ATISs, because final users (travellers) can be oriented by categorical results as well as in the case of fully quantitative predictions (or perhaps better due to natural ordering and better understanding of the categorical levels). Different strategies have been proposed for modelling of categorical time series, including Markov chain models, DARMA models, multinomial logit and so on [4]. The present method can be considered as a model-free one in the sense that no structured modelling and consequent (model) parameter fitting is implied.

1) Building a categorical speed pattern

Speed patterns for a specified link can be constructed by lining up present and past categorical speed values of the target and of the spatial correlated upstream/downstream links, so spanning on a temporal as well as on a spatial scale and configuring a reference profile. Fig. 6 presents an example pattern, where the time step k represents the actual time, Ls the target link, Ls_{-1} and Ls_{+1} adjacent upstream and downstream links; the forecast horizon is constituted by the Ls values at time k+1, k+2, etc…

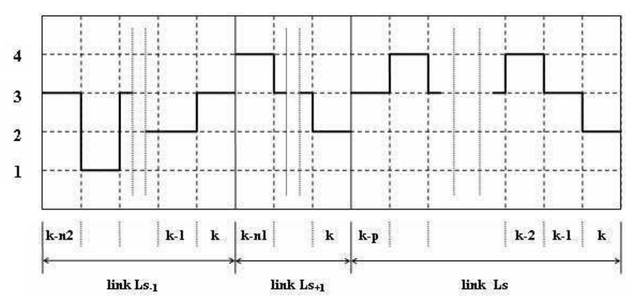

Fig. 6. An example of speed pattern

The composed speed pattern carries out sufficient information about the actual state of the link Ls as long as the time correlation is well justified by the regression parameters p, n_1, n_2, … and the spatial correlation by the chosen upstream/downstream links Ls_{-1}, ..,Ls_{-i}, , Ls_{+1}, ..,Ls_{+h}.

A pattern so structured constitutes the reference pattern when referred to a target link at the current time k; the scanning of historical data base produces a quantity of patterns with an analogous structure delayed in the time, to be compared with the reference pattern in terms of similarity/dissimilarity.

2) Pattern matching process

The assumption of time recurrence of traffic patterns can enable a computationally reduced searching procedure for the patterns most similar to the current one, based on a scanning of all previous days in the historical database within a time frame of $\pm$ x minutes from current time step k [1]; found candidates are then evaluated in terms of their similarity to the current pattern and chosen (or discarded) for the subsequent steps. The Euclidean distance alone is not able to fully represents similarity between two categorical time series (small distances don't correspond necessarily to similar shapes); in categorical case similar trends/shapes could be better represented by measures of rank correlation, like the Spearman, Kendall, Gini etc. coefficients as defined in any standard statistical textbook. In our procedure we use jointly the Euclidean distance E_n (normalized to its greatest value: $0 \leq E_n \leq 1$) and the Spearman coefficient S $(-1 \leq S \leq 1)$ to drive the process of similarity-based selection among the candidate patterns: only the past speed patterns having both E_n and (1-S) within fixed limits: $0 \leq E_{ni} \leq l_{Ef}$ and $0 \leq (1 - S_i) \leq l_{Sf}$ are admitted to the subsequent process of estimation. Selection is also associated to a weighting procedure, in the sense that more emphasis is given to nearest examples through the application to every pattern of a weight w_{ni} inversely proportional to $\sqrt{E_{ni}^2 + (1 - S_i)^2}$ and normalized so that $0 \leq w_{ni} \leq 1$ and $\sum_i w_{ni} = 1$.

3) Estimating the future

Our prediction process relies on the premise that sufficiently similar patterns that occurred in the past history produced dynamical evolutions analogous to those expected in our near future. Once that we have defined a weight for every admitted past pattern, the speed categorical prediction $\hat{s}(k+1)$ at the time step k+1 will be evaluated as:

$$\hat{s}(k+1) = round\left(\sum_i w_{ni} s_i(k+1)\right),$$

$s_i(k+1)$ being the categorical speed value at time (k+1) of the i-th selected past pattern. Similar evaluations can be produced for (k+1), (k+2), etc…

4) Free parameters

Above outlined procedure has several free parameters: upstream/downstream links to complete the pattern together with the target link, regression orders p, n_1, n_2, …, interval limits l_{Ef} and l_{Sf}, all needing a careful tuning. We adopted a trial and error procedure for parameter tuning, obtaining the following perhaps simplifying result: the "best" categorical speed pattern consists of the target data, regressed in time for about half an hour, of the adjacent upstream link, regressed in time for about a quarter of an hour, and of the adjacent downstream link, also regressed in time for about a quarter of an hour. This structure assured good results on prediction testing conducted on the historical data. Interval limits l_{Ef} and l_{Sf} were chosen on the basis of a trade off in order to assure sufficient sample sizes and significant levels of similarity $\left(l_{Ef} = l_{Sf} \cong 0.1\right)$.

5) Results

Fig. 7 presents the 15 min ahead prediction results on March 10th 2008, from 7:23 to 20:53, for the link “19”, showing (upper diagram) the comparison between true values (blue crosses) and estimated five-step predictions (red circles), and (lower diagram) the corresponding number of selected past examples (higher curve, blue crosses) every half an hour. As it can be noted, whenever we have a sufficient number of similar past patterns (of the order of several hundreds), the estimated speed class results right (with exceptions, as in the prediction # 12, where the numerous past examples conspire to give a wrong result). This is an expected limit of the method, in the sense that it is incapable of generalization, so when past examples are absent or insufficient, the estimation process fails or can degrade. A more general analysis on all GRA links reports that the 15 min. ahead prediction suffers from an average misclassification error of about 18.7%.

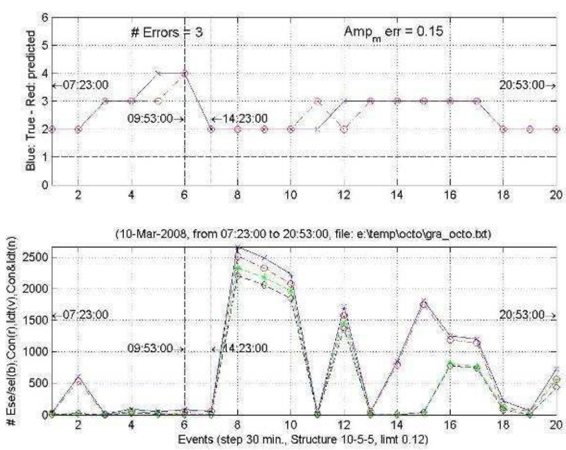

Fig. 7. Pattern matching prediction results for the GRA link “19”

B. *Artificial Neural Networks based approach*

Artificial Neural Networks (ANNs) are quantitative models which learn to associate input and output patterns adaptively with the use of learning algorithms without understanding the fundamental or physical relationships between them [9].

In general, feedforward ANNs consist of processing elements (neurons), or units, arranged in layers and relations between neighboring layers' units, whereas units in the same layer are not connected to each other. Feedforward ANNs comprise an input layer, one or more hidden layers and an output layer, furthermore each layer contains different number of units.

As a rule, the type and number of units in the input layer, as well as the appropriate number of units and hidden layers are chosen through a preliminary analysis of the data or by empirically comparing the results from different ANN architectures having different input variables and units in the hidden layers.

The relations between neighboring layers’ units are defined by the weights given to the connections during the training process. The output of each unit is given by a transfer function fed up with the weighted sum of the incoming units values and then transmitted to all of the units in the next layer. Log-sigmoid or tan-sigmoid are commonly used as transfer functions.

In the GRA case study, two feedforward ANN models for each link with one hidden layer (including at most 40 units) were proven to perform best link travel speed predictions in the learning-testing process.

The two ANN models, aimed at predicting the link travel speed respectively at 5 and 10 steps into the future (15 and 30 minutes), incorporated as input the current and the near-past 10 and 15 FCD travel speeds of the target link, respectively.

Moreover the two ANN models considered as input the current and at most the near-past 10 FCD travel speeds of the immediate neighboring upstream and downstream links to reflect the correlation degree (higher than 0,60) between neighboring links found in the correlation analysis.

FCD link travel speeds stored from 7:00 am to 9:00 pm were used in the learning-testing process. In particular, forty-seven working days were considered for the learning and testing process, respectively.

The Levenberg-Marquardt learning algorithm was used for training the ANN models whereas the mean absolute percentage error (MAPE) and the root mean square error (RMSE), defined by equations (2) and (3), were calculated for investigating the accuracy of the models in the testing process:

$$MAPE = \left(\frac{1}{N} \sum_{i=1}^{N} \left| \frac{x_i - \hat{x}_i}{x_i} \right| \right) * 100 \qquad (2)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left(x_i - \hat{x}_i \right)^2} \qquad (3)$$

where N is the total number of testing cases, $\hat{x}_i$ the predicted link speed and x_i the FCD link speed.

According to the calculated MAPE and RMSE values, the two ANN models, incorporating current and near-past FCD travel speeds from the target link and the neighboring correlated links, showed good prediction accuracy and generalization ability.

The MAPE ranged from about 2% to 8% for 15-minute predictions and from about 3% to 16% for 30-minute predictions. The RMSE varied from about 2 to 7 km/h for

15-minute predictions and from about 3.5 to 9.5 km/h for 30-minute predictions (Fig. 8).

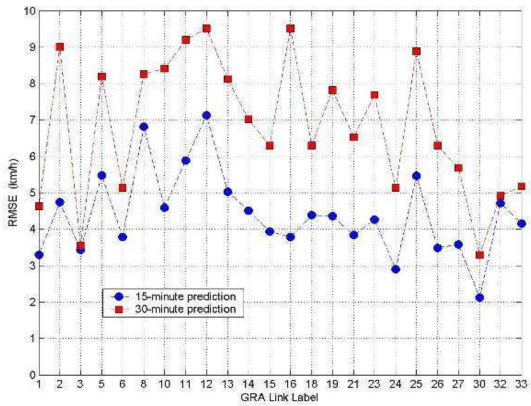

Fig. 8. The resulting RMSE for each GRA links

The proposed models were also able to adequately capture FCD travel speeds fluctuations during transitions from uncongested to congested and back to uncongested conditions. Nevertheless, a larger learning and testing data set is needed to best evaluate the performance of the proposed models mainly in the transition periods caused by non-recurring congestion events.

In addition, better performance could reasonably be expected by incorporating into the neural network structure other information such as FCD travel speeds of adjacent radial street links and/or traffic flow, density and occupancy from fixed traffic sensors installed along the GRA.

VI. CONCLUSIONS

The use of large scale real-time FCD is gaining an important role as component of ATIS applications because of its cost-effectiveness compared to other traffic data sources. A fundamental requirement is its statistical consistency that can be assured only when the number of traveling monitored cars achieves a significant penetration level and the single car transmission rate is adequate. The Italian FCD system developed and operated by OCTOTelematics is a wide-ranging and still growing application, currently reaching a penetration level of about 1.7% in the Italian privately owned car fleet and projected to rise to 3% by the end of 2009.

Actually, the system updates every 3 minutes link travel speeds along the Italian motorway network (more than 6.000 Km) and some important arterial streets located in major Italian metropolitan areas. According to field tests, the accuracy of the LSFCD System in estimating current link travel speeds is about 90%.

Based on this data consistency and reliability, two methods were developed for short-term speed predictions. The former applicable to categorical speed data is based on a procedure of pattern matching and usable when only simplified information is available, as in the case of data freely issued by OCTOTelematics web site. The latter uses the well established modeling by means of neural networks, that deals with fully quantitative data and makes associations between input and output patterns. Both methods performed good prediction capabilities, each one in its particular context, and their utilization into a real-time ATIS application resulted proven.

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