A Motorway Safety Analysis Model Based on Artificial Neural Networks

Bosurgi G.
Associate Professor – University of Messina

D'Andrea A
Professor– University of Messina

Trifirò F.
PhD– University of Messina

SYNOPSIS

The main objective of road maintenance management is to guarantee adequate safety and comfort levels to the users.
Road safety analysis can represent an operative instrument to manage the safety to network level. In fact it could be used to select the maintenance activities for pavement sections.
In the last years a lot of studies have been realized and it has been very important the use of artificial neural networks.
In fact, the accidents are the result of the influence of different factors that all influence their happening. So it's necessary to use a model that is able to consider all these factors simultaneously.
In this paper, a procedure based on the use of artificial neural networks was realized for predicting the motorway accidents.
Input data were geometry factors, environemntal conditions, climatic conditions, traffic flows and pavement conditions. Output was the number of accidents.
This model was completed by the calculation of the "weights" of identified factors. In particular a model of neural network was realized and was applied to the data used to train and to test the accident prediction model.
These two models were applied to the A18 motorway (Messina-Catania). So it was possible to prove their potentiality.

SOMMARIO

L'obiettivo principale che si persegue con la gestione delle attività di manutenzione delle infrastrutture viarie è quello di garantire adeguati livelli di sicurezza e comfort di marcia per i veicoli che la percorrono.

L'analisi di sicurezza delle strade in esercizio, pertanto, può rappresentare per l'ente gestore uno strumento operativo per gestire la sicurezza a livello di rete e, quindi, di notevole importanza per l'individuazione delle necessità e priorità d intervento per i singoli tronchi.

Tra i molti studi effettuati, negli ultimi anni hanno avuto un largo consenso quelli che proponevano il ricorso alle tecniche di intelligenza artificiale e, in particolare, alle reti neurali.

L'utilità di ricorrere alle reti neurali è motivata dal fatto che l'apparente casuale sinergia dei fattori scatenanti l'incidente necessita di uno strumento che legga in modo aggregato i dati.

In questa memoria è stato messa a punta una procedura basata sull'utilizzo delle reti neurali per prevedere l'incidentalità in campo autostradale e per valutare nel contempo i "pesi" delle variabili caratteristiche del problema.

In particolare, i dati di input hanno riguardato le caratteristiche plano-altimetriche dell'infrastruttura, il contesto ambientale, le condizioni climatiche e di esercizio, nonché lo stato delle pavimentazioni in termini di aderenza. Come output è stato considerato il numero di incidenti.

Il modello suddetto è stato completato con la valutazione dei pesi di ciascuna variabile. A tal fine, è stata applicata una rete neurale al set di dati definiti per addestrare e testare il modello di previsione dell'incidentalità.
Per far comprendere le notevoli potenzialità dei modelli realizzati è sembrato opportuno applicarli ad un caso reale ed, in particolare, all'autostrada A18 (Messina-Catania).

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INTRODUCTION

The main objective pursued with the motorway infrastructure maintenance activities is to guarantee adequate safety levels and driving comfort. The correct interpretation of accident phenomena is therefore an important and crucial aspect in the overall management of the roadway maintenance.
In general, accident rate analysis consists of defining the significant variables of the problem, the risk level, the problem management methods and the cause-effect relationships.
Various criteria exist to face the problem, although the aim remains the interpretation of the cause-effect relationships between the factors determining the accident. This is especially true if it is wanted to develop of mitigation measures to be activated in the planning phase or in the management phase.
Among the various studies carried out in the last few years, the most successful ones were those proposing the use of artificial intelligence techniques and, in particular those using neural networks [Dia et al. 1997, La Torre et al. 1997, Bevilacqua et al. 1998, Bella et al. 2000, Abdelwahab et al. 2002, Giuliani et al. 2002, Jin et al. 2002]
The usefulness of neural networks is related to the fact that the apparently random synergy of the factors causing the accident needs an instrument capable of interpreting data in a multi-layered way.
In fact, artificial neural networks simulate the structure and the functioning of biological neurons. These powerful models are composed by many simulated neurons or simple computational units that are connected in such a way that are able to learn in a similar manner to people (Lawrence, 1994). This distributed architecture makes neural networks particularly appropriate for solving nonlinear problem and input-output mapping problems.
Unlike the usual digital calculation systems, requiring a program to carry out operations using input data, neural networks require a training phase in order to acquire, through the presented examples, the necessary experience to provide a correct output from the given input. This allows therefore to eliminate the need for an algorithmic link between input and output, so they can be trained to assess an observed function when its shape is unknown; it also allows to establish particular rules, with consequent time saving, simplification of the phenomenon analysis for the programmer and simplicity of utilization for the final user. If correctly organized and “instructed”, neural networks allow the reconstruction of the cause-effect relationships which are at the basis of complex multivariable systems; they can make generalizations, and are particularly appropriate in those cases in which there is a significant amount of examples available.
There are different types of neural networks. The more used Neural networks have a flow of information one-directional, generally from the input layer, through hidden layer, and then to the output layer, which then provide the response of the network to the input stimuli. In this type of networks, there are generally three distinct types of neurons, and each group forms a “layer”. The input layer contains the input variables. The hidden neurons are contained one or more “hidden” layers consisting of a set of neurons that processes information within the network. The hidden layer receives the processed input data and then processes and passes them to the output layer. The number of hidden layers and the number of neurons contained within them is very important for the accuracy of the network. The output layer contains the target output vector. A weight coefficient is associated with each of the connections between any two neurons inside the network. The processing in the neurons is done by an “activation function” which controls the output of each one.
ANN trains through adaptation of their connection weights. The network is trained by learning from the training set. The ANN training is performed iteratively until the error between the computed and the real output over all the training patterns is minimized. Output errors are calculated by comparing the desired output with the actual output. Therefore, it is possible to calculate an error function which is used to propagate the error back to the hidden and to the input layer in order to modify the weights. This iterative procedure is carried out until the error at the output layer reduces to a pre-specified minimum or for a pre-specified number of epochs. The training phase is very long and complex and it must be carried out by using many examples which must be organized beforehand in an efficient and aimed manner. Validation of the performance of an ANN is done using a separate set of data (testing data). If the error obtained in the training and testing phase is satisfactory the neural network can be used for pratical applications.
In this paper, a procedure for predicting the number of accidents and for evaluating the weights of the significant variables for the A18 motorway (Messina-Catania) was defined using artificial neural networks.
This procedure was very efficacious in relation to the many variables and to the necessity to carry out a systemic approach.

THE PROPOSED METHODOLOGY

The model realized using neural network was applied to a real case and, particularly, to A18 motorway, managed by C.A.S. (Consorzio per le Autostrade Siciliane), which represents one of the most important communication roads in Sicily.
The designed neural network permitted the definition of an accident prediction model and the valuation of the weights of the characteristics variables (the characteristics of the infrastructure, the pavement surface characteristics, the climatic conditions and the operating conditions)
The functionality of neural networks is given by a correct determination of those variables which more than others participate in the generation of the accident phenomenon. For this very reason it is necessary to pay particular attention to the methods of data identification to be used in the construction of examples.
In order to establish an accident prediction model the accidents occurred in the three years following the pavement maintenance activities carried out between 1996 and 1999 were considered.
The first phase of the procedure regarded the definition and the construction of a database containing the values of the individuated variables.

Database and Construction of the Examples

A database was created and structured in order to easily cross the data concerning the motorway's characteristics with the ones concerning the operating conditions and the maintenance activities carried out throughout the years. In detail, the data was classified according to:

- characteristics of the infrastructure;
- operating conditions;
- characteristics of the road work zones and of the maintenance activity carried out;
- pavement surface characteristics (before and after the intervention);
- climatic conditions;
- characteristics of the accidents.

The homogeneous sections were therefore determined using the results obtained through the safety analysis in the road work zones and analysing the scenarios of the accidents occurred after the closing of the road work zones.
In particular, the first analysis was carried out through a multivariable regression analysis applied to the accidents that occurred in the road work zones opened during the maintenance activity between 1996 and 1999 [Bosurgi et al. 2003)]. The results obtained highlighted the fact that the length of the road work zone, averaging 1,5 km, was the parameter which mostly caused such accidents. Such first result brought to the definition of a homogeneous section whose length was lower than 1,5 km in order to reduce the risk of accidents in the road work zones to be planned in the future.
On the other hand, it seemed demeaning to use a length lower than 1 km; because of the continuous presence of viaducts and tunnels all along the infrastructure, the environmental scenario of the accident would not be well represented. The chosen length of the homogeneous section was therefore equal to 1 km.
Individuated homogeneous sections it was possibile to construct the examples for training the network. In particular, the input variables were defined through parameters concerning the characteristics of the infrastructure, the pavement surface characteristics, the climatic conditions and the operating conditions. As an output parameter the number of accidents occurred was assumed.
a) Characteristics of the infrastructure
Some indicators were defined:
- Planimetric index:

$$I_p = \frac{\sum_{i=1}^{n} \frac{l_i}{R_i}}{\sum_{i=1}^{n} l_i}$$

where R_i and l_i represent, respectively, the radium of the curve and the length of the planimetric elements within the homogeneous motorway section considered.
- Altimetric index:

$$I_a = \frac{\sum_{i=1}^{n} p_i l_i}{\sum_{i=1}^{n} l_i}$$

where p_i and l_i respectively correspond to the slope and to the length of the vertical elements present in the homogeneous motorway sections considered.

- Viaduct index:

$$Iv = \frac{\sum_{i=1}^{n} l_{vi}}{L}$$

where l_{vi} is the length of the generic viaduct considered present in the homogeneous motorway section and L the length of the section itself;

- Tunnel index:

$$It = \frac{\sum_{i=1}^{n} l_{ti}}{L}$$

where l_{ti} is the length of the generic tunnel present in the homogeneous section considered and L the length of the section itself;

b) Pavement surface characteristics

To characterize the pavement surface characteristic, it was used an artificial neural network developed to predict the Sideway Force Coefficient (SFC) values for the pavement of the analyzed motorway [Bosurgi et al. 2004]. In particular, The value of the initial SFC (I_{SFC}) after the maintenance interventions was considered.

c) Climatic conditions

To reconstruct the climatic conditions, it was decided to use the data of the "Assessorato Agricoltura e Foreste" of Sicily and in particular of the "Servizio Agrometereologico Siciliano" (SIAS).

The utilizable rain stations were individuated analyzing the SIAS' network (Figure 1).

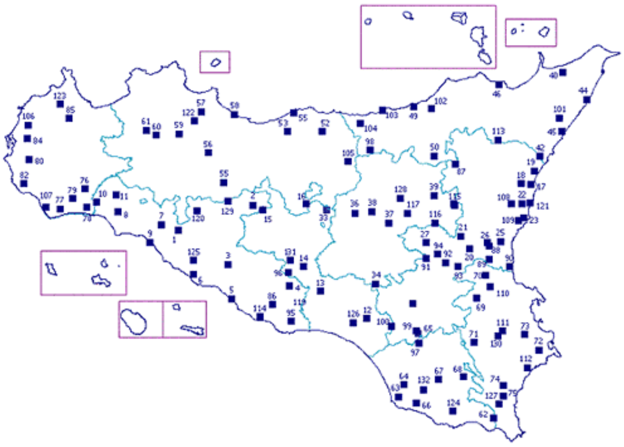


Figure 1: SIAS' rain stations

In particular, le following stations were utilizable:

- Messina;
- Savoca;
- Mascali;
- Acireale;
- Catania.

Using the available data, it was chosen to characterize the climatic conditions in terms of rainfall which occurred in the three years following the closing of the road work zones.

Once the rain stations were identified, the Thiessen method was used to determine the rainfall occurred in each homogeneous section (I_{rain}).

One of the applications realized using the Thiessen method is represented in the following figure (Figure 2).

Figure 2: The Thiessen method applied between the stations of Messina and Savoca

c) Operating conditions

e operating conditions were characterized evaluating the traffic in transit during the analysis period in the homogeneous sections considered ($I_{traffic}$).

d) Number of accidents

It was chosen to consider the number of accidents as an explanatory parameter for the accidents occurred after the closing of various road work zones (I_i). Particular attention was paid to the identification of the accidents that could directly be correlated to the usage or infrastructural characteristics, leaving out all the events due to different causes (alcohol or drugs, etc.).

Model of Neural Network and Results

After the identification of the input and output parameters and after the reconstruction of the corresponding values for each homogeneous section it was possible to develop a database containing the necessary examples to train and test the network.

The sets of available data were 154. 65% of these were selected randomly to train the network (learning set) and the remaining 35 % to test it (testing set).

The topology of the adopted neural network was the multilayer perceptron with back propagation, in fact it proved to be the most appropriate network for the analyzed problem.

The architecture of the network was defined with an input layer composed of seven neurons (I_p, I_a, I_v, I_t, I_{SFC}, I_{rain}, $I_{traffic}$), a hidden layer and with an output layer with one neuron (I_i) (Figure 3).

After that 200 ANNs were trained, the best result was obtained using three neurons in the hidden layer, a simmetric sigmoid transfer fuction $f(x) = \tanh(x)$ (Figure 4) and the Levenberg-Marquardt method as minimization algorithm [Hagan et al.1994] which permits to obtain an absolut minimum quickly.

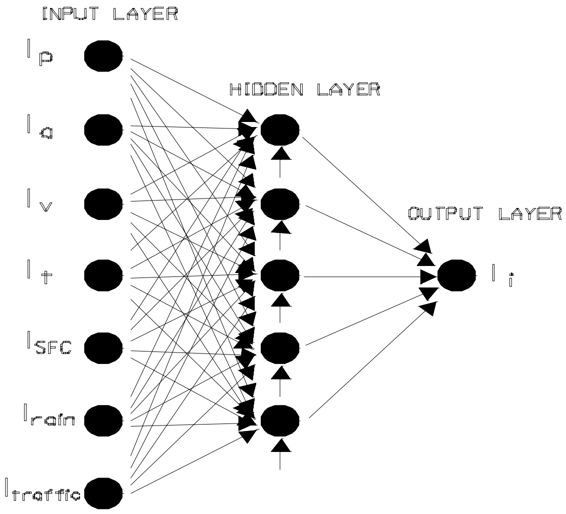


Figure 3: Architecture of the network

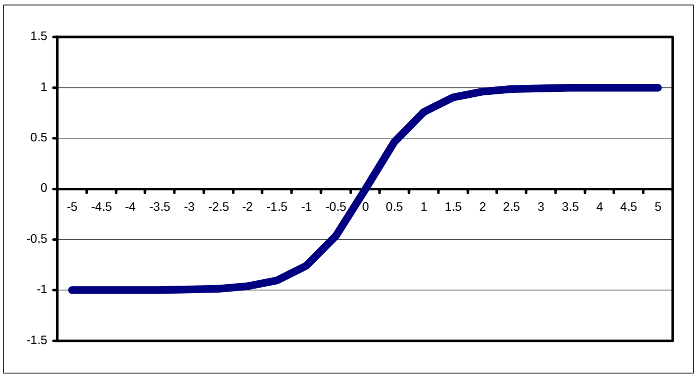


Figure 4: Sigmoid function

The preprocessing of inputs was done, in fact normalization of the input data is needed before the network is trained. This was done to increase the performance of the network, decrease the training time, and make consistent input data and transfer fuctions.
In order to verify the learning capacity of the network, the following verifications were performed on the obtained results:

- Variance analysis of the residue error (MSE) in the testing and training phase (Table 1 and Figure 5);
- Representation of the error histogram (Figure 6);
- Representation of the error auto correlation curve in the two phases (Figure 7).

Table 1: MSE values

Training phase	Testing phase
0,0037	0,0063

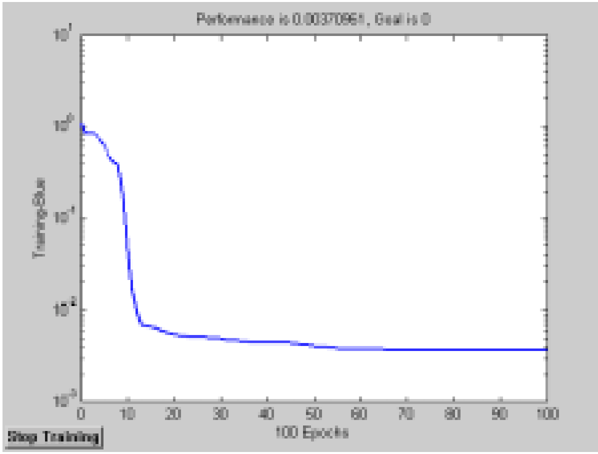
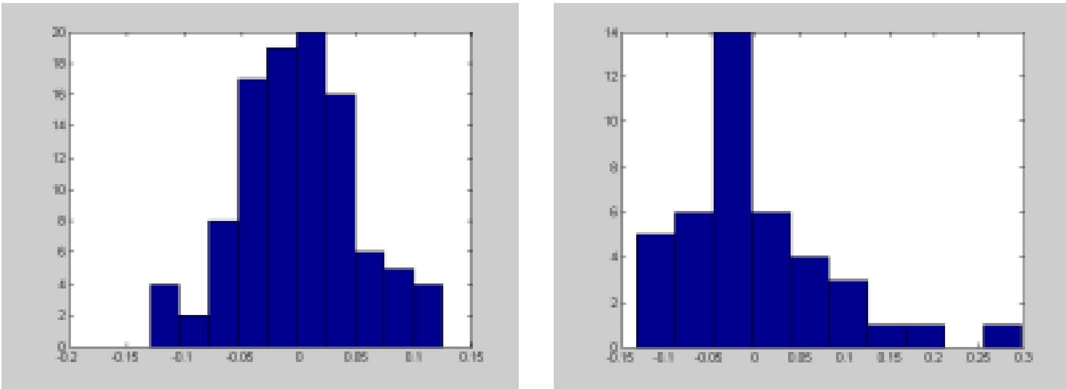
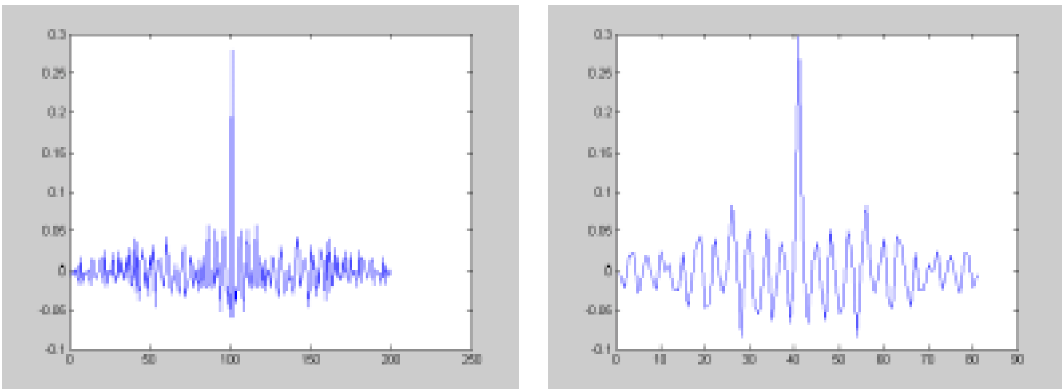


Figure 5: Error during the iterations (training phase)



Training phase **Testing phase**

Figure 6: Error histogram



Training phase **Testing phase**

Figure 7: Error autocorrelation

It was obtained that:

- The MSE values were almost equal in the two phases;
- The trend of the error histogram was similar in the two phases and came near to a gaussian curve;
- The trend of the error autocorrelation came near to a white noise in the two phases;

So, the results obtained confirmed that the neural network well interpreted the phenomenon and that it managed to figure out the internal correlations existing between the variables

In order to evaluate the possible error and therefore the acceptability, it was finally necessary to carry out a further test, which consisted in comparing the number of accidents estimated from the network with the real values (Figures 8 and 9).

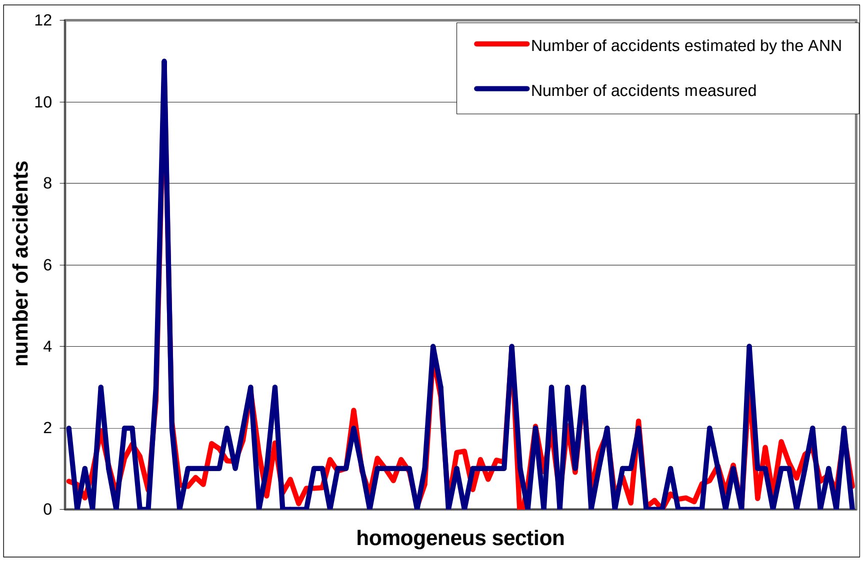


Figure 8: Comparison between accidents measured and estimated by the ANN in the training phase

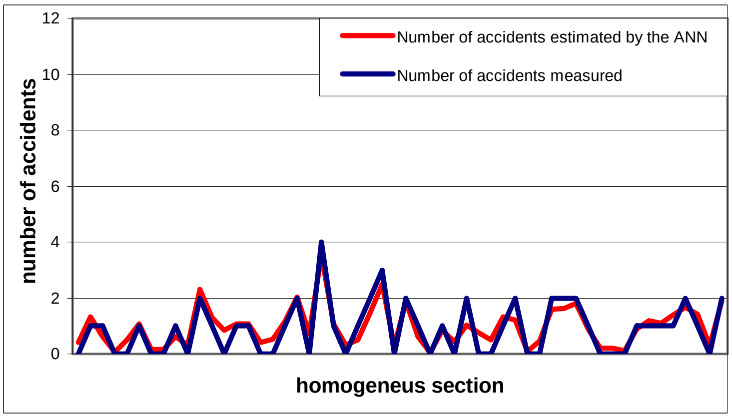


Figure 9: Comparison between accidents measured and estimated by the ANN in the training phase

From the graphs it can be seen that the trends can almost be approximated and therefore the neural network can be used as an accident prediction instrument.

In the second phase of the analysis, the “weights” of the identified factors on the accidents were calculated. In particular, a commercial software [Ward System Group 1990] based on the Turboprop2 (a neural network using the Scott Fahlmann correlation [Fahlmann 1988] as learning algorithm) was used. The architecture of this network is feedforward and is carachterized to add a neuron in the hidden layer in every step. The hidden neurons can be connected both the previous hidden neurons and the input neurons.
If the problem is well interpreted, it is possible to calculate the “weights” of identified factors on the output.
The results represented in the following figure (Figure 10) were obtained using the defined procedure and using the same examples constructed to train the neural network for predicting the number of accidents,

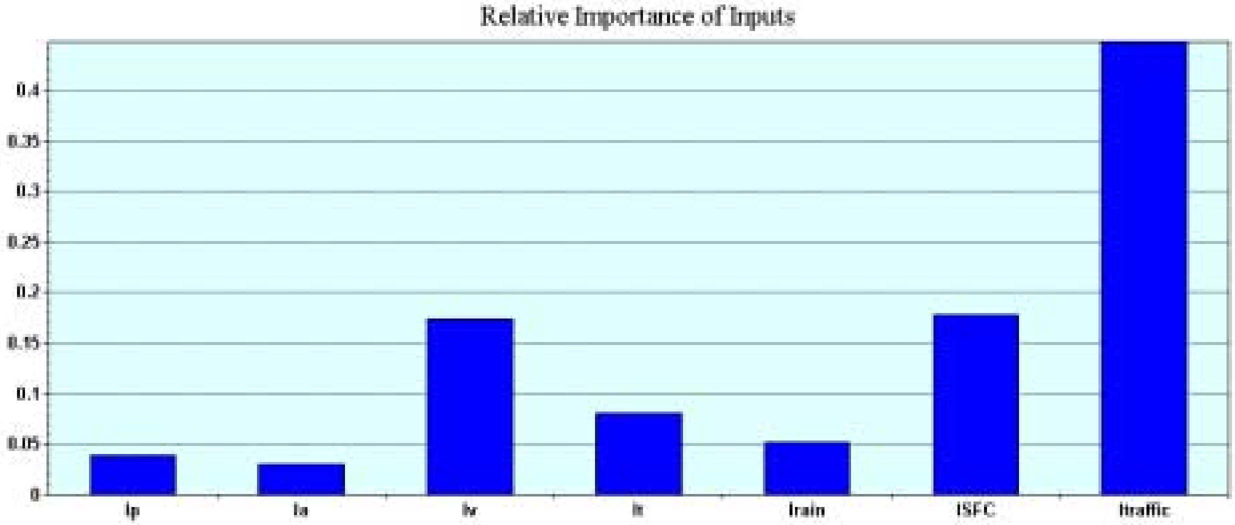


Figure 10: The "weights" of the identified factors

The obtained results highlighted that the traffic, the SFC values and the viaduct index were the parameters which had the greater influence on the happened accidents.

CONCLUSIONS

In this paper, a model was defined for predicting the number of accidents using the artificial neural networks. This procedure was applied to the A18 motorway managed from C.A.S. (Consorzio per le Autostrade Siciliane)

The used neural network was the multilayer perceptron with back propagation, while the architecture was defined with an input layer composed of seven neurons, a hidden layer and an output layer with a neuron representing the number of accidents.

The obtained results were very satisfactory and highlighted the potentiality of the defined procedure and its applicability as model for predicting the accidents.

Moreover, another procedure was realized for evaluating the weight of the identified variables on the happened accidents. This analysis highlighted that the traffic, the SFC values and the presence of viaducts were the parameters which had the greater influence on the accidents happened in the studied period for the analyzed motorway.

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