Urban Traffic Flow Forecasting Using Neural-Statistic Hybrid Modeling

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Abstract. In this paper we show a hybrid modeling approach which combines Artificial Neural Networks and a simple statistical approach in order to provide a one hour forecast of urban traffic flow rates. Experimentation has been carried out on three different classes of real streets and results show that the proposed approach clearly outperforms the best of the methods it combines.

1 Introduction

Transportation is a wide human-oriented field with diverse and challenging problems waiting to be solved. Characteristics and performances of transport systems, services, costs, infrastructures, vehicles and control systems are usually defined on the basis of quantitative evaluation of their main effects. Most of the transport decisions take place under imprecision, uncertainty and partial truth. Some objectives and constraints are often difficult to be measured by crisp values. Traditional analytical techniques were found to be not-effective when dealing with problems in which the dependencies between variables were too complex or ill-defined.

Moreover, hard computing models cannot deal effectively with the transport decision-makers' ambiguities and uncertainties.

In order to come up with solutions to some of these problems, over the last decade there has been much interest in soft computing applications of traffic and transport systems, leading to some successful implementations[3].

The use of Soft Computing methodologies (SC) is widely used in several application fields [1][10][24][25]. In modeling and analyzing traffic and transport systems SC are of particular interest to researchers and practitioners due to their ability to handle quantitative and qualitative measures, and to efficiently solve complex problems which involve imprecision, uncertainty and partial truth. SC can be used to bridge modeling gaps of normative and descriptive decision models in traffic and transport research.

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Transport problems can be classified into four main areas : traffic control and management, transport planning and management, logistics, design and construction of transport facilities.

The first category includes traffic flow forecasting which is the topic tackled in this work. This issue has been faced by the soft computing community since the nineties [8, 11, 15, 22, 27, 28, 29] up today [7, 9, 16, 21] with Artificial Neural Networks (ANN) [2,13]. As example, among the most recent work [16] focuses on traffic flow forecasting approach based on Particle Swarm Optimization (PSO) with Wavelet Network Model(WNM). [21] reviews neural networks applications in urban traffic management systems and presents a method of traffic flow prediction based on neural networks. [7] proposes the use of a self-adaptive fuzzy neural network for traffic prediction suggesting an architecture which tracks probability distribution drifts due to weather conditions, season, or other factors. Among the other techniques SVR[14], Adaptive Hinging Hyperplanes[20] and Multivariate State Space [26] are worth mentioning.

All the mentioned applications have one feature in common : they use one single global model in order to perform the prediction. Therefore, the main novelty of the proposed work is to combine different heterogeneous models in order to get a meta-model capable of providing predictions more accurate than the best of the constituent models. In particular, we compose a neural networks ensemble with a simple statistical model and compare the results over the one hour forecast.

2 Methods

2.1 Naïve

In order to perform a meaningful comparison for the forecasting, a naïve model should be introduced in order to quantify the improvement given by more intelligent and complex forecasting techniques. For seasonal data a naïve model might be defined as:

$$x_t = x_{t-s} \tag{1}$$

with S the appropriate seasonality period. This model gives a prediction at time t presenting the value observed exactly a period of S steps before. For this work we put the value of S = 1 which corresponds to the previous hour. It means that to predict the flow rate of the following hour it is used the current flow measure.

2.2 Statistical

One the simplest and most widely used models when dealing with regular time series (as urban traffic flows) is to build an average weekly distribution of the traffic flow sampled hourly. Thus, from the data we compute for each day the average flow rate hour by hour in such a way that we get an average distribution made of 24X7=168 points.

2.3 Neural Networks Ensembling

The other method, as suggested also by literature, we applied is ANN and ANN ensembling. The term 'ensemble' describes a group of learning machines that work together on the same task, in the case of ANN they are trained on some data, run together and their outputs are combined as a single one. The goal is obtain better predictive performance than could be obtained from any of the constituent models. In the last years several ensembling methods have been carried out [6, 18, 19]. The first one, also known as Basic Ensemble Method (BEM), is the simplest way to combine M neural networks as an arithmetic mean of their outputs. This method can improve the global performance [5, 23] although it does not takes into account that some models can be more accurate than others. This method has the advantage to be very easy to apply. A direct BEM extension is the Generalised Ensemble Method (GEM) [5, 23] in which the outputs of the single models are combined in a weighted average where the weights have to be properly set, sometimes after an expensive tuning process. Other methods are Bootstrap AGGregatING (BAGGING) [17] and Adaboost [4, 12].

2.4 Hybrid Model

Hybrid models are an extension of the ensembling approach in the sense that the final goal is to combine different models in such a way that the accuracy of the composition is higher than the best of the single models. The difference is that the combination is performed among highly heterogeneous models, that is models generated by different methods with different properties and thus the composition among them is a complex rule taking into account the peculiarities of the models and/or of the problem itself.

Therefore, in this work we propose a novel hybrid model which combines an ANN ensemble with the statistical model.

The composition rule is the following :

"IF the statistical model has a high error (meaning that for some reason we are out of a normal situation) THEN use the neural model ELSE use the statistical one"

This criterion is based on the absolute error of the statistical model, thus the composition rule turns into

$$\begin{array}{lcl} |x^t - y^t_s| > \varepsilon & \Rightarrow & y^{t+1} = y^{t+1}_n \\ |x^t - y^t_s| \leq \varepsilon & \Rightarrow & y^{t+1} = y^{t+1}_s \end{array} \qquad (2)$$

Where y^{t+1} is the outcome (one hour prediction) after the composition rule, y^{t+1}_n is the prediction of the neural ensemble, y^t_s is the current outcome of the statistical model and y^{t+1}_s is its prediction.

This basically means that if we are in normal statistical conditions (where the statistical model makes a small error) then use as prediction model the statistical one (which is very accurate in this condition), else (when out of normal statistical situations) take the neural ensembling estimation.

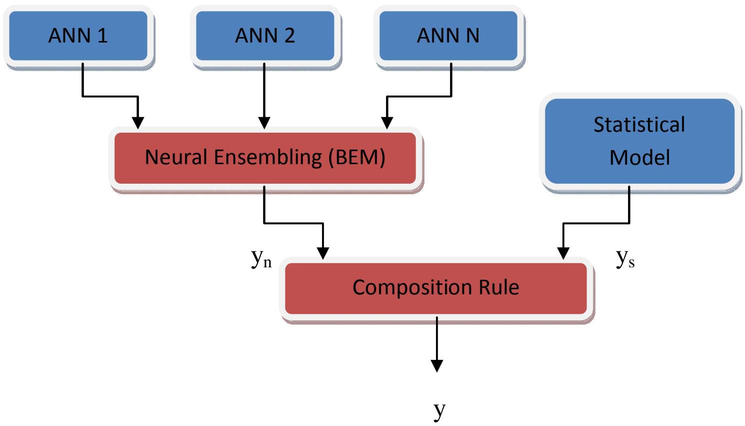

Fig. 1. Proposed hybrid modeling approach

3 Experimentation

In this paragraph we test and compare the methods presented in the previous section. The test case has concerned the short term traffic flow rate of three different streets (tab.1) located in the town of Terni (about 90km north of Rome). The data set is made of 3 months (13 weeks) of measurement corresponding to 2184 hourly samples. The data set has been partitioned into training/testing and validation made respectively of 10 and 3 weeks each.

Table 1. Street features

	Maximum traffic flow rate
Street 1	600
Street 2	800
Street 3	950

The ANN are feed-forward MLP with 10 hidden neurons and one output (the one hour flow forecast) with sigmoid as activation function for all the neurons. The number of inputs N has been chosen with a preliminary analysis by calculating the validation prediction error after ensembling for different values of N (tab.2). By this analysis it turned out the optimal number of input neurons (namely the length of the history window) to be eight.

Training has been performed through the Back-Propagation algorithm with adaptive learning rate and momentum stopping after 100000000 iterations and a 'save best' strategy to avoid overfitting. The reported result are averaged over 10 different runs (with standard deviation in brackets) and the ensemble is therefore made by the same 10 models.

The reported errors are measured as

$$e = |x\text{-}y|/(M\text{-}m) \tag{3}$$

Where x is the real value to be predicted, y is the output model, M is the real maximum value and m is the minimum.

Table 2. History length selection

N (hours)	Street 1	Street 2	Street 3
3	5.72%	6.88%	5.81%
5	3.9%	5.07%	3.99%
8	3.29%	3.43%	3.02%
10	3.54%	4.12%	3.74%

Afterwards, it has been tuned (tab.3) the parameter ε of the hybrid model (2).

Table 3. Hybrid model parameter ε tuning

	ε=10	ε=20	ε=30	ε=40	ε=50	ε=60
Street 1	2.98%	2.83%	2.81%	2.8%	2.88%	2.99%
Street 2	2.85%	2.69%	2.65%	2.66%	2.68%	2.75%
Street 3	3.25%	3.13%	3.08%	3.04%	3.03%	3.04%

At last, the following table shows the comparison of the models considered in this work in terms of prediction accuracy over the validation set and figure 2 shows a graphical comparison.

Table 4. Model comparison

	Naive	Statistic	ANN	ANN Ensembling	Hybrid
Street 1	8.92%	5.90%	3.74% ±0.10%	3.29%	2.8%
Street 2	9.99%	7.14%	4.00% ±0.10%	3.43%	2.65%
Street 3	7.66%	5.56%	3.48% ±0.09%	3.02%	3.02%
Average	8.86%	6.20%	3.74% ±0.10%	3.25%	2.82%

From this analysis it is clear that in general the proposed hybrid approach outperforms the best of the 'classical' models (which turns out to be ANN ensembling) providing a remarkable improvement in prediction accuracy. Such level of precision is very important when dealing with applications like traffic and lighting control where the higher the model accuracy is the more effective the control system is.

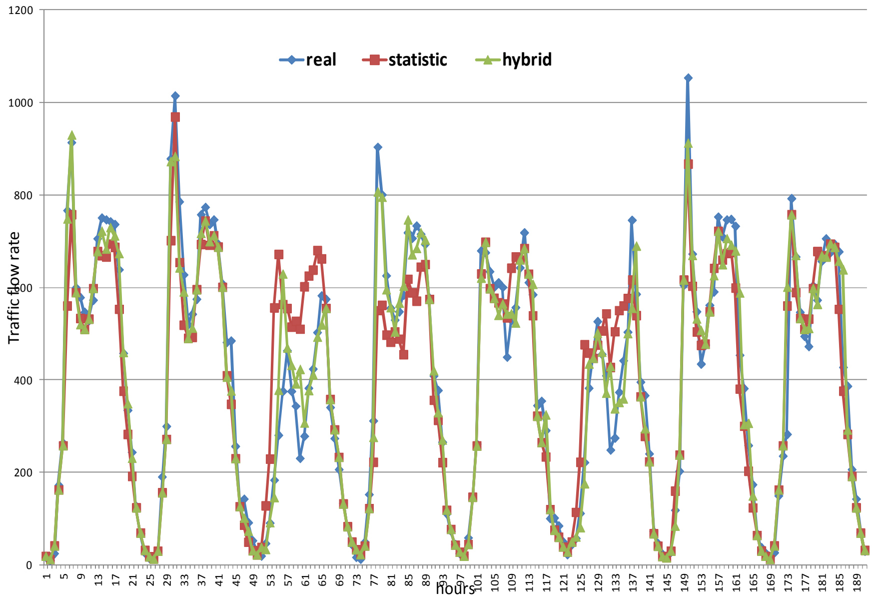

Fig. 2. Model comparison

From this graph it is clear that the hybrid model performs much better than the statistical model because, when out of normal conditions, it switches to the neural ensembling method which takes into account the real traffic dynamics.

4 Conclusion

In this paper we showed a novel hybrid modeling approach which combines Artificial Neural Networks and a simple statistical approach in order to provide a one hour forecast of urban traffic flow rates. Experimentation has been carried out on three different classes of real streets and results showed that the proposed approach clearly outperforms the best of the methods it puts together achieving a prediction error lower than 3%. The reason for that is that the neural ensembling model is capable to provide more reliable estimations when out of standard conditions because it considers the real traffic dynamics.

The accuracy of the proposed hybrid modeling approach is such that it can be applied for intelligent monitoring, diagnostic systems and optimal control.

Future work will focus on further modeling improvements using more sophisticated ensembling methods as well as different composition methods for the hybrid model based on fuzzy sets rather than fixed thresholds. Moreover, the proposed method will be compared to other approaches already used in the field as Wavelets, SVR, Adaptive Hinging Hyperplanes and Multivariate State Space.

As application, we are going to use these models in public lighting control in order to reduce energy consumption.

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