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DEFINITION AND BUILDING OF A DATABASE FOR STUDYING DRIVER BEHAVIOUR IN URBAN TRAFFIC FLOWS

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Abstract

Driver behaviour features are not yet known exhaustively. Particularly, driver behaviour near intersections, signalised or not, seems to be important not only in view of calculating saturation flow (according to the Webster model) and evaluating how much driving is within legal limits (forbidden lane changes, utilisation of only-bus lanes, etc), so as to improve control of signalised intersections, but also of completing knowledge of driver reaction to prescriptive road signs.

INTRODUCTION

One of the most important issues in traffic regulation and control is how drivers behave when they are on the road and exactly how they react to specific external stimuli. It is also often a weak link in the analysis of situations and therefore in the control chain because of difficulties in acquiring information and in defining the model.

Computer simulation is not always satisfactory because in the effort to reduce computational complexity, the tendency is to eliminate from the model all irrational or instinctive driver behaviour and consequently end up with an incomplete description. Irrational behaviour can be put down to the greater or lesser influence of environmental conditions on individual choices. This connection can be seen as opening a field of investigation into the relation between environmental conditions and their effects and an opportunity for collecting sufficient data to analyse the relations between the variables. It is therefore chosen to collect data on traffic flow and reactions to outside conditions where it was easiest, ie at all access points to a certain number of intersections with traffic lights, chosen in Milan and Pavia (Northern Italy). At a later stage, all efforts were focused on the data collected at one particular intersection in Pavia so as to guarantee a greater number of samples and more stability in the population.

The aim of this project is to construct a model of the relationships between driver behaviour, and in particular, incorrect behaviour, and specific conditions in traffic flow, within the environment and the requirements of the highway code. A large part is also played by other factors such as type and performance of vehicle driven, drivers' sex, age etc, and driving habits. All these factors are connected in some way and our aim is to discover how.

Most dependencies in this type of model will be non-linear, but it is not known beforehand what kind of non-linearity this might be, so it is necessary to use a flexible tool capable of representing all kinds of function. Therefore the choice fell on multi-layered feedforward artificial neural networks with backpropagation learning that have been shown through a large number of theorems which approximate all functions.

The variables taken into consideration in building the model are: time of day (15 minute intervals), type of vehicle, weather conditions, type and number of violations, w/c ratio and vehicle flow. Other parameters included in the survey not used in the model are: driver's age and sex, driving style, and number plate.

It may be assumed that the violations committed by the drivers may be expressed as a non-linear function as follows:

$$N_{inf} = F(t, r, v, m, z) \tag{1}$$

where t is the time, r is w/c ratio, v is the vehicle type, m is the weather condition, z is the vector containing the traffic flow variables.

STATE OF THE ART

In the field of modelling and analysis of driver behaviour, seen as a decision process that takes into account all the possibilities and conditions of a journey, there is not much material compared to the complexity of the problem. What there is undoubtedly of great interest for all applications of transport and particularly for real time control and planning of traffic flow, but much more remains to be discovered.

One direction that has been explored by a number of researchers is that of advanced information systems for travellers (ATIS and DIS projects), the aim of which is to guide the user in his choices and make both transport systems and general mobility more efficient. Information was gathered involving drivers selected by telephone poll (Bhat et al. 1993), or interviewing commuters on the road (Conquest et al. 1993). Drivers' skill to absorb and quickly interpret information and the benefits that follow in terms of traffic redistribution have also been studied (Ben-Akiva et al. 1991).

Other studies, also in the field of evaluation of user information, VMS or RDS, compare lab experiments with field results (Schofer et al. 1993) with various degrees of control and complexity. Behaviour has been measured in some cases with automatic instruments working in real time, but problems with reliability and costs occur. In this kind of study a lot of attention must be paid to human factors like ability, experience, physical condition, age, education (Dingus and Hulse 1993). All these factors define a user and determine his behaviour. Other aspects of perception may have an important role, for example background noise. Three different aspects of visual capabilities in particular are analyzed (Armstrong and Upchurch 1994): objective value, reading distance and ease of vision, taking into account unfavourable conditions (backlighting and washout).

Descriptive parameters of driving (Delhomme 1994) vary considerably, because of their influence on one another and extreme sensitivity to variations in flow. In evaluating behavioural aspects of driving it is necessary to distinguish violations that produce effects only on the driver (eg no seat belt, no helmet) from those that may affect other drivers (speeding, not giving way, etc). Definition of these elements is important for a correct evaluation of flow conditions.

Even scarcer are studies on driver behaviour analysis using artificial neural net models. In this area we have studies by (Dougherty and Joint 1992) and (Yang et al. 1993). Both works cover the subject of user behaviour in route selection using neural net models. Decisions are influenced by the kind of information relayed to the user by means of road signs or any other means of communication. Data is collected using highly realistic scenario simulators, which put the user in conditions very similar to those of real traffic. The models are geared to obtain different results: in the first case to produce a function of route selection, in the second to evaluate users' perception of the information relaying devices employed. Both cases testify to the usefulness of neural nets in defining models with many variables whose relationship is unknown.

THE SCENARIO

The intersection concerned (Figure 1) is very busy, especially during rush hours. Formally it is an intersection of two roads although in fact there are more than four branches due to the implementation of the one way system. Width of access carriages ranges between 6 and 7.5m (19 and 25 ft), so they have been divided into two lanes in either direction, at least in the vicinity of the traffic lights. At the intersection, traffic on the S.S.35 Milan-Genoa through route crosses on one axis ingoing or outgoing flow on one of the town's main arteries on the other. Surveys were taken only on statistically significant days, in spring 1994, in time slots during the morning, afternoon and evening rush hours and in different weather conditions.

Two distinct types of survey sheets were used: the first to note traffic flow and composition in fifteen minute time slots; the second to note what violations were being committed and, in each case, the main characteristics of the driver and vehicle involved. This second sheet was designed for optical reading, so that each kind of violation was associated with the relevant data, thus considerably speeding up input operations.

Three different violations were taken into account: crossing a red light, turning in a different direction from the one indicated by the lane markings, not giving way when required. Multiple violations by the same driver were noted and included in the totals.

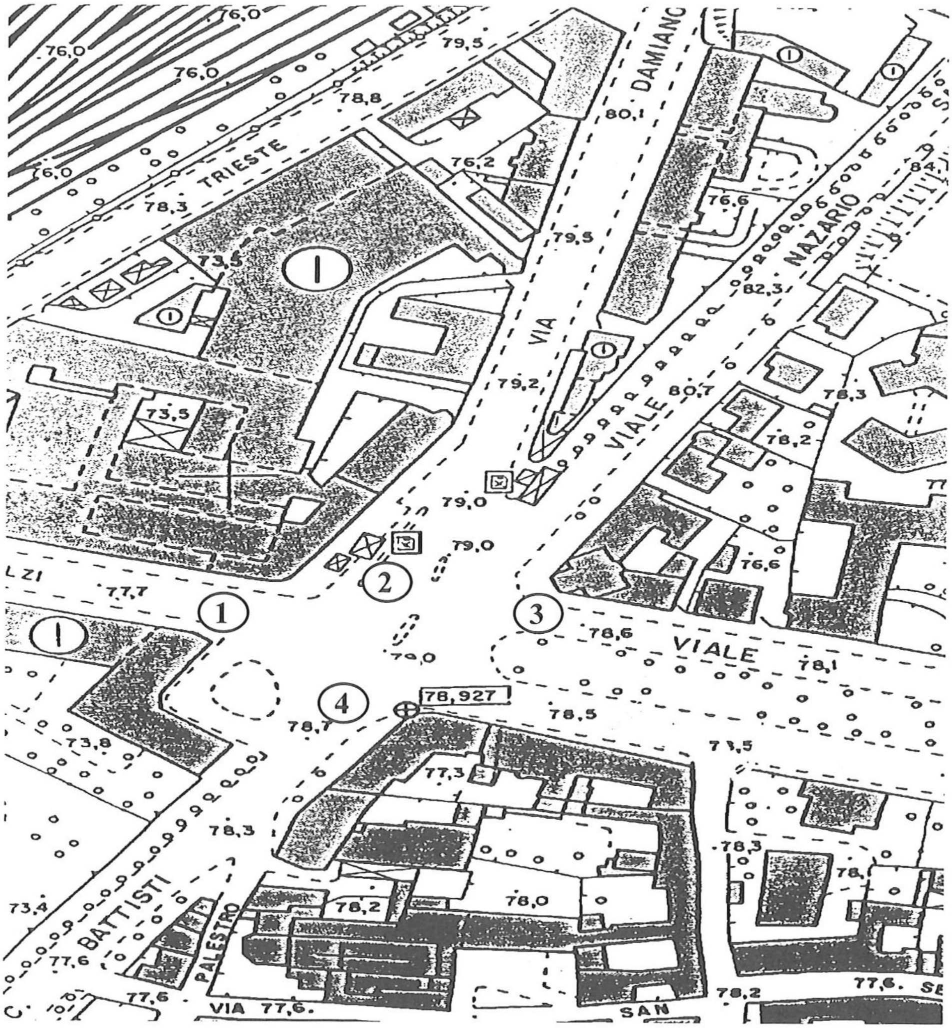

Figure 1 **Layout of the intersection used for the model**

DATA ANALYSIS AND DATABASE CONSTRUCTION

Data collected on the sheets were transferred to two spreadsheets. The first comprises two kinds of tables covering driver behaviour and traffic flow. Space-time coordinates shared by the two tables allow data about violations to be correlated to data on traffic flow. The second sheet is a résumé and is intended as a synopsis of the first concentrating on the most significant data gathered every fifteen minutes. It includes reference coordinates, traffic flow and number of violations, classified by type of vehicle and type of violation. This sheet also gives an idea of the size of the database: 20.829 vehicles observed, 1223 violations noted with an average of 0.06 violations per vehicle.

Table 1 shows how violation 1 (crossing a red light) is the most common occurrence (56%), while type 3 (not giving way) is almost non-existent at 1.4%. It is also important to notice that violations tend to increase with traffic flow and as the weather gets worse, and diminish as night comes on. At a fixed value of traffic flow, we also note that the number of violations tends to be inversely proportional to the w/c ratio. As for classes of vehicles, a large majority are cars (83% of the total flow), followed by two-wheelers, which are more than the total of heavy vehicles. As regards the number of violations, cyclists were proportionately the most undisciplined category. Data on drivers showed the typical highway code breaker to be male (76%), young (56.7%) and with a normal driving style (57%).

Table 1 Distribution of violations

Type	Percentage
Passing a red light	56.0%
Turning from a wrong lane	42.6%
Not giving way	1.4%

The set of input data includes 5760 different combinations of parameters, obtained by combining the ten classes of vehicle compositions defined with all the values of the other parameters such as weather conditions (3 cases), environmental conditions (2), w/c ratio (4), traffic flow (6), survey station (4).

The artificial neural network used consists of 20 neurons (11 in, 8 hidden, 1 out) and evaluates 16,000 iterations. The transfer functions associated with input, hidden, and output neurons are respectively: linear, hyperbolic tangent and sigmoid. The model allows reconstruction of the total number of violations. All inputs are numerical with values in the range of 0-1; all descriptive factors have consequently been reduced to numerical values.

The net associates an input to every output, which is a number that represents the total number of expected violations, expressed in fiftieths, Both the input and the output data are referred to a fifteen minute interval.

The model is thus able to elaborate any potential situation, even if it has not actually been monitored during surveys, because, by suitably varying the input parameters, it is possible to create any scenario that may occur.

ARTIFICIAL NEURAL NETWORKS

Artificial neural nets (ANN) can be used to solve identification problems, underlining any difficulty or problem with the algorithm, as is usually done with more traditional statistical techniques (Sjöberg et al. 1994).

The definition of a model depends on the identification of the relationship between known cases of input and output, so as to infer output values for new cases, given a finite number of known cases. For this purpose, starting in the 1980s, research in the field of neural nets has increased. Many different models are now included under this heading, but in this article it refers only to feedforward and recurring nets. These models are referred to without inferring anything from their physical characteristics, using the "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 (Dougherty et al. 1994).

In general terms, neural nets are structures consisting of process elements, neurons, and connections. The neurons can be grouped into distinct subsets called layers within which they possess the same transfer function (also called activation function). In this case the net is said to be multi-layered or simply layered. The intermediate layers between the input and output layers are called hidden because they are not connected to the outside. The hidden units resolve the problem of having a finite, fixed set of representation primitives so that the net can be adapted to the set of data to be represented (McClelland et al. 1986). By the term feedforward (Figure 2) we refer to a layered neural net structure, in which there is a fixed direction for the output value calculation flow.

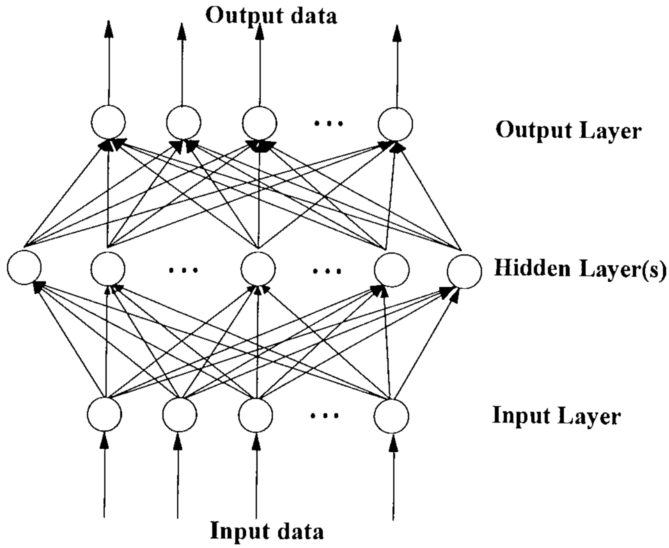

Figure 2 Feedforward network with layers completely connected (Rumhelart et al. 1986)

The neuron combines the signals coming from the n input connections of a single class (or layer) k, weighting them according to the value of their connections and transforming them according to their particular transfer function, which may be, in general terms, a step function, sign function, a linear function, or (among the C^∞ functions) a sigmoid or logistic function, a hyperbolic tangent or a sine function.

From the theorem published in 1957 by the mathematician Kolmogorov on the possibility of representing continuous functions (Hecht-Nielsen 1991) was derived a theorem of existence according to which a feedforward neural net is able to implement any continuous function; the proof is derived from that given by Sprecher in 1964 for the original theorem. From this theorem of existence it is possible to derive only an upper-limit estimate of the number of hidden neurons, from the size of the input field and the error margin (Kurkova 1991). Other theorems state that multi-layered feedforward neural nets (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 with a small margin of error (Cybenko 1989, Hornik et al. 1990, Hornik 1991, Girosi et al. 1991, Koiran 1993, Leshno et al. 1993). The number of hidden neurons, and the number of layers needed to obtain the desired approximation is still being studied (Hecht-Nielsen 1991).

The backpropagation technique (BP), rediscovered on many occasions and again recently (Rumhelart et al. 1986), applies only to multi-layered feedforward architectures, and is a heuristic solution to the training problem in feedforward nets, which, it should be remembered, is an NP-complete problem. For this reason it is often necessary to proceed by trial and error to find the number of hidden neurons (Sankar et al. 1991). BP is a method of calculating the connection values which minimize the average quadratic error between observed data and those calculated by the net. In practice it can be described as a chain rule for the calculation of partial derivatives in the error function so as to find the descent gradient. Other techniques are now being proposed (Sjöberg et al. 1994), such as the faster and more efficient Gauss-Newton method.

The method of calculation differs according to whether the net has one or more hidden layers. If we define mij as the value of the connection between a generic ith and jth neuron, and k as the iteration, this can be written:

$$m_{ij}\,(K+1) = m_{ij}\,(k) + \lambda_k\,\Delta m_{ij}\,(k) + \gamma_k\,\Delta m_{ij}\,(k-1) \tag{2}$$

where λ_k is the so-called learning term and γ_k the momentum (or acceleration) term. The role played by the learning term may be important for a rapid convergence of learning, while the momentum term, which acts as a lowpass filter in the choice of the descent values of the gradient, prevents wild oscillations during training.

Many authors, such as Weiss et al. (1991), Sjöberg et al. (1994) and Masters (1993), underline the difficulties of training, and in particular the problems of overfitting or overtraining which adversely affect the performance of the neural net. This phenomenon depends on the size of the error rate of the model, which is always inversely proportional to the number of iterations if it is calculated on the same data set used for training, but if calculated on new data (validation or test set) it can start to increase after a certain number of iterations. One explanation is that with increasing iterations it tends to adapt excessively to the training data so that the model loses general applicability; on the other hand it is presumably due to the fact that the training data did not perfectly represent the whole population, so that the test set is slightly different from the training one. A second explanation is that there is an excessive number of hidden neurons, so the network cannot generalize correctly. If there is insufficient data, the overfitting problem cannot be eliminated, requiring particular attention in error correction with the test set. Before training begins, the training and testing sets must be generated, both sets being of the same size and extracted at random from the same population.

In the models used in the following paper a sample of 92 cases was used, divided at random into test and training sets, both comprising 46 elements. All data was normalized to the maximum value of the variable: for the number of violations the normalization factor was 50. The optimum model is that shown in Figure 3. The models with only one hidden layer always have better results than those with two. The optimal transfer function for the hidden layer is the hyperbolic tangent; however, the sigmoid also gives very similar results. The output transfer function is the sigmoid which, with all other conditions constant, gives much the best results.

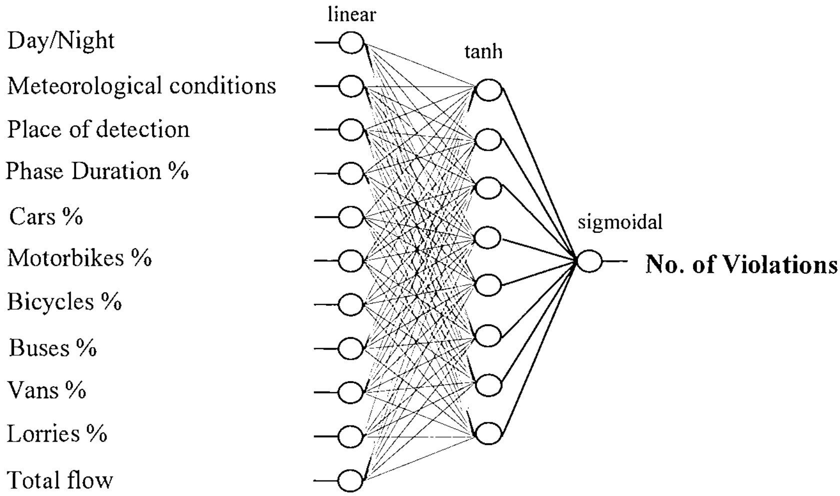

Figure 3 Model used to reconstruct the total number of violations

The error margin is:

- on the training set: — absolute error average = 0.0546,
  — rmse = 0.07016;
- on the test set: — absolute error average = 0.0911
  — rmse = 0.1272;
- overall the two sets: — absolute error average = 0.0728
  — rmse = 0.1025;

these values were obtained with 16000 iterations with the training set which has its output data average value near 0.30.

RESULTS

The model applied gives as its output the total number of violations committed in a particular traffic flow and gives a very complete picture of the phenomenon as a function of the reference parameters. A few brief comments and some remarks on the results are given below.

In each survey point the number of violations is a function increasing with the flow, but with a law which differed according to the w/c ratio: in general, the greater is w/c, the slower is the growth ratio of the curve, at least up to a certain flow value, that is 200-250 vehicles/15′.

The increase also varies with the weather conditions and the time of day: other conditions being equal, there are fewer violations after dark, especially if it is raining. This tendency is not however universal, but depends on the flow and on the w/c ratio. The curve also depends on the proportion of vehicles in the traffic flow: there are fewer violations if there is a higher proportion of cars, especially for small traffic volumes.

The growth rate then slows noticeably above the 35 violations level, where we often find a flex point, and becomes practically constant round 40. When the flow value passes the 350 vehicles/15′ limit the influence of the different variables becomes smaller, with a possible exception for the w/c ratio; there is in fact a very noticeable convergence towards common values for all configurations, which demonstrates that a limit situation has been reached (Figure 4).

It would appear that for flow values over 380 vehicles/15′ the different curves rapidly tend to overlap, at a point corresponding to about 40 violations. If the composition of flow is varied so as to have a smaller percentage of cars and a larger one of two-wheeled vehicles, the convergence point moves to the left, which means that is the flow value which gives the greatest number of violations diminishes.

The conclusion is that each intersection has a maximum number of possible violations, related to its geometrical shape, the composition of the traffic flow and the duration of the green light. This applies in a high degree to violations due to crossing a red light; it could be slightly proportionate to the flow in the two other kinds of violations (being in the wrong lane and not respecting priority).

For flows below 150 vehicles/15′ and high w/c values, the number of violations is almost negligible in all conditions (usually smaller than 5), while in high flows they make a considerable difference. The change of slope is usually situated between the values of 200-260 vehicles. On the other hand, if the w/c value is low, the number of violations is rather high even if the flow is low, especially during daylight and for combination number 1 (60% cars). This is even clearer if instead of the number of violations, the I ratio (number of violations/flow ratio) is considered: in this case the curve sometimes decreases, varying according to flow values, the time of day, the weather and the w/c ratio (Figure 5).

In combination number 8 (an almost homogeneous composition of the traffic flow with 95% cars) there is an inversion of tendency, again with a low w/c ratio and a flow of between 140 and 260 vehicles. In bad weather conditions the index values tend to increase (Figure 6).

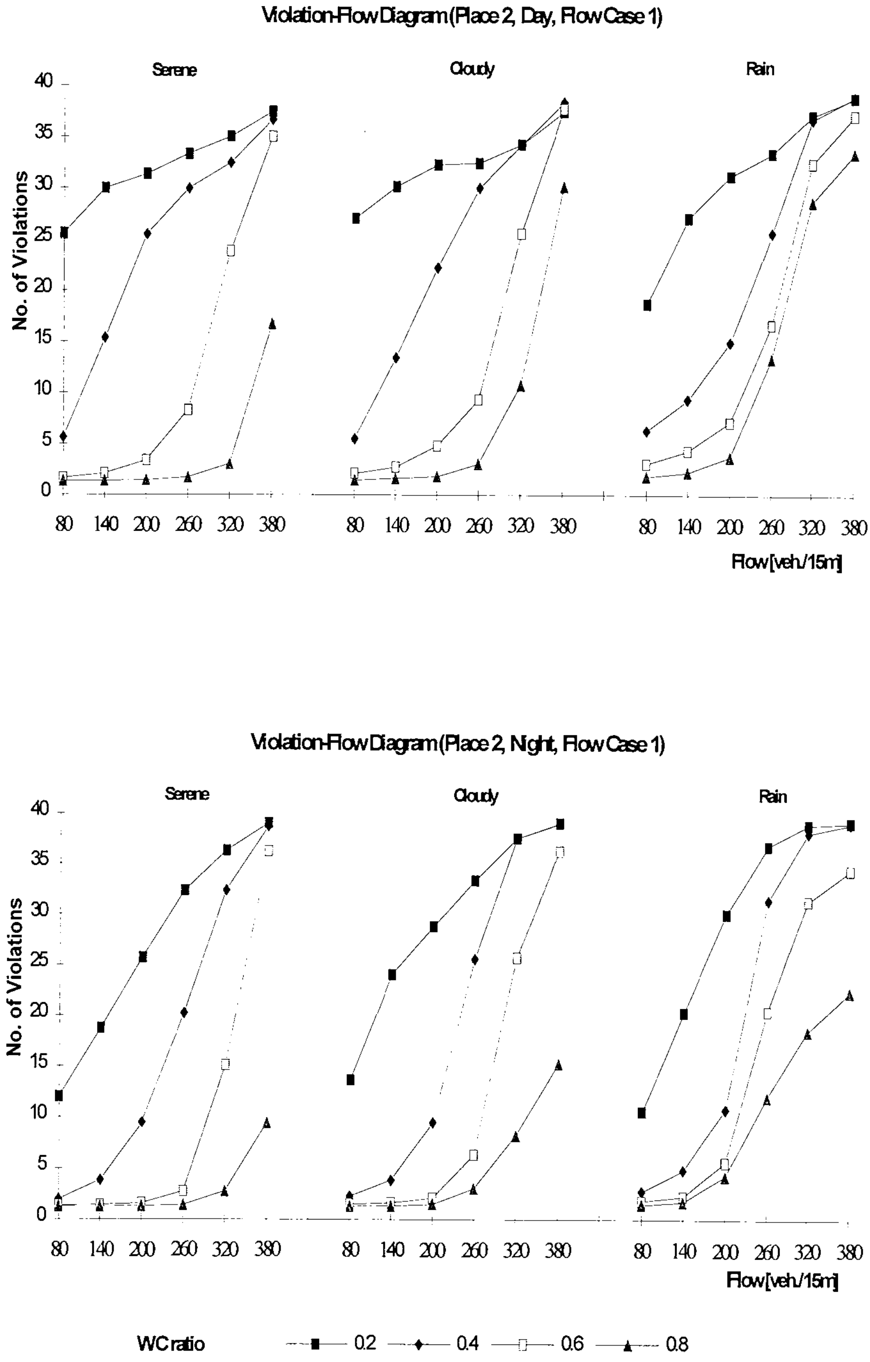

Figure 4 Influence of the w/c ratio and of weather conditions on the number of violations

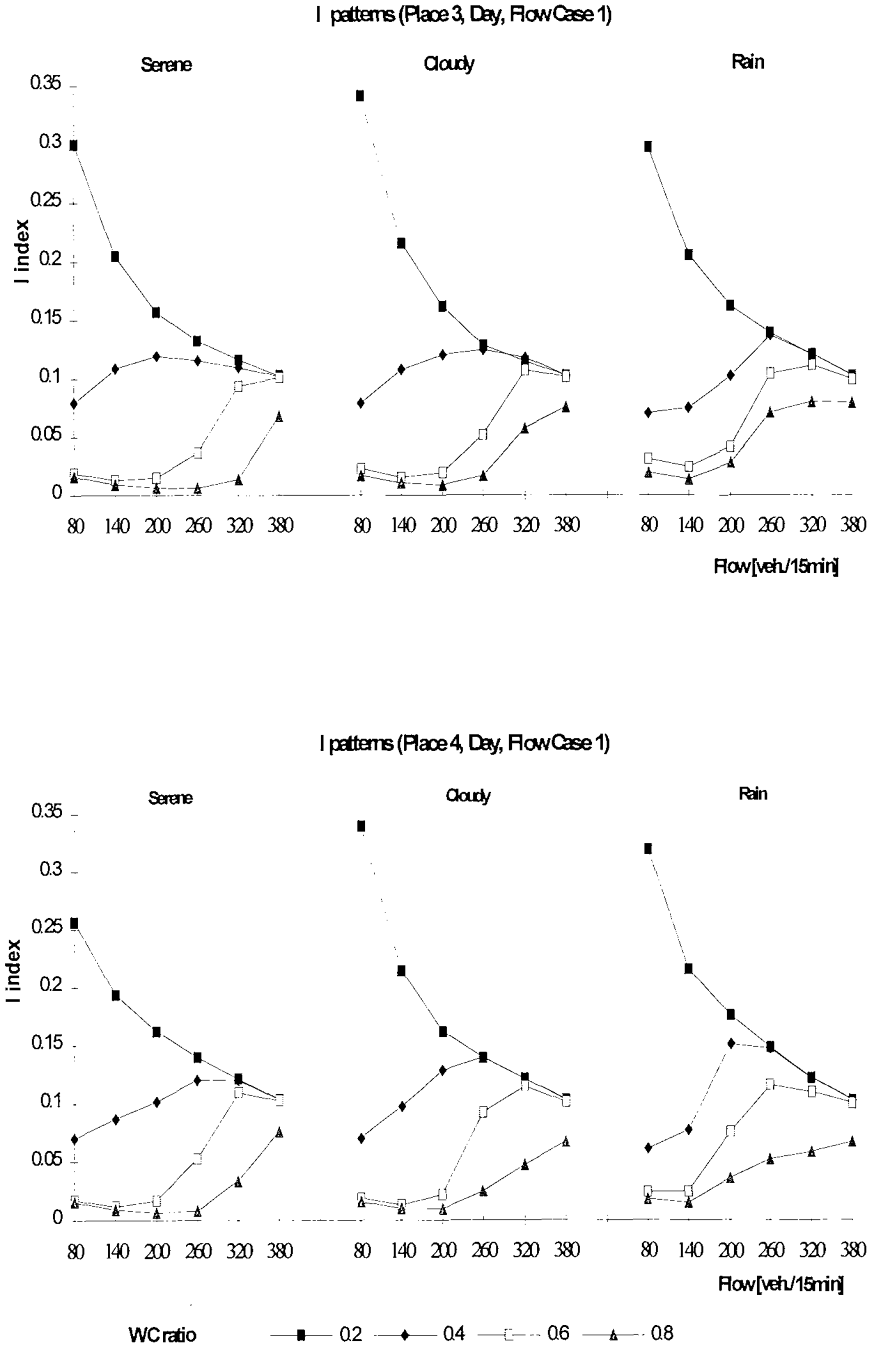

Figure 5 Influence of the w/c ratio on the I index

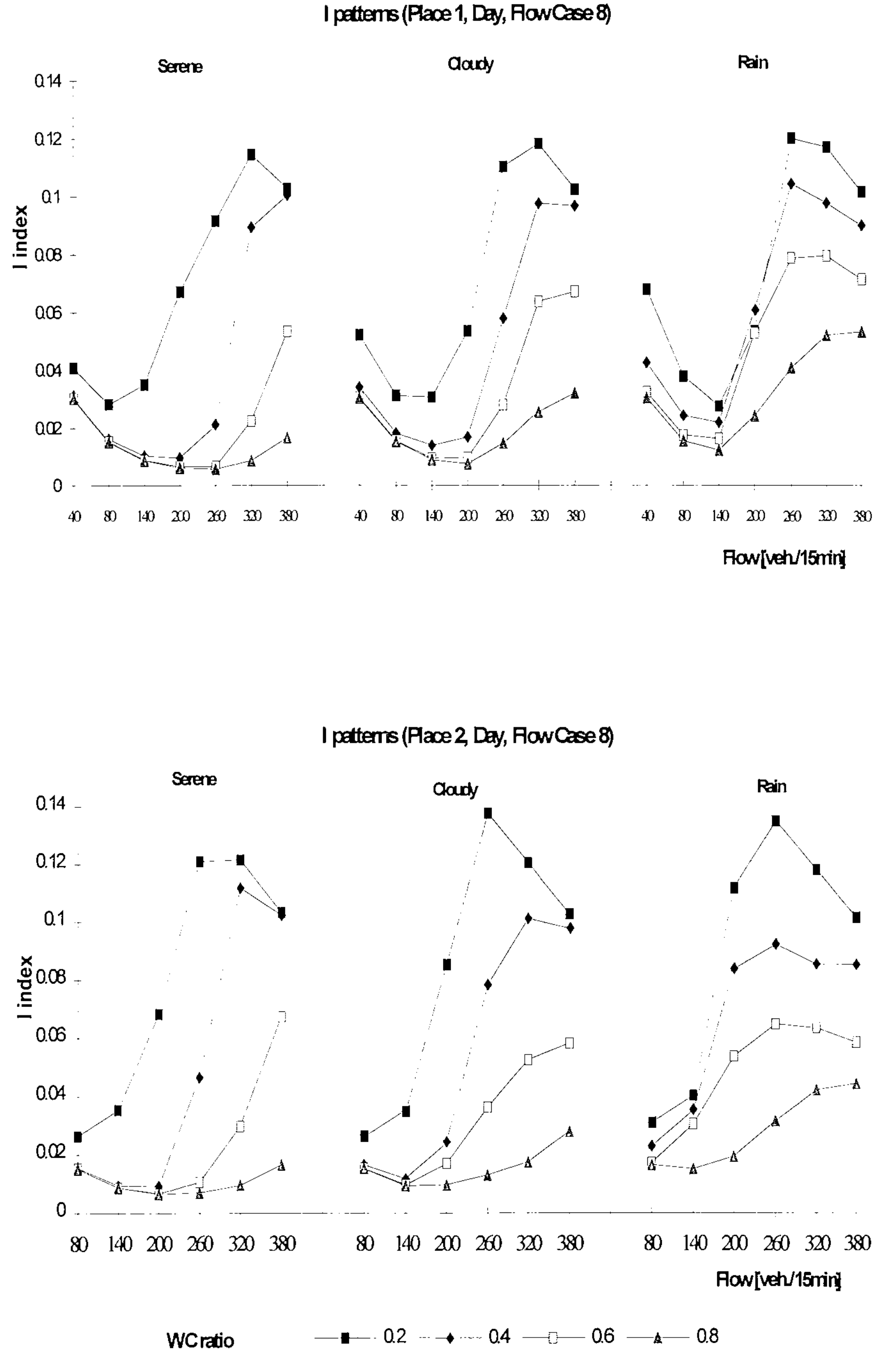

Figure 6 Influence of weather conditions on the I index

Even in absolute magnitude, still with reference to combination 8, as weather conditions worsen there are more violations for small flow values while for big flow values they diminish (Figure 7).

As already shown, the greater the percentage of cars, the fewer violations are committed: this is affected neither by weather conditions nor by environmental conditions (Figure 8). In general, for equal flow and reference conditions, the influence of the combination of vehicles is greater with small w/c values. Differences of behaviour between the different approaches to the intersection are small with low traffic flows but increase with the flow value and are also influenced by weather conditions (Figure 9).

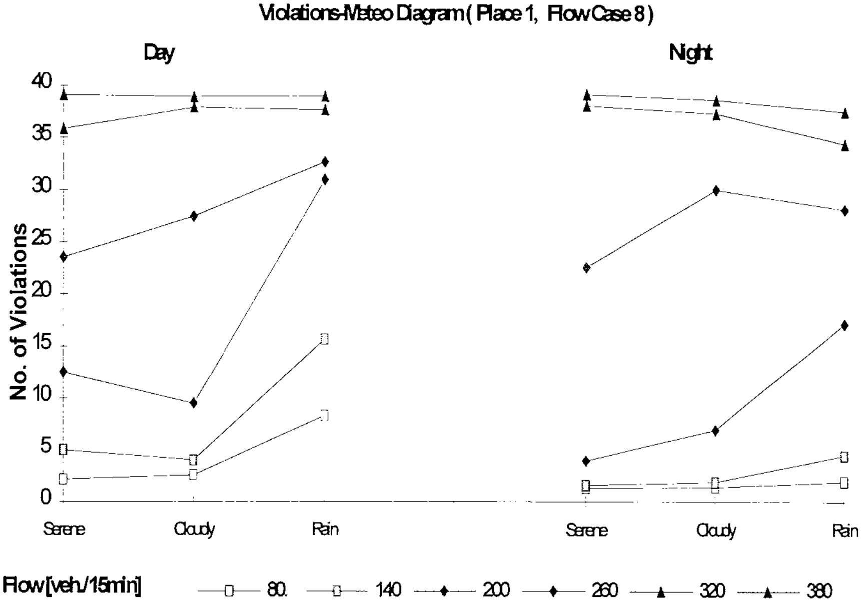

Figure 7 Influence of weather conditions on the number of violations

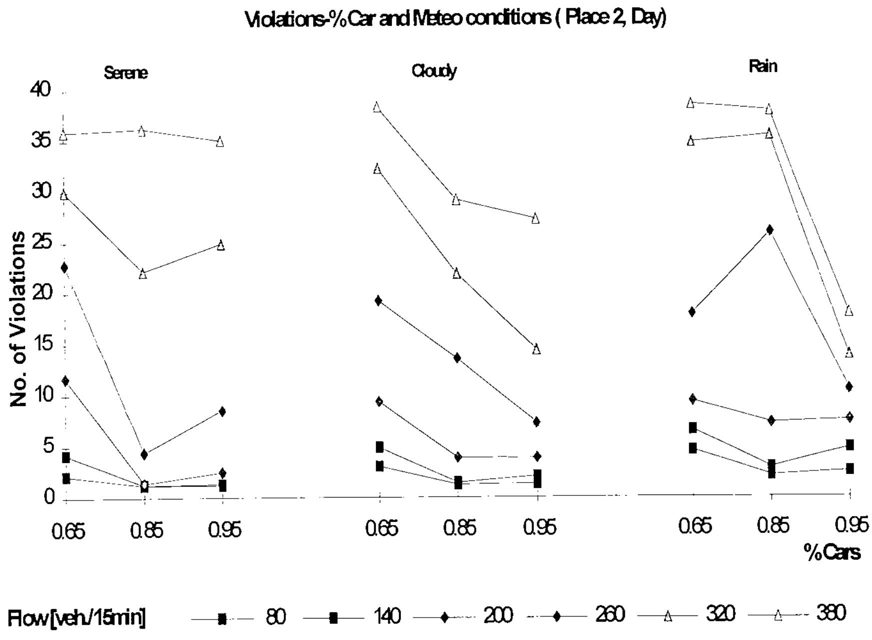

Figure 8 Influence of the traffic flow composition on the number of violations

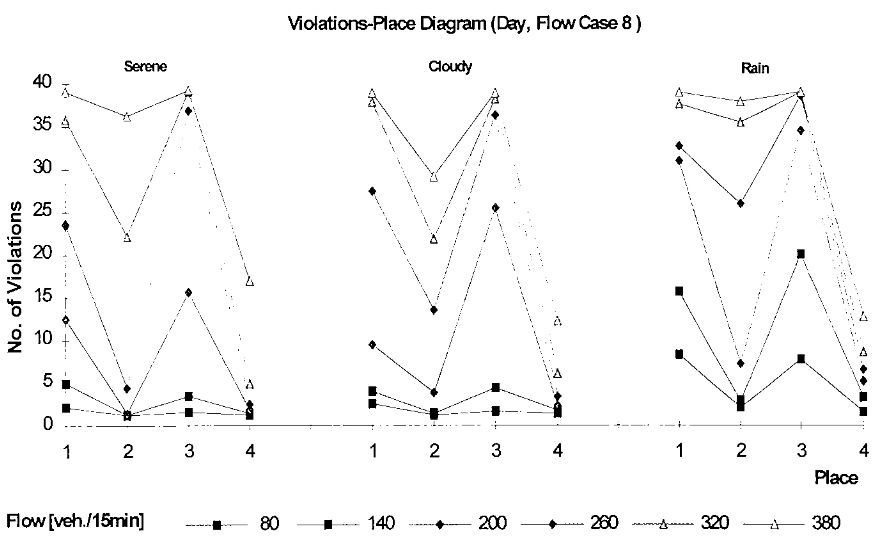

Figure 9 Influence of the approach road on the number of violations

CONCLUSIONS

With this model, driver behaviour can be anticipated by using certain parameters: changes in some of these (for example the w/c ratio or the traffic composition percentages) produce noticeable results. It also shows how external conditions are an important influence in drivers' reactions to traffic regulations: it is therefore useful to have an instrument of inquiry which will help planners in their decisions.

This method also allows, if more detailed study were necessary, to build more sophisticated models to take account of more variables, so as to obtain more specific answers in each sector (for example, to distinguish between different violations or between the vehicles which commit them).

One possible limitation is the small size of the survey sample which could have been bigger and more complete; however this would have required an excessive investment of money. However, the results, thanks to the rapid training convergence of the neural net, are encouraging, and it is unlikely that greater precision would substantially modify the tendencies so far discovered. In future, as a development of this study, it is expected that new models will be built, since not all the information in the database has been fully exploited. Later on it would be useful to carry out a new survey so as to confirm the results and add new elements to the information obtained.

ACKNOWLEDGMENTS

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