LANE OCCUPATION MODELS IN MOTORWAY SECTIONS BEFORE A TOLL-GATE STATION

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Abstract. The paper analyses lane occupation in some three lane motorway sections preceding a toll-gate station. Using data collected on a Northern Italian motorway over a period of about nine months and by treating them appropriately the distribution of flow over the three lanes for four sections is studied.
This distribution depends on the three fundamental variables, speed, flow and density, but also on composition of flow (percentage of heavy vehicles), environmental variables (brightness and visibility) and on which section is considered (near or far a toll-gate).

Keywords: Traffic Control, Flow, Models, Neural Networks, Backpropagation

1. INTRODUCTION

It appears very important to investigate driver lane distribution both for control purposes and for planning. Up to now, how and how much these choices are conditioned by the presence of traffic disturbances, in particular those produced by a toll-gate, is not yet investigate in-depth.

A lot of models were developed to describe lane occupation of vehicles (Gipps, 1986; Alvarez et al., 1990; Fisk, 1990; Schmidt et al., 1991; Wemple et al., 1991). They are based on hypotheses related to driver behaviour and on the used flow model such as, for example, the hydrodynamic or the car-following model. Real flow data are used only to fit model parameters but not to reveal particular driver behaviour.

The aim of this paper is to carry out a model of lane occupation without making any a priori assumption about driver behaviour and influence on driving due to flow composition and environmental conditions. In authors' previous works (Mussone, 1995; Florio and Mussone, 1995b) flow models for different sections and meteorological conditions are proposed by means of using neural networks and these models have shown the influence of meteorological data and flow composition to determine the capacity value for a single section. In the previous works the authors used neural network technique with the only assumption that a function (linear or not linear) relating variables exists and can describe that process. In the same way the relationships among flow distribution over lanes and flow, environmental data can be treated. Neural network approach guarantees approximability of any continuous function and therefore are well suited for the above-mentioned objective.

2. DATA COLLECTION AND EXTRACTION

The data used in the present study, were collected in the "Easy Driver" environment (FIAT, 1992), a traffic control system which was employed in Italy on the Padua-Mestre (Venice) motorway, a rectilinear section from the tollgate of Dolo to the end-motorway tollgate of Mestre, over a distance of about 11 km.

Data collection has already been described in previous papers (Florio and Mussone, 1995a, 1996) and here only some synthetic information are reported.

Along the “Easy Driver” section detection stations are set up: 20 detection points (from 1.1 to 10.2) for the detection of flow characteristics (one every 0.5 km) by using electromagnetic inductive loops, five stations for detecting visibility, 2 for weather conditions, two for the presence of ice, 10 portals with variable message signs for driver information. The portals are set up along the whole section.

Over a nine-month period, from December 1992 to August 1993, flow values relative to the following parameters were collected: average spatial speed, density, traffic flow for each lane, percentage of heavy good vehicles, brightness, weather conditions, visibility. Brightness evaluates the presence of light according to a scale from 1 (night) to 6 (vivid light).

Data were grouped according to the results of each single detection station and identified by the microprocessor which controls their loops. The formal difference among these "files" essentially consists of the different sampling period, which ranges from 20 to 120 seconds for the flow data (density, average space speed and vehicular count), from 60 to 120 seconds for weather condition, 2 minutes for brightness, 10 minutes from messages and 15 minutes for the flow characteristics per vehicular category. The subdivision of the flow into light vehicles and heavy goods vehicles was performed on the basis of ANAS Italian code, thus vehicles belonging to the first three categories (up to 5.5 meter long) were considered as light, whereas those belonging to the last three categories (longer than 5.5 meters) were considered as heavy. Information on weather conditions was not monitored on all the sections and the sampling period adopted within file data was different. Therefore a method to group together data is necessary considering both time and space.

The spatial association concerns the files of data relative to brightness and meteorological conditions. The files relative to vehicle categories and diagnostic of detection loops, are instead available for each section. In this case the criteria is that of linking to each section information of the nearest meteorological or brightness station.

For time resolution, the file of reference was the flow detection file (present for each station) which turned out to have the major sampling frequency (40s average). A procedure which, starting from the flow data file associates all consistent compatible data to that file, thus generating a single "file" whose records include all useful information. For each station the records available are almost 360,000.

Another topic is related to data distribution over the considered variables. In fact, the various flow conditions detected on a motorway are usually fairly different in their frequency. The samples of unstable flow or near to capacity, for example, are far less numerous that those relating to stable flow. Since the aim is to represent all the features of the flow, the extraction of the sample for the learning process should be preceded by a data classification, grouping data into categories.

For this purpose, a further variable was created, related to a first associating criterion which is based on the detection of the following information: presence of rain, snow/ice, percentage of heavy goods vehicles (the mean value among the three lanes), visibility and brightness. Considering these values as a part (one or two bits) of complex information (byte), the category which the datum belongs to, is then represented by a binary word, which is to be built up for this purpose. In the present case, 8 bits are enough to identify the various cases.

A second classification was performed according to density. A numeric variable represents a density category. Since all the characteristics of the process should be represented, the extraction of data is performed by class of data including a maximum number of elements, consistent with the mean frequency of classes.

For the present study four sections are considered, 2.1,5.2, 7.1, 10.1, and the same methodology was applied to them. The number of extractions from each class were found to consist of 5 or 6 according to the section considered and the extracted data are quite homogenous around 900. It can be observed that the low frequency in each class is fairly well compensated by the iterative learning procedure of neural networks, which usually considers the same learning set several times.

With regard to the learning process and to the cross-validation technique of the neural network, two sets of data, one for learning and one for validation, were created, as explained in the following paragraphs, by means of an extraction from all the data. Data are then normalised according to their highest values; results are therefore normalised to those values. For the traffic flow, the maximum value of 6,000 veh./h for the three lanes was assumed; for speed the maximum value was 200 km/h and for density 150 veh./km per lane.

3. THE NEURAL NETWORK MODELS

The model is worked out by means of using feedforward neural networks, whose capabilities in the field of non-linear dynamic systems modelling are well known (Mussone, 1995), (Dougherty, 1995).

These networks are well described in technical papers and a lot of theorems state that multi-layered feedforward neural networks (with at least one hidden

layer), by using neuron transfer functions of a sigmoidal type and linear input combinations, can approximate any function which belongs to L^2 space with a small margin of error (Cybenko, 1989; Hornik et al., 1990; Hornik, 1991; Girosi et al, 1991; Leshno et al, 1993). These models are referred to without inferring anything from their physical characteristics, using the so called "black-box" approach. It should be said that the attempt to deduce anything from the values of the connections appears a long and difficult operation which gives few useful results. The number of hidden neurons, and the number of layers needed to obtain the desired approximation is still being studied.
The paradigm used in learning networks was backpropagation (BP) (Rumelhart et al., 1986): it is a heuristic solution to the training problem. Many authors, such as (Weiss et al., 1991; Sjöberg et al., 1994; Masters, 1993) underline the difficulties of training, and in particular the problems of overfitting or overtraining which adversely affect the performance of a neural network.

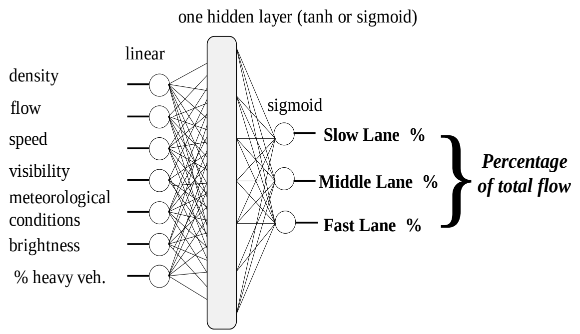

Fig.1: The neural network model scheme

The building of a feedforward neural network model, with backpropagation learning, requires the determination of the proper number of hidden neurons and layers in an attempt to minimise the error on both learning and test data. The proper number of neurons refers to the minimisation of the output error i.e. to the best performance of the network.

There are many techniques to an optimum exploitation of data: cross-validation, Jacknife and Bootstrap (Efron, 1982), (Weiss et al., 1991). Cross-validation is the most known technique and it essentially consists in dividing data into two disjoint sets, one for training and the other for validation. Different topological networks are evaluated on the basis of these two sets. The Jacknife technique (Efron, 1982) divides data into N disjoint sets; each of these sets contains one element for validation and N-1 for training. Then N+1 identical neural networks are created; only one network, called master, is trained on the basis of all data; the other networks, called slaves, are trained and tested on the basis of the N disjoint sets. Test error evaluated on slaves networks is an estimation of generalization capability of the master network. In Bootstrap technique extraction of the two sets is randomly and repeated more times. Then, for validation cross-validation or Jacknife technique can be used.

The optimum configurations of the network (in the sense of performance) are necessarily related to the phenomenon of overfitting. Recent studies suggest that overfitting occurs essentially because of two main reasons: firstly, the network is not properly sized compared to the available data; secondly, data are not sufficiently representative of the function to be implemented, thus the two sets of data, the test and train sets, are remarkably different from each other.

To work out the models the authors used the cross-validation technique which appears to fit better to the dimension of data set. To overcome the above-mentioned learning problems, a lot of network configurations with one or two hidden layers, with a different number of hidden neurons and different transfer function (sigmoid, tangent hyperbolic and sine function) were built up. The first layer, the input one, has always neurons with linear transfer function.

After several trials the optimal models are carried out. The number of learning iterations varies according to the model. In Tab. 1 these features and other performance (on the test set) of the optimal models are reported. The first column refers to the motorway section considered, the following three refers to the characteristic of the hidden layers (number of hidden layers and neurons, and neuron transfer function); the number of iterations is the number of learning iterations for the model; correlation is the correlation between desired and real data calculated over the three lanes; the coefficient of linear regression is reported to see if there is any bias in data; Sxy is the standard error calculated according to (1):

$$Sxy = \sqrt{\left(\frac{1}{n(n-2)}\left[n\sum y^2-\left(\sum y\right)^2-\frac{\left[n\sum xy-\sum x\sum y\right]^2}{n\sum x^2-\left(\sum x\right)^2}\right]\right)} \quad (1)$$

where y is the real data, x the desired data, n is the dimension of the test set and the summations are from 1 to n; RMSE is the root mean square error calculated according to (2):

$$RMSE = \sqrt{\left(\frac{\sum(x-y)^2}{n}\right)} \quad (2)$$

where y,x, n and summation are the same as for Sxy.

It must be noted that the sum of the three percentages is almost always correct and quite close to 1 with a maximum error of 2-3% in few cases.

This result is particularly interesting because in the learning data this information was not explicit. Nothing it is possible to say about the use of tangent hyperbolic or sigmoid transfer function in the hidden layer: probably it depends on data distribution but until now it cannot be demonstrated.

Tab. 1: Features and test errors of the four optimal models.

Models	**Hidden Layers**	**Hidden neurons**	**Transf. function**	**Iterations No.**	**Correlation**	**Lin. Reg. Coeff.**	**Sxy**	**RMSE**
Section 2.1	1	4	tanh	10.000	0.718	0.521	0.1017	0.1389
Section 5.2	1	7	tanh	3.000	0.782	0.701	0.1149	0.1168
Section 7.1	1	8	sigmoid	10.000	0.755	0.577	0.0930	0.1215
Section 10.1	1	6	tanh	10.000	0.739	0.527	0.1275	0.1269

4. RESULTS

The models reflect the neural network black-box approach so that a large number of input cases are prepared to ask the network and to know its characteristics and the following figures are only a small number of those obtainable by the model.

Flow, speed, and density values, necessary to ask the models, are obtained from previous models (Mussone, 1995; Florio and Mussone, 1995b) of density-flow and speed relationships (Fig 2) which relate these variables to the environmental variables (visibility, meteorological conditions, brightness) and the percentage of heavy vehicles, one for each section considered.

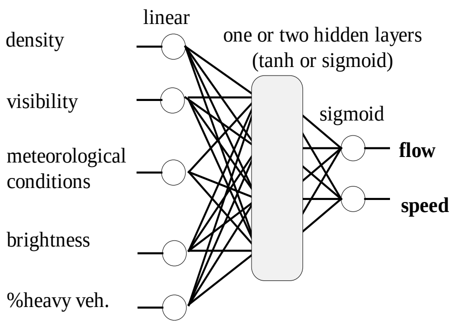

Fig. 2: The flow-speed-density model used to calculate their combined values

The cases consider different values of density from 1 to 90 veh./km (higher values are not meaningful because represent strong congestion situations), daytime and night-time conditions, visibility and brightness; the percentage of heavy vehicles is varied from 0% to 20% and 40%.

In Fig.s 3 to 5 the results concerning section 10.1 which is rather near the toll-gate are reported; in Fig.s 6 to 8 those concerning section 5.2 which is five kilometres far from the toll-gate are reported.

It is possible to assert that each section exhibits a different shape only partially due also to model error but that some similarities are rather evident; the more meaningful of these are:

- the middle lane is the most used lane in all conditions except when the percentage of heavy vehicles becomes greater than 20%;
- increasing the heavy vehicle percentage, the flow distribution over lane changes drastically and the slow lane has the highest percentage reaching also the 70% (it must be remembered that in the Italian motorways heavy vehicles must run on the slow lane and they can use the middle lane only to overtake);
- decreasing visibility the middle lane (and less the fast lane) occupation increases;
- rain does not affect significantly the shape of the curves;
- lane occupation is not a linear relationship with density: when density increases the fast lane occupation increases a lot (in some cases over the 70%);
- because flow is also not a linear relationship with density it must be expected that flow distribution on lanes will have rather different paths;
- the difference of percentage among lanes may be rather high (50%) when flow is far from congestions (a peak is observed near capacity for middle and fast lanes);
- approaching the pay-toll station (section 10.1) the slow lane may have the greatest percentage; the same effect is seen at the beginning of the detected motorway (section 2.1) where there is a merging point for an input-output station;
- in sections far from disturbance (sections 5.2 and 7.1) the middle lane has always the greatest percentage except when heavy vehicles percentage overtakes the 40%;
- approaching the toll-gate lane or leaving a merging point occupation becomes more sensitive to all parameters; the 10.1 and 2.1 sections show this phenomenon rather well;
- brightness (that is, daytime or night-time) affects the shape of the curves; the middle lane and, in a smaller extent, the slow lane occupation increases

significantly.

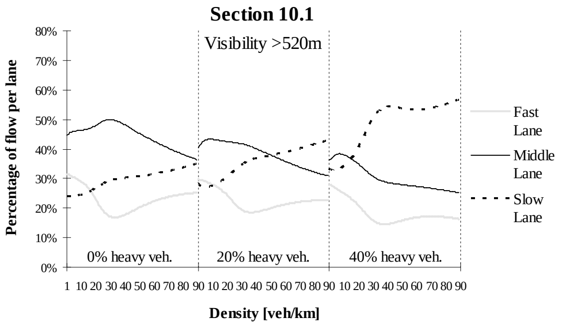

Fig. 3: The percentage of flow per lane in a section (10.1) near the toll-gate when visibility is good and changing the percentage of heavy vehicles.

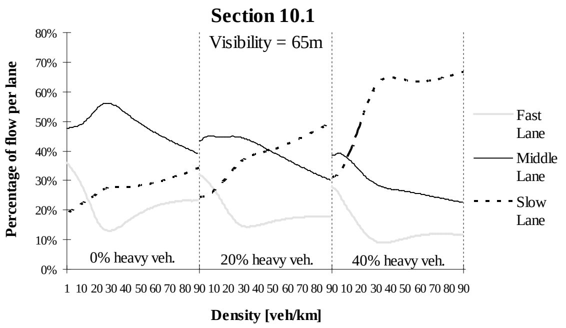

Fig. 4: The percentage of flow per lane in a section (10.1) near the toll-gate when visibility is limited to 65 metres and changing the percentage of heavy vehicles.

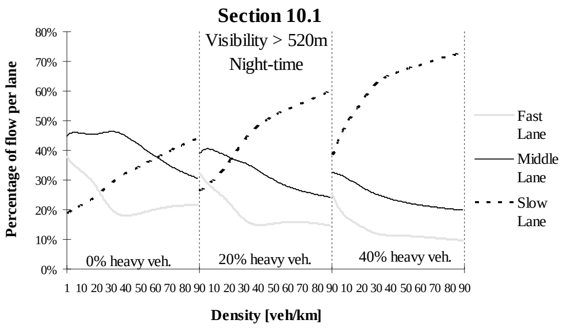

Fig. 5: The percentage of flow per lane in a section (10.1) near the toll-gate when visibility is good in night-time and changing the percentage of heavy vehicle.

5. FINAL REMARKS

Results highlight the influence on lane occupation of the proposed input parameters. Density, brightness and percentage of heavy vehicles lead to considerable modifications in the curves, and the consequent effects are clearly distinguishable.

Rain does not affect considerably the curves. This surprising result may be explained by the fact that

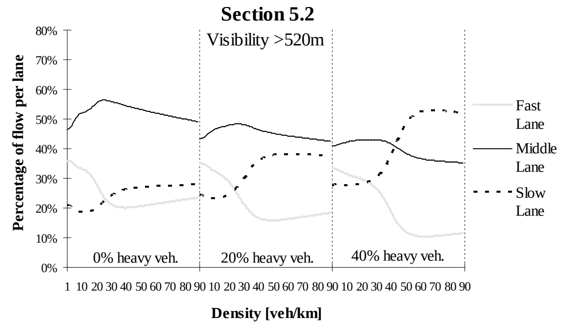

Fig. 6: The percentage of flow per lane in a section (5.2) far from the toll-gate when visibility is good and changing the percentage of heavy vehicles.

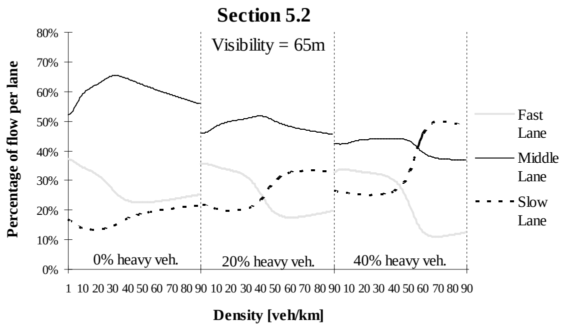

Fig. 7: The percentage of flow per lane in a section (5.2) far from the toll-gate when visibility is limited to 65 metres and changing the percentage of heavy vehicles.

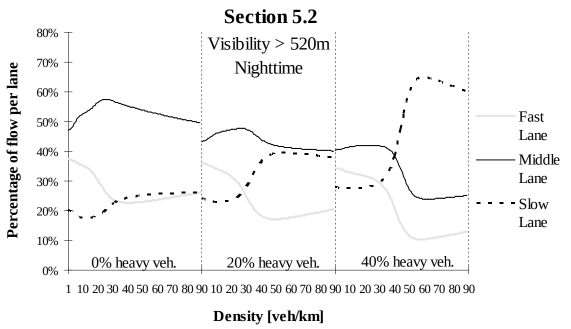

Fig. 8: The percentage of flow per lane in a section (5.2) far from the toll-gate when visibility is good in night-time and changing the percentage of heavy vehicles.

this parameter reduces capacity and decreases speed but probably does not affect the driver choice of the lane.

There are some important differences among sections. It is not possible to say if these differences arise because drivers know the presence of the down-stream toll-gate station or flow characteristic which induce them to behave in a different way.

Approaching the toll-gate, lane occupation becomes more sensitive to all parameters. The 10.1 section shows this phenomenon rather well.

A first conclusion may be that driver behaviour in each section is quite different and each of them needs a dedicated study to know the prevalent driver behaviour style. Besides this, further studies need to better knowledge about spatial effect on lane occupation particularly when a motorway has different planimetric developments other than rectilinear.

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REFERENCES

Alvarez A., Brey J.J., Casado J.M. (1990). A simulation model for traffic flow with passing. *Transpn. Res.*, Vol. 24B, No. **3**, pp. 193-202.

Cybenko G. (1989). Approximation by superpositions of sigmoidal functions. *Mathematics control, signals and systems* , **2**, 303-314.

Dougherty M. (1995). A review of neural networks applied to transport. *Transpn. Res. -C,* Vol. 3, No. 4, pp.247-260, 1995.

Efron B. (1982). The Jacknife, the Bootstrap and other resampling plans. *Society for industrial and applied mathematics*, 1982.

FIAT, Società Autostrade Venezia Padova (1992). EASY DRIVER: Sistema di controllo del traffico sull'autostrada Padova/Mestre, HOTEL Sheraton, Padova, 19 Giugno 1992.

Fisk C.S. (1990). Effects of heavy traffic on network congestion. *Transpn. Res.,* Vol. 24B. No. **5**, pp. 391-404.

Florio L., Mussone L. (1995a). Neural network models for classification and forecasting of highway traffic flow stability. In: *Transportation Systems: Theory and Application of advanced technology* (Liu B., Blosseville J.M., Ed.s), pp. 773-784, A postprint volume from the 7th IFAC Symposium, Tianajin, August 24-26, 1994, Pergamon.

Florio L., Mussone L. (1995b). Freeway section capacity for different meteorological conditions using neural networks. 7th WCTR, World Conference on Transport Research, 19-23 July 1995, Sydney, Australia, to be published by Elsevier.

Florio L., Mussone L. (1996). Neural network models for classification and forecasting of highway traffic flow stability. *Control Engineering Practice*, Vol. 4, No.**2**, pp. 153-164, 1996.

Gipps P.G. (1986). A model for the structure of lane-changing decisions. *Transpn. Res***.**, Vol. 20B, No. **5**, pp. 403-414.

Girosi F., Poggio T. (1991) Networks for learning. In: *Neural networks: concepts, applications and implementation* (Antognetti P., Milutinović V., Ed.s), 110-154, Prentice Hall, Inc., 1991.

Hornik K., Stinchombe M., White H. (1990). Universal approximation of an unknown mapping and its derivative using multilayer feedforward networks. *Neural Networks* **3**, 551-560.

Hornik K. (1991). Approximation capabilities of multilayer feedforward networks. *Neural Networks* **4**, 251-257.

Leshno M., Lin V. Ya., Pinkus A., Schocken S. (1993). Multilayer feedforward networks with a non polynomial activation function can approximate any function. *Neural Networks* , **6**, 861-867.

Masters, T. (1993). *Practical Neural Network recipes in C++*. Academic Press, Inc.,1993.

Mussone L. (1995). Neural Networks to evaluate motorway flow relationships in different meteorological and flow conditions. In: Artificial Intelligence *Applications in Engineering* (Chianese A., Sansone L., Teti R., Zollo G., Ed.s), pp. 145-154, Liguori Editore, Napoli 1995.

Rumelhart, D., Hinton G., Williams R. (1986). Learning representation by backpropagation errors. *Nature*, 1986, 323 (9), 533-536.

Schmidt G., Stappert K.H.(1991). Some aspects of speed-flow relations on German motorway. In: *Highway Capacity and Level of service* (Brannholte U., Ed.), pp. 329-336, Karlsruhe, July 1991, Balkema.

Sjöberg, J., Hjalmarsson H., Ljung L. (1994). Neural Networks in System Identification. *NATO ASI course, From identification to learning*, Como, Villa Olmo, 22 August-2 September 1994.

Weiss, S.M., Kulikoski C.A. (1991). *Computer systems that learn*. Morgan Kaufmann Publishers, Inc., San Mateo California, 1991.

Wemple E.A., Morris A.M., May A.D. (1991). Freeway capacity and flow relationships. In: *Highway Capacity and Level of service* (Brannholte U., Ed.), pp. 329-336, Karlsruhe, July 1991, Balkema.