TOPIC 16
TRAVEL SUPPLY-DEMAND
MODELLING

FREEWAY SECTION CAPACITY FOR DIFFERENT METEOROLOGICAL CONDITIONS USING NEURAL NETWORKS

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Abstract

Meteorological features (such as rain, fog, low clearance, etc.) cause a capacity reduction of a road section and this reduction is usually computed using the method of the superimposition of effects. We propose the setting -up of an artificial neural network that in real time is able to estimate and forecast a freeway road section capacity in the function of both meteorological conditions or traffic composition by using a layered feedforward network.

INTRODUCTION

The fundamental equation of the flow provides a satisfactory representation of any relation among fundamental parameters, flow, density and speed, as bidimensional projections. What is of particular interest with regard to control problems, is the prediction of any possible traffic change, from a state of free flow to traffic congestion and vice versa. Since such changes are likely to occur for flow values which are not always equal to capacity (Forbes and Hall, 1990), they tend to represent a very non linear process. Other studies (Ferrari, 1988), (Ferrari, 1989), (Ferrari, 1991), (Ferrari, 1992) focused particularly on the parameter of speed (an ARIMA process, autoregressive integrated mobile average of the first order) and prediction of which may be used to evaluate flow stability.

Flow characteristics are obviously subject to weather conditions, such as rain, snow, fog, brightness, etc. The macroscopic effect of these conditions in reducing capacity have often been treated in published articles (Carter et al., 1982), (McShane and Roess, 1990), (Transportation Research Board, 1985), and to a lesser extent, their influence on subsequent changes in the flow characteristics. A recent study (Seddiki, 1993) highlights the variation of the flow curves in the presence of rain. This suggests the existence of complex functional relations, depending upon time and space, which should be taken into account in describing the flow process.

According to the theorems reported in the next section, a layered feedforward neural network is guaranteed to approximate a functional relation $R^N \rightarrow R^M$, provided that a proper number of hidden layers and neurons are used. Therefore, it is a worth approaching the mathematical problem of the use of neural networks for the analysis and prediction of the vehicular flow conditions. The reconstruction of flow relationships, which don't vary with time, is to be considered as a step in the implementation of a flow model, to be used in a freeway traffic control system.

AN OUTLINE ON ESTIMATION OF CLASSIFYING SYSTEM PERFORMANCE

The word "classifier" is the one most used to describe learning systems. The quality of a classifier is measured in inversely proportional way by the number of wrong classifications. The relationship between the number of errors and the amount of cases analysed is called the error rate. If the number of cases is reasonably high, then it will be called the "true" error rate.

The "apparent" error rate of a classifier is the error rate resulting from the sample cases used in learning it (training or learning set). This kind of error is also known as resubstitution or reclassification error, and it tends to be polarized optimistically; thus the true error rate turns out to be invariably higher. The implementation of a classifier whose prediction capability is found only in the learning data not in new cases, is obviously useless. Consequently, the employment of only the apparent error to evaluate the performance of the classifier may lead to wrong results. The problem is therefore that of finding the proper number of cases, so as to make the apparent error uninfluential. The relationship between the number of test cases and the sample test error is empirical. Generally, it may be observed that, with a sample test of 50 cases, the resulting error in the evaluation of the true error is slightly over 10%. With a sample of 250 cases, the error is usually 5% and with 1,000 cases it is basically nil (Weiss et al., 1991). When the number of cases is not great enough to allow a proper partition of data into the two train-and-test sets, the performance of a randomized partition into the two sets might turn out to be difficult. In such cases, data resampling methods may prove helpful for a better evaluation of the true error.

The use of neural networks as classifiers has been consolidated by several theorems which have been published. (Girosi et al. 1991) reported that a single hidden layer would be sufficient to approximate any continuous function. The usefulness of such a result, depends upon the number of necessary hidden units whose correct evaluation is not a priori known. In some cases, this number might rise exponentially, according to input units (Hertz et al. 1991). Other authors reported a not strict demonstration, which was first introduced by Lapedes and Farber in 1988, according to which two is the sufficient number of hidden layers. The main points of such a demonstration are:

- any "reasonable" function may be represented by a linear combination of localized functions, whose value equals zero over an almost complete existence interval, the only exception being in the limited region of pertinence;
- these functions may be implemented by a network with two hidden layers.

The choice of the optimal size (in the sense of performance) of a network for a given application, is still controversial. Therefore one of the best methods to identify such an optimum, is that of oversizing the network and of successively reducing it.

The learning of a network is an iterative process, therefore it should be clearly specified convergence criterion. It must be added that one kind of unexpected behaviour in the mapping networks, might be overtraining: in this case, an increase in learning cycles leads to a asintotic worsening of the network performances. This problem is still unknown, and seems to be connected with the way in which the network builds up its own mapping. The point at which the learning process is to be stopped is usually detected empirically by measuring the performance of two distinct sets of data: the learning and testing set.

Any increase in the learning set corresponds to an increased complexity in the decision limits; learning time would therefore be typically longer. In this case, the convergence of learning turns out to be remarkably slow. Since the number of parameters in a network is frequently huge, the detection of weights by the related minimization problem may be difficult. In certain cases, if the number of variables is particularly large, computation could turn out to be an unsolvable problem, therefore proper minimizing techniques may be required. The use of these techniques provides a shortening in the time needed for computation and a significant widening of the set of problems, which may then be positively worked out (Shanno 1990). Resampling techniques provide a reasonable alternative. The values of the connections, chosen before learning, contribute to the elimination of the local minima. The initialization of the connections by low random values, is the only rule which has been commonly followed (Weiss et al. 1991), (Wessels et al, 1992), since high values cause hidden neurons to be either too active or too inactive, and therefore not susceptible to the learning process. The random partition is aimed at breaking up eventual symmetries which may rise inside the network.

Back-propagation

A backpropagation network has been shown to be capable of learning even complex problems. Furthermore, it can be successfully applied to prediction problems (Klimasanskas 1992). In certain cases, however, it might happen that the network doesn't work at the first set up, thus a further adaptation of some parameters is required.

To overcome this limit, new learning techniques have been introduced; among them, can be mentioned: the Extended Delta-Bar-Delta (EDBD), the Projective Backpropagation (PBP), and the Direct Random Search (DRS). The problems for which a solution is needed are: an appropriate choice of the descent step in the search for the minimum (EDBD); the global minimum identification, also in the presence of broad noise, without being selective at higher frequencies (DRS). The PBP performs the mapping of the input space into a sphere (like a z transform) thus allowing a simple construction both of plan and elliptic spaces. The convergence is fast and can guarantee a good degree of immunity from noise. There are several variants of backpropagation techniques. One variant is that which uses the Ordinary Differential Equation (ODE) with the advantage that it removes the need for setting parameters (Weiss et al, 1991). Another is represented by an architecture, called neural tree network (NTN), which is made of a tree endowed with a single neuron layer for each of its nodes. The final structure is not set in advance, but is defined through learning (Sankar et al. 1991). Other studies (Yu X.H. 1992), demonstrated the necessity of employing non conventional algorithms (in other words, the algorithm described by Hecht-Nielsen 1991) for backpropagation learning, since this latter might not converge into a global minimum, for a given configuration of weights. Furthermore, even if the error surface of backpropagation is without local minima, the learning algorithm might fall into a local minimum, with considerable consequences even on the convergence speed of the algorithm itself.

Within the project of a BP network, one or two hidden layers can be used (a higher number would be of no advantage). With this structure along with a sufficient number of neurons, the network will be able to approximate any function. As was previously pointed out, the problem of a correct sizing of the network is still open; furthermore the proper size is often (tautologically) thought to be the one that gives the best predictions (in the sense of performance) (Weiss et al. 1991). Some experiments (de Villiers et al. 1993) have shown that, given equal complexities, the two architectures behave in the same way, with the only exception being a four-layer network, which is easy to fall into a non global minimum. (The complexity of a network can be measured on the basis of the Vapnik-Chervonenkis size (VC), that is strictly connected with the number of weights found in the network.

In short, the learning process of a backpropagation network is a complex problem: it is necessary to determine its architecture (number of neurons, number of layers), size and characteristics of learning data, starting values (starting weights) (Rohani et al. 1992), the most suitable learning parameters (learning steps) and finally, it is necessary to avoid overfitting. The above-mentioned indications might be further reelaborated and better arranged. It is important to use two or three disjoint sets of data for the network implementation: one for learning, one for validation (in order to avoid over-training) and one for testing (this latter will include data which have never been used before) to evaluate network performance. The learning step is most important and plays a crucial role in the practical application of backpropagation. If too small, the convergence of the whole network would turn out to be too long, if too big, there may be oscillatory phenomena (Davalo et al. 1991). Nonetheless, with any network, an infinitesimal learning step would lead to the discovery of those weights which give the lowest possible error (Weiss et al. 1991).

In order to improve learning time, (Allred et al. 1990) suggested the use of the following techniques:

1. the learning process is to be limited to those examples, for which the network exhibits incorrect values, while it is to be enlarged to all the examples when performance improves;
2. fastening learning process of those neurons which do not turn out to be susceptible to the example data;
3. optimizing the learning rate together with that of momentum.

With regard to this last technique, the proposed learning rate values, λ, are lower than or equal to λ_{eff} (included between 1 and 3 in the absence of momentum, μ), and between lower values in the presence of momentum, μ, according to the following relationships:

$$\mu = 0.5^{1/n} \tag{1}$$

$$\lambda = \lambda_{eff}(1-\mu) \tag{2}$$

where n is the size of the learning set. The value of the momentum, μ, is usually assumed to be 0.9 (Hecht-Nielsen, 1991). Within applications of Boolean problems, Burkitt et al. (1992) choose a momentum values of 0.94 and 0.86 respectively for a problem of parity (XOR) whose dimensions are two and four.

Drucker et al. (1992) suggested the opportunity of using a double backpropagation in order to increase the generalization of the network without enlarging the learning set. A further approach aimed at obtaining a reduction in learning time and at enhancing its robustness to avoid local minima, was proposed by Denoeux et al. (1993). According to this technique, weights are initialized by means of significant data prototypes before using the entire learning set. This method provides positive results with regard to problems of both sample recognition and function approximation. According to the authors, this approach also results in a better generalization. The question as to what the best number of prototypes should be used, remains controversial.

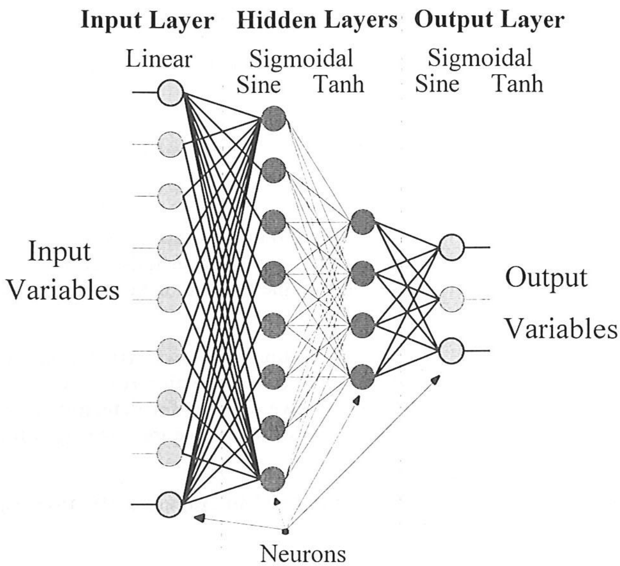

Figure 1 A feedforward network architecture

APPLICATIONS TO TRANSPORT

Future systems for traffic control, related information management, transport systems planning and traffic safety, will be increasingly based on computer systems, in order to obtain all the necessary performance with regard to speed, comfort and safety (Wild, 1991).

In a recent overview (Burke and Ignizio, 1992), neural networks have been regarded as an alternative to traditional methods, such as linear programming, discrete optimization, statistical discriminant analysis, regression and cluster analysis. The application fields are several and multifaceted: recognition of samples, recognition of signs, analysis and recognition of the voice, making decisions, mapping.

Even though neural networks are far from being the universal panacea, possible advantages are considerable. Neural networks may also be used as an integrative or substantial support to other techniques, such as expert systems or fuzzy logic (Nanda and Kikuchi, 1992). The potential of neural networks in the field of non-linear dynamic systems, statistical analyses, and modelling in general, has been investigated by several authors (Narendra and Mukhopadhyay, 1992), (Sartori and Antsaklis, 1992). A recent review of the advantages connected with the use of neural networks is in (Mussone, 1994).

The sectors in which AANs have been successfully applied are the following:

- Evaluation and updating of O/D matrices for extra-urban flows (Yang et al, 1992);
- Identification of driver behaviour with advanced traveller information systems (Dougherty and Joint, 1992), (Yang et al. 1993);
- Freeway incident detection (Ritchie and Cheu, 1993);
- Recognition of images to detecting flow (Belgaroui and Blosseville, 1992);

- Prediction and recognition of urban traffic condition (Dougherty et al. 1992a), (Dougherty et al. 1993);
- Prediction of freeway flow data (Dochy and Danech-Pajouh);
- Evaluation of gap (area of dilemma) at signalized intersections (Pant, 1994).

A recent overview on some of the above-mentioned fields of application, may be found in (Ambrosino et al. 1994) and (Mussone, 1994).

DATA COLLECTION

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

Along this section detection stations are set up as follows: 10 stations (corresponding to 20 detection points) for the detection of flow characteristics (one every 1,000 km) by using electromagnetic inductive loops (Figure 2), five stations for detecting visibility, 2 for weather conditions, two 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
- percentage of heavy good vehicles
- brightness
- weather conditions
- visibility
- presence of messages on the variable message signs.

Brightness evaluates the presence of light according to a scale from 1 (night) to 6 (vivid light).

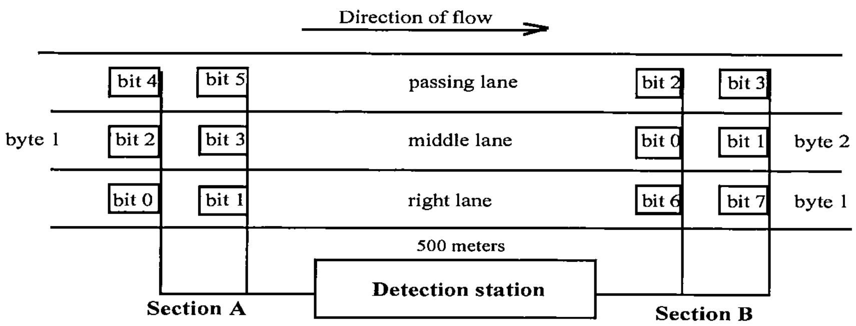

Figure 2 Data detection system

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 counting), 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. Only the messages concerning accidents, queues or fog were taken into consideration. Furthermore, among the data taken into consideration, there were also included the data on the correct working of the inductive loops, on the basis of which, the rejection of any flow datum could be decided. Information on weather conditions was not monitored on all the sections and the sampling period adopted within file data was different. A procedure which, starting from the flow data file that exhibits the maximum space-time resolution, 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 were almost 360,000.

It was not possible to use the information relative to rainfall; the information relative to the presence of rain is fairly frequent within data and is not significant in the description of the traffic flow process. During the detection of data, no presence of snow nor ice was detected on the freeway pavement.

The step of precomputing data and performed through a PC 486 DX66, by a program written in Superbase language, required on average of about 2 days computing for each station under consideration. The set of data was then classified for each section, according to the possible combinations which the considered variables can have.

With regard to the learning process of the neural network, two sets of data, one for learning and one for validation, were created through an extraction at random from all the data. Data are then normalized according to their highest values; results are therefore normalized to those values. For the traffic flow, the maximum value of 3,000 veh/h for a single lane was assumed; for speed the maximum value was 200 km/h.

Pre-elaboration of data

As has already been pointed out, data detection does not occur at the same time, and time differences may be found among both stations and for different types of detection. Moreover, some stations were not endowed with all the detecting parameters. Therefore, it was necessary to find an answer to the problem of making all data homogeneous in terms of time and space, so that all data from the different sections and all types of detection could be used.

The spatial association concerns the files of data relative to brightness, meteo and VMS messages. The files relative to flow categories and diagnostic of detection loops, are available for each section. The criterion for the file relative to VMS messages, which have been sent along the freeway before the sections taken under consideration, was that of associating this information to all the sections. In fact the messages sent through the signs are likely to affect the whole motorway. The remaining files were grouped according the criterion of spatial proximity.

For time resolution, the file of reference was the flow detection file, which turned out to have the major detection frequency. Flow data were then associated with remaining data. The intervals found in the sampling of subsidiary data, may be completely or partially overlapping over the intervals found in flow data. In the first case, complete overlapping, the subsidiary datum must be associated with the flow datum; in the second case, the association is made with the subsidiary datum, which turns out to have the major overlapping, or with the following datum in case of equality. When the detection frequency is much lower than the average, a gap in the detection process should be suspected. In this case, the latter detection is considered valid for a period four times as long as the average. If no further detections are available, data cannot be associated. All the data are normalized according to the maximum value they can exhibit, this being a specific necessity for the neural network shell that is being used. In Table 1, these values are reported.

Table 1 Range of values used to normalizing variables

Parameter	Min	Max
Flow (veh./h)	0	6000
Density (veh./km)	0	150
Speed (km/h)	0	200
Heavy vehicles%	0	100
Brightness	1 (darkness)	6 (vivid light)
Visibility (m)	0	>520
Meteorological	0 (serene)	1 (rain) 2(snow/ice)
VMS	0 (absence) 1(incident)	2 (queue) 3 (fog)

Data classification

The several flow conditions detected on a motorway usually are 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.

On this purpose, a further variable called *CATEGORIA*, was created within the database *ESTRATTI*. This variable was associated to a first associating criteria which is based on the detection of the following information: presence of rain, snow/ice, VMS messages, percentage of heavy goods vehicles (the mean value among the three lanes), visibility and brightness. Considering these values as a part (bit) 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.

If all the information is found, the maximum code of the variable *CATEGORIA* will be a value of 175. Therefore, a value of 255 has been used to classify those records which could not be used for this particular task since they did not include all the subsidiary data.

A second classification was performed according to density. A numeric variable *DENSCLAS*, represents a density category which is calculated according to the following algorithm:

$$DENSCLAS = (density/3+1)*[-(density \le 39)] + (density/10+10)*[-(density > 39)] \quad (3)$$

where *density* is the variable including the density value. The expression in the square brackets represents a logic IF: when it is false (in SUPERBASE) its value is 0, when it is true, the value is -1. The purpose of this approach was to separate the density categories which were close to 0, from those which were close to saturation, because a greater resolution is needed in the first case. Density classes whose values are lower than, or equal to 39 veh./km, have a resolution of 3 veh/km, the remaining classes have values of 10 veh./km. The choice of the value 39 (veh./km) for the density, was performed empirically, by considering such a value as reasonably capable of including all the optimum density values which may occur in any flow condition; moreover, 39 can be divided by 3 and 40 can be divided by 10. The merging of the two variables (*CATEGORIA* and *DENSCLAS*) is called *COMPINDEX*, and defines the classification key.

The extraction of random samples

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, consistently with the mean frequency of classes. This problem rises because of the non-homogenous distribution of data among classes. In fact, some classes have far higher frequencies which correspond to stable flow conditions, whereas others have a few elements, corresponding to the particular features of the parameters or to unstable flow conditions.

The aim of the extraction is that of obtaining the highest possible number of elements from each class while keeping the number of the elements extracted from each class as equal as possible. This criterion, I, is represented by the following relationship:

$$I=\sqrt{\frac{\sum_{i=1}^{N_c}(N-N_i)^2}{N_c}} \qquad (4)$$

where N_i represents the number of samples which could actually be extracted (if the number of samples to be extracted is higher than the number of elements of the class, N_i equals this latter); N is the number of samples whose extraction was expected, and N_c is the number of the classes found. Obviously, N is always higher than, or equal to N_i. Therefore, if all the classes contained at least N elements, the indicator I would equal 0. Since this does not occur other than with values of N=2, and moreover, since a good homogeneity of the whole sample is desirable more than the homogeneity of each single class, the values for N are chosen in such a way that $I \leq 2$. For the model, the number of extractions from each class were found to consist of 5 elements. It can be observed that the low frequency in each class is fairly well compensated by the iterative learning procedure of the neural network, which considers the same learning set several times.

Section 8.1 was chosen to reconstruct the flow relationships curves. This choice was based on the fact that proximity to the exit tollgate leads to a frequent presence of queues, therefore the density values are likely to increase up to the optimum density. It is assumed that in this section the distribution of data is better than that found in sections which are a longer distance from the tollgate. Furthermore, the presence of all meteorological detections in this section led to disregard of the sections towards the tollgate. The number of records extracted from the detecting stations was 360.000, and became 346.000 after the rejection of those records which turned out to be incomplete or mistaken. The classes were 191. The extraction of 5 elements from each class gives a sample of 811 records (complete by 85%). From this sample, two sets of data, test and learning, were then extracted at random: 405 for the first set and 406 for the second set.

The neural network model

The implementation of a feedforward neural network model, with backpropagation learning, requires the determination of the proper number of hidden neurons and layers in the attempt of minimizing the error on both learning and test data. The optimum configuration of the network is necessarily linked to the phenomenon of overfitting. Recent studies (eg Master, 1993) have suggested that overfitting essentially occurs because of two main reasons: first, the network is not properly sized compared to the available data; second, 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.

Besides the modification of the network size, it is possible to modify the transfer function of the single neurons as well. Theoretically, all the neurons in all layers may be given any transfer function, provided it is continuous and infinitely derivable. The applications of this architecture, which are teated in published articles, use a linear transfer function for the first layer, namely that of the input; the same method is then applied to each model which is implemented in this research. In fact, all the attempted applications of different transfer functions have provided not satisfactory results. A further device, whose widespread use may also be found in literature, is that of applying the same transfer function to the neurons belonging to the same layer. This should simplify the determination of the optimal configuration.

The transfer functions which were adopted for searching the optimum are the sigmoidal, the hyperbolic tangent (tanh) and the sinus. The sinus did not provide appreciable results, since it required a higher number of cycles while the learning error remained unchanged. The hyperbolic tangent gave comparable results.

The architecture of the model implemented to analyze flow-density and flow-speed relationships by using density as input variable and flow and speed as output ones, it not less of meaning because these relationships are not bijective but they are injective only for density. The idea of setting the speed value at the output layer, instead of creating a further model with density as input and with speed at output, has derived from the consideration that a relation $R^n \rightarrow R^2$, rather than $R^n \rightarrow R^1$, allows a better representation of a process which is characterized by three joint variables; the resulting error surface is undoubtedly more complex with a relation $R^n \rightarrow R^2$ and, by this way, the neural network can learn problem complexity better .

It is noticeable that high values of λ, λ=5, do not provide appreciable results. This is presumably due to the fact that an excessively large learning step is a constraint for the determination of too localized minima in the error function. The configuration set out in Figure 3, is the one which gives the best results: a network endowed with a single hidden layer having 4 neurons with a sigmoidal transfer function. A comparable RMSE is shared by a two-hidden layer network, 8 + 4 neurons, with sigmoidal transfer function, yet the error rate is remarkably worse (namely it is more polarized). Moreover it turns out to have worse performances with regard to the flow parameter which is instead the most important one. Other configurations with a different number of neurons or with different transfer functions, have not given comparable results.

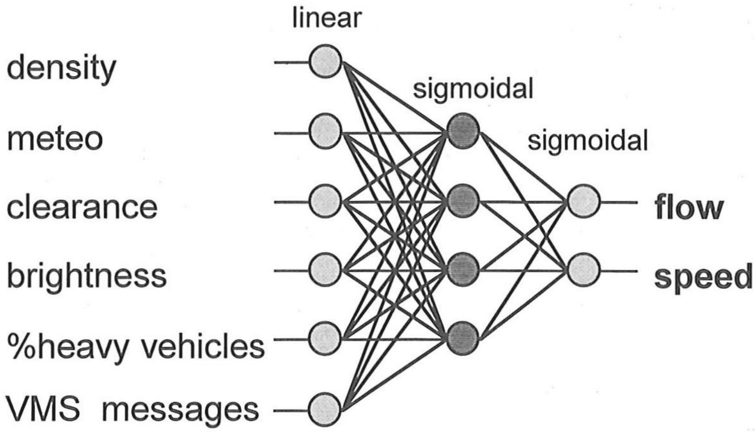

Figure 3 **Optimal model for reconstruction of flow relationships**

To better evaluate the importance of the learning step, the above mentioned configuration was studied more in detail. The best results are obtained with a learning coefficient λ=0.5 and with a momentum term μ=0.6. The best configuration is that obtained with 60,000 iterations. The flow error is RMSE=0.09330; error percentage = 0.31598; mean error = 0.06567; speed error is RMSE = 0.06322, error percentage = 0.12188, mean error = 0.04558. The model used for the reconstruction of both flow-density and flow-speed relationship is obviously the same one, as the same is the sample file used for the employment of the network. Results are set out separately for exposition purposes.

RESULTS

Flow-Density relationship

The results reported in the following figures, are only the ones which can explicate better the possibilities of this model. As was already pointed out, provided a given knowledge for the learning process, this model allows the network to predict the behaviour of the process in the presence of changing input data, through minimizing the error of the classifier. This explains the reason why this particular model cannot give any reliable result with regard to snow, since such a meteorological event never occurred.

The analysis of Figures 4 and 5 highlights the influence on the flow values due to the used parameters. Visibility and percentage of heavy goods vehicles lead to considerable modifications in the curve, and the consequent effects are clearly distinguishable. Interestingly, variations in the optimal density value are induced not only by the corresponding variations in the flow maximum value, but also by changes occurring in the input parameters. This fact however, requires further validations on other data in other contexts. The effect of the VMS messages may be observed in Figures 6 and 7; in conditions of traffic congestion, the effect of VMS messages may be evaluated in terms of a clear improvement of the flow process rather than in an increased capacity of the system itself.

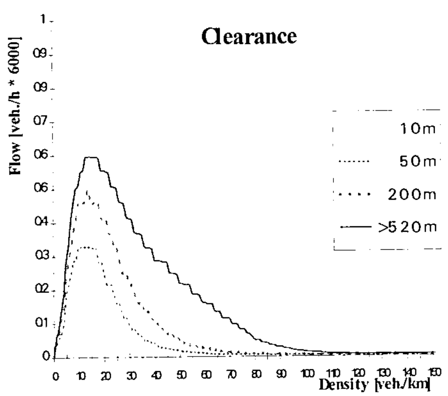

Figure 4 **Flow-Density relationship vs. clearance distance**

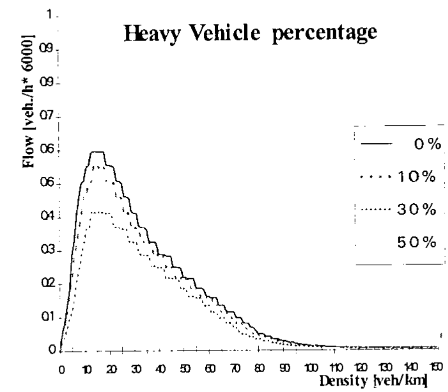

Figure 5 **Flow-Density relationship vs. heavy vehicles percentage**

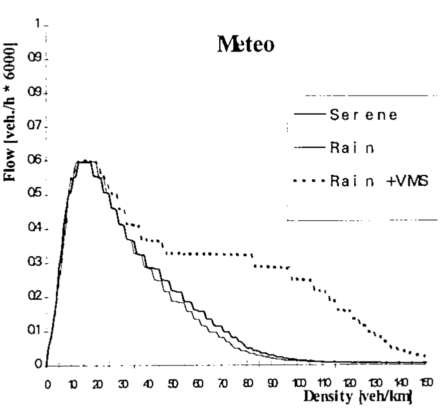

Figure 6 **Flow-Density relationship with and without VMS messages vs. meteo conditions**

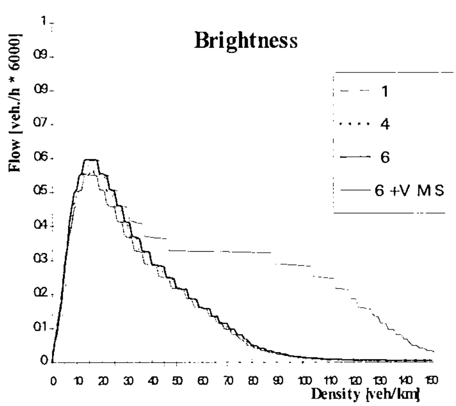

Figure 7 **Flow-Density relationship vs. brightness and with VMS messages**

Moreover, Figures 6 and 7 clearly demonstrate that both brightness and rain exert a slight influence on the flow characteristics. This result was somehow expected with regard to brightness, since this parameter is more likely to influence the degree of danger in traffic flow conditions.

With regard to rain, the result is only partially valuable, since the datum concerning rain quantity could not be used: the information about rain (present in about one third of the data) does not allow the system to discriminate a variation in the curve, because of a considerable scattering of this parameter. Any constraint consequent to rain (heavy rain for example) should be probably ascribed to visibility. Figures 8 and 9 show the combined effect exerted by both the percentage of heavy goods vehicles and reduced visibility. It is observable that the presence of variations in the percentage of heavy goods vehicles, corresponds to slight variations in the optimal density value. The latter turns out to be not susceptible to the variations in the parameters, and tends to stabilize on a single value.

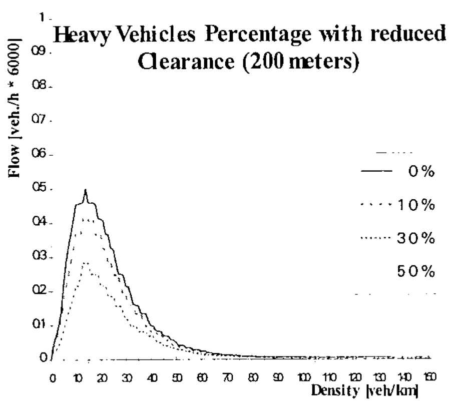

Figure 8 **Flow-Density relationship vs. heavy vehicles percentage with reduced clearance (200m)**

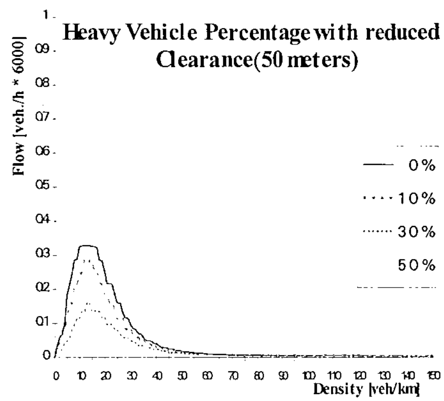

Figure 9 **Flow-Density relationship vs. heavy vehicles percentage with reduced clearance (50m)**

Speed-Density relationship

Figures 10 and 11 show the first two curves obtained through the same combinations of variables as those reported in the previous chapter with regard to the flow-density curve (Figures 4 and 5). These curves are undoubtedly less significant than those concerning flow-density. The influence of the variables on the definition of the curves is less remarkable or totally absent. A decreased maximum flow value in the flow-density curves, corresponds to a decreased free-speed value in the speed-density curves. The trend of the curves is fairly similar, since their shape is mostly concave, and only in a few cases it turns out to be convex. Furthermore, all the curves asymptotically fall to zero on the density axis.

The relationship among flow, speed and density do not exactly correspond to that of the fundamental flow equation. The available data, however, are not sufficient (in statistical sense), so as to allow a complete removal of the noise which may be found on the flow values. Therefore, it is not possible to draw more precise evaluations.

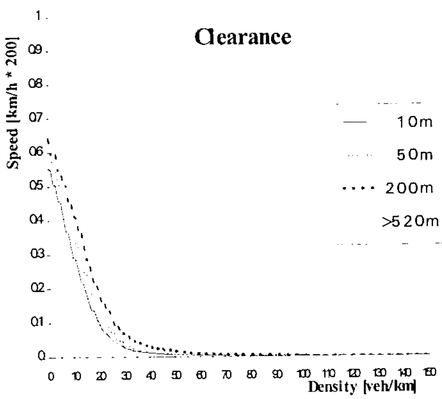

Figure 10 **Speed-Density relationship vs. clearance**

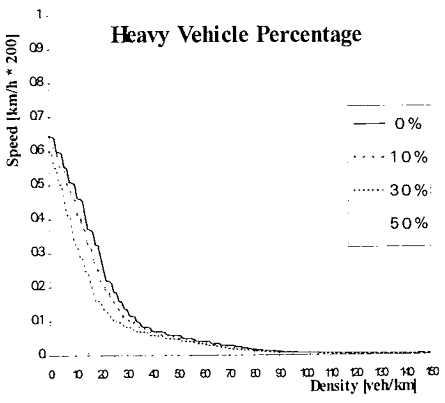

Figure 11 **Speed-Density relationship vs. heavy vehicle percentage**

CONCLUSIONS

The results reported in this study, show how the instruments and methods applied may help in the study of flow characteristics within a dynamic traffic process. The remarkable influence which some parameters have been seen to exert on the flow-density relationship, and which have been confirmed by analogous studies on traffic flow features (Seddiki, 1993), could be the subject for further research aimed at formulating a completely functional instrument. These results should be considered as descriptive, because it was impossible to use the data concerning rainfall and snowfall. Complete knowledge does not necessarily imply a larger number of data; it would simply require a longer follow-up period. It must be remembered that the reconstruction of the curves was made according to the data collected in a single detecting station. Nonetheless, the availability of more detecting stations, such as in the case of the Padua-Mestre motorway, allows the reconstruction of the flow curves for each station, and the parallel evaluation of their statistical and dynamic characteristics.

The main applications of a model with such features are two:

a) The evaluation of flow stability for a specific section. This approach is based on the evaluation of the sign of the first derivative on flow-density curve.

b) The evaluation of the statistical characteristics of the section under consideration; the curves obtained by this method are a direct consequence of both the flow and other characteristics, such as for example, weather and geometric ones. According to the results obtained from the flow-density curves relating to the motorway Padua-Mestre, the capacity value is 3,600 veh/h. Such a datum would be unacceptable if it was related to a three-lane motorway. Yet, the presence of a toll-gate, the capacity of which was nearby 2,600 veh./h, justifies it. Therefore, the results cannot be applied to other sections unless the flow features detected by the different sections are comparable. This limits the possibility of making a generalization about any specific result. Nonetheless, it also represents an advantage, since the method guarantees a proper adaptation to the particular conditions of the section under consideration.

The results which may be achieved through the ANN in the reconstruction of the flow relationships are fairly evident, even though the data provided here are partial.

The reconstruction of these relationships obtained by neural networks shows the clear influence of both weather conditions and flow characteristics on the definition of the curve shape. In fact the above mentioned parameters, not only induce variations in the maximum flow datum, but also lead to variations in the optimal density value. It is important to note that, this model provides the opportunity of performing the same reconstruction for any combination of the input variables, without the necessity of specific detections and with relatively slight errors.

It is intention of the authors to carry out further experiments using other data, in order to investigate the impact of the meteorological variables, such as rain and snow, and to introduce further flow variables, such as headway. With the data they have at present, they are planning to evaluate the influence of vehicle length and distribution of vehicles over lanes, in the definition of the flow-density relationship.

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TOPIC 1
TRANSPORT AND
LAND USE (SIG)

URBAN GROWTH AND TRAFFIC ENVIRONMENT UNDER A ROAD NETWORK CONSTRAINT

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Abstract

In this paper we discuss the relationships between urban growth and the traffic environment by examining the relationships between car travel demand and a road network capacity. We assume that the road network in a city is fixed. The congestion level allowed by the city society is a parameter of the traffic environment.