ARTIFICIAL NEURAL NETWORKS FOR PREDICTING ROAD PAVEMENT CONDITIONS

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ABSTRACT

The knowledge of the curves to predict deterioration of pavement condition is fundamental to the optimal planning of maintenance activities. Well developed models contribute to select the optimum maintenance plan. Significant research has been done in the last few years regarding pavement deterioration models. Many difficulties are associated with the measurements and/or precise estimations of the inputs involved in the deterioration models, such as traffic flows, environmental condition, etc.

Within this context, emerging technologies, such as artificial neural networks, provide efficient techniques to define the prediction models.

In this paper, a Sideway Force Coefficient (SFC) prediction model is carried out for an Italian motorway. In particular, a model based on a neural network has been carried out using a series of instrumental check-ups concerning friction and traffic measurements. The obtained results compared with those obtained using a linear regression, have showed the efficacy of neural networks in the analysis of this important road problem.

Keywords: Sideway Force Coefficient, Artificial Neural Networks, Motorway, Prediction model, Least Mean Square model

1. INTRODUCTION

Transportation infrastructure asset management is a particularly complex and articulated task, which must be the result of a global analysis which takes into account the transportation agency's objectives and the existing constraints. Transportation officials are faced every day with competing investment demands and limited economic resources in order to maintain transportation infrastructure in the best possible condition. It is therefore important that decision makers have access to valid asset management tools, which should be mathematically reliable.

Pavement condition assessment and deterioration estimation is an integral part of all pavement and infrastructure management system. They are usually based on models which predict pavement deterioration based on present condition, deterioration factors such as traffic, environmental and construction proprieties and the effects of maintenance.

However, many difficulties are associated with the measurements and/or precise estimations of the inputs involved in the deterioration models, such as traffic flows, environmental condition, etc. The uncertainty in the determination of these and other factors contributes to the difficulties encountered while developing pavement condition prediction models.

Significant research has been done in the past few years regarding pavement deterioration models [Ahmed et al. 2004, Attoh-Okine 2002, Choi et al. 2004, Felker et al.2003, Fwa et al. 1997, Kerali and Odoki 2000, La Torre et al. 1988, Shekaran 1998, Van der Gryp et al. 1998, Yang et al. 2003]; AASHTO (2001) presents a good overview of available techniques and models.

Between the applied methodologies, neural networks models have demonstrated to be particularly appropriate for these types of predictions.

In the infrastructure management field ANNs are an integral part of the new concrete pavement 2002 AASHTO design procedure. However, some agencies and transportation practitioners still have reservations about implementing this procedure. This is due to resistance to change, difficulty in integrating the principles and techniques with existing practices and legacy systems, lack of understanding of this technique, lack of data to develop reliable models, lack of quantitative evidence supporting the benefits of using this technique.
A practical application to demonstrate the potentiality of this approach for predicting the pavement condition deterioration is presented in this paper. In particular, the application describes the use of neural networks for developing a SFC prediction model.

The proposed model has been developed for an Italian motorway and has been carried out using a series of instrumental check-ups concerning friction and traffic measurements realized on this infrastructure.

To highlight the potentiality of the model, it has been compared with a Least Mean Square (LMS) model, used by the road agency which manages the analyzed motorway, carried out using the same data.

2. ARTIFICIAL NEURAL NETWORKS: A SHORT INTRODUCTION

Artificial Neural Networks are a system of simple processing elements, neurons, that are connected into a network by a set of weights. They simulate the structure and the functioning of biological neurons [Fortuna et al. 1999].

Unlike the usual digital calculation systems, which require 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 eliminates 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.

The function of the network is determined by the architecture of the network, the magnitude of the weights and the processing element's mode of operation.

In particular, the neuron is a processing element that takes a number of inputs, weights them, sum them up, and uses the result as the argument for a singular valued function, the activation function. The input to a unit can either be outputs of other units or they can be external inputs.

Units can be combined into a network in numerous fashion. The most common of these is the mulilayer perceptron (MLP) network. The basic MLP-network is constructed by ordering the units in layer, letting each unit in a layer take as input only the outputs of units in the previous layer or external input. The most used neural networks have a one-directional flow of information, generally from the input layer, through hidden layer, and then to the output layer, which then provides the response of the network to the input stimuli.

The depicted network is said to be fully connected since all inputs/all units in one layer are connected to all units in the following layer.

For most ANNs' architectures there are two stages in preparing them to be implemented in different applications. A training stage, in which the network learns from an existing dataset, and a testing stage that uses a different dataset to check the effectiveness of the learning phase. Because the knowledge incorporated in the ANNs is extracted from a given dataset during the training stage the ANNs are model-based and data driven systems. Usually the learning phase uses a back-propagation algorithm to adjust the connections' weights, based on the known data of input-output pairs. This means, after each presentation of all the data samples, which are the input-output pairs, the weights are adjusted such that the overall error output of the network is minimized. This complete cycle of running the data through the network and the weights adjustment process is called an epoch. A training stage of an ANN is completed based on different criteria. For example, the learning stops after a certain number of epochs or if the error reaches a certain limit or if the network's performance does not improve after a consecutive number of epochs. Another method to control the efficiency of the training stage is to test in parallel the error of the network performance on a test data set, usually smaller than the learning dataset. The role of test set is to test for the network's generalization capabilities during the training process. If the network is over-trained a sudden degradation of the network based on the test dataset will trigger the training process to stop.

The training process is to achieve a good network performance when employed in on-line implementations. Recall that ANNs are data-driven systems and if the training process is not done properly the network may suffer of insufficient representation of the data or from overtraining. Insufficient data representation means that the dataset does not cover the complete solution space of the problem, such that when the network is tested with 'unseen' data it may not be able to perform satisfactorily. Conversely, overtraining occurs when the data is presented to the network in the learning stage for too many epochs. One solution to have a better control of the training issue is the use of a test dataset. The test dataset approach doesn't allow the network to 'memorize', because this would impair dramatically the network performance on data with different characteristics from the training dataset.

3. THE SIDEWAY FORCE COEFFICIENT PREDICTION MODEL

The efficacy of the prediction model depends strongly on the correct individuation of the problem characteristic variables.

So, the first phase of the procedure has regarded the reconstruction of all the information about the examined infrastructure and the individuation of the significant variables.

The analysis has been carried out on the motorway A18 which streches along the coast of Eastern Sicily (77 km).

In particular, this motorway has been characterized from pavement maintenance activities from 1996 to 1999. To construct the database, these maintenance activities have been characterized in relation to their typology and space-temporal position.

A series of instrumental check-ups concerning friction (Grip Tester) were carried out in the past (1994 and 1997). These measurements were complemented with three additional measurement surveys in 2001, 2002 and 2003 using the Grip Tester equipment.

Analysing the maintenance activities carried out, it was possible to individuate the pavement sections rehabilitated with the same thickness of the layers and the same materials before September 1997. This was done to select homogeneous pavement on which to make friction deterioration evaluations.

These additional measurements allowed of having, for each selected pavement section (50 meters), the following four SFC values: the SFC values measured in September 1997 after the maintenance interventions, in December 2001, in October 2002 and in October 2003.

The database was completed using the cumulative traffic in the period of time elapsed between the analyzed SFC measurements.

After that the parameters were defined by the interpretation and the elaboration of the database, it has been possible to construct the examples for realizing the prediction model. In particular, for every SFC value measured in September 1997 after the maintenance interventions, three data set were defined. The input data were the SFC measured in 1997 and the cumulative traffic elapsed between this measurement and the measurement realized in 2001, 2002 or 2003, while the output data was the SFC value measured in 2001, 2002, or 2003 (figures 2 and 3).
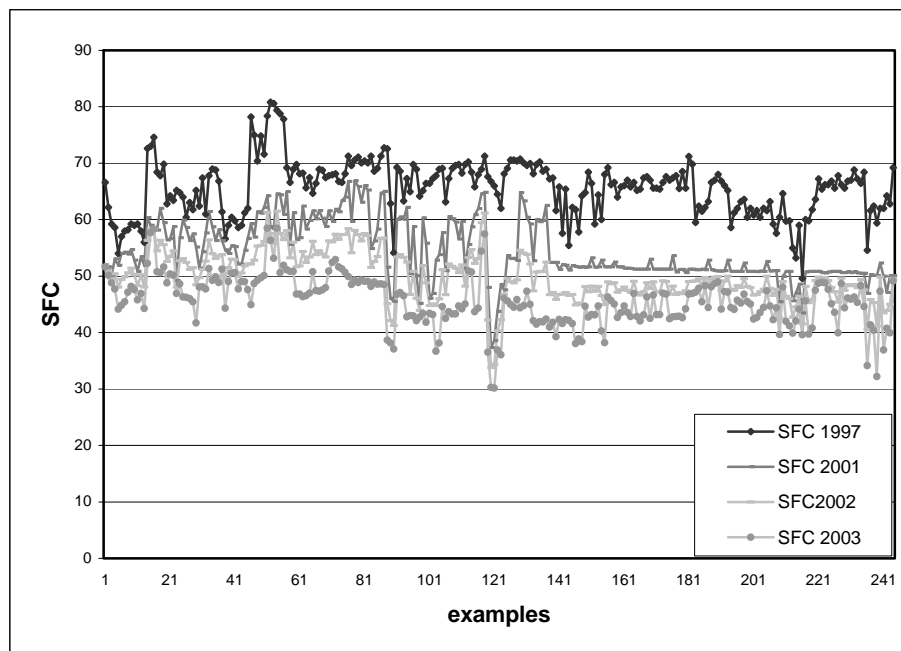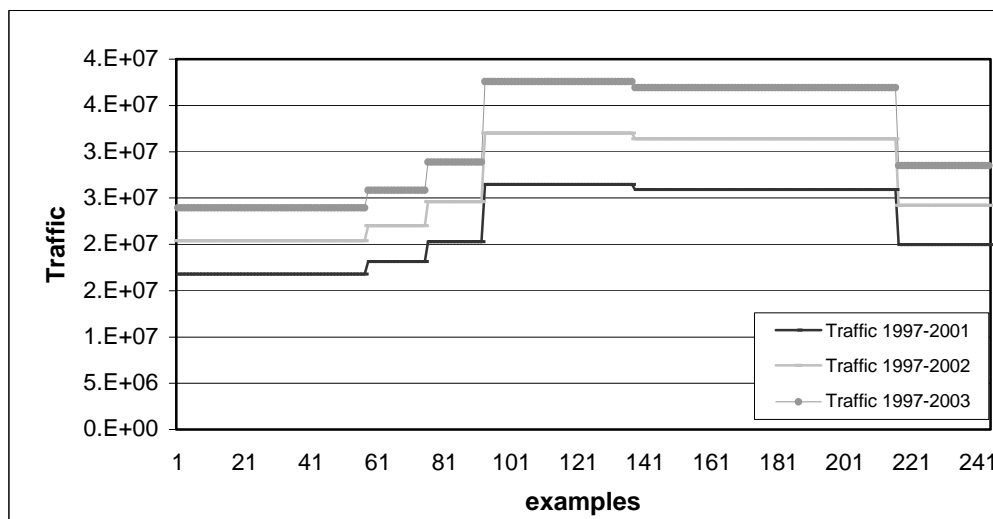
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Figure 2 Experimental SFC Values

Figure 3 Cumulative Traffic Elapsed between the SFC Measurements

In particular, for every selected homogeneus section, the three data set were built as follows:

- The first data set was obtained considering as input parameter the SFC value measured in September 1997 and the traffic elapsed between this measurement and that carried out in 2001, while the SFC value measured in 2001 was considered as output parameter;
- The second data set was obtained considering as input parameter the SFC value measured in September 1997 and the traffic elapsed between this measurement and that carried out in 2002, while the SFC value measured in 2002 was considered as output parameter;
- The third data set was obtained considering as input parameter the SFC value measured in September 1997 and the traffic elapsed between this measurement and that carried out in 2003, while the SFC value measured in 2003 was considered as output parameter.

The reconstructed pattern were 713; they were set in column vectors:

$$SFC_{initial} = [SFC_{i1}, SFC_{i2},...,SFC_{in}]^T ;$$

SFC_{ij} is the initial SFC value of j-th pavement section considered (SFC 1997);

$$SFC_{final} = [SFC_{f1}, SFC_{f2},...,SFC_{fn}]^T ;$$

SFC_{fj} is the final SFC value of j-th pavement section considered (SFC 2001 or SFC2002 or SFC 2003);

$$Traff = [traff_1, traff_2,..., traff_n]^T ;$$

$traff_j$ is the traffic elapsed on the j-th pavement section between two analyzed SFC measurements

The function to interpolate is therefore:

$$SFC_{final} = f(SFC_{initial}, traff) \qquad (Eq.1)$$

where f can be either a linear or a nonlinear function.

The data set was divided into two groups: the training set (65% of the data) and the test set (remaining 35% of the data).

Both a linear regression and an ANN have been used to derive a suitable model.

3.1   The model of linear regression

The training set and the test set were interpolated through the Least Mean Square (LMS) technique.

So (1) can be rewritten as:

$$SFC_{final} = a_0 + a_1 \cdot SFC_{initial} + a_2 \cdot traff \qquad (Eq.2)$$

where a_0, a_1 and a_2 are regression coefficients.

Results are reported in Figs. 3 and 4 and in Table 1.

In particular in these figures, it is represented the comparison between measured SFC and SFC predicted using the training data and testing data. While the correlation coefficient between the actual and estimated data are reported in Table 1.
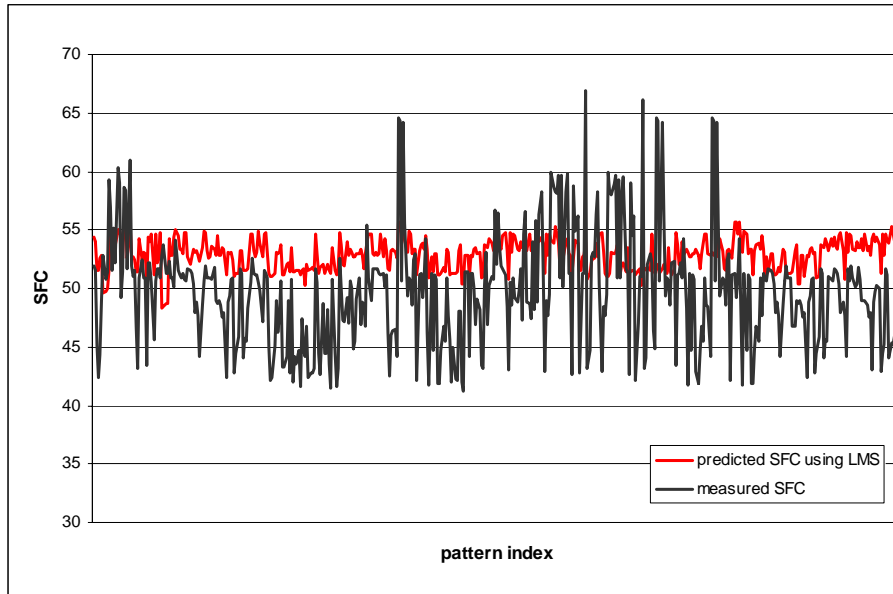

Figure 3 Training Data Set - Comparison between Measured and Predicted SFC Values
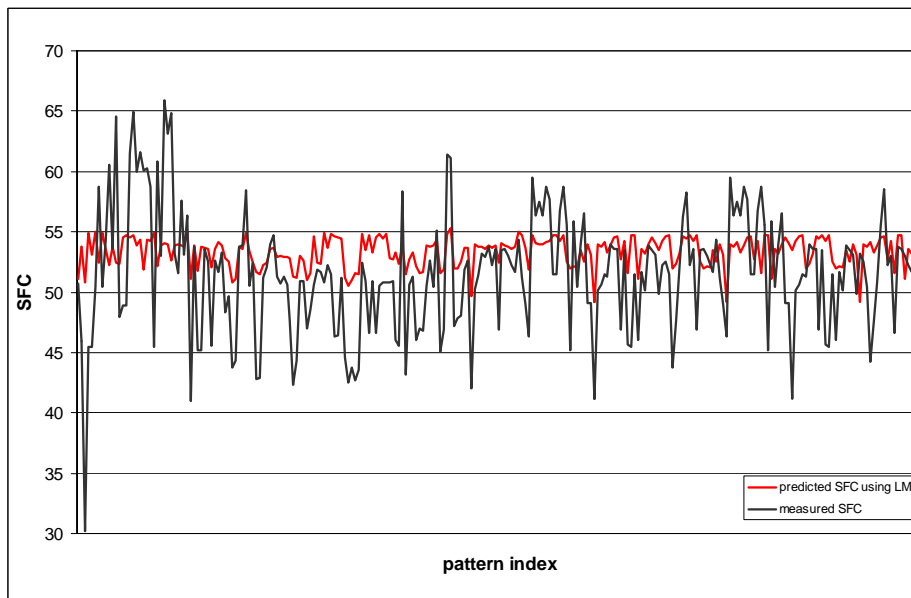

Figure 4 Testing Data Set - comparison between Measured and Predicted SFC values

Table 1 MSE Values and Correlation Coefficient (Linear Model)

Training set		Testing set	
MSE value	Correlation coefficent	MSE value	Correlation coefficent
0,172	0,421	0,225	0,289

How it can be observed, the performance obtained with LMS is poor. So in the following paragraph, the results obained by training an ANN on the same data will be analyzed.

3.2 The model of neural network

The first step consisted of the choice of the network topology. Among the possible types of topology, the multilayer perceptron with back propagation seemed to be the one that could best be adapted to the examined problem. The quick success of this model and its training algorithm is demonstrated from the theoretical results obtained by Stone-Weierstrass theorem. In fact, this theorem gives a strict demonstration of the interpolation capability of a multilayer perceptron (MLP) with at least one hidden layer [Cotter 1990]. The network architecture selected consisted of a network composed of three layers: an input layer composed of two neurons, a hidden layer, and an output layer with one neuron.

Since there are not specific guidelines regarding the necessary number of neurons for obtaining the wanted precision, the number of hidden neurons was selected through an organized trial-and-error process. In particular, to obtain the optimal neural architecture, it was necessary to train many networks with different numbers of hidden neurons. The best results were obtained using three neurons in the hidden layer, a symmetric sigmoid transfer function and the minimization algorithm was the Levenberg-Marquardt method with early stopping strategy to prevent overfitting [Hagan and Menhaj 1994].

The MSE on the testing and training data and the correlation coefficients between measured and predicted SFC values, computed on the training and testing data are reported in Table 2.

Table 2 MSE Values and Correlation Coefficient (Nonlinear Model)

Training set		Testing set	
MSE value	Correlation coefficent	MSE value	Correlation coefficent
0,045	0,888	0,072	0,853

A comparison between measured and predicted SFC for training and testing data sets is reported in Figs. 5 and 6.
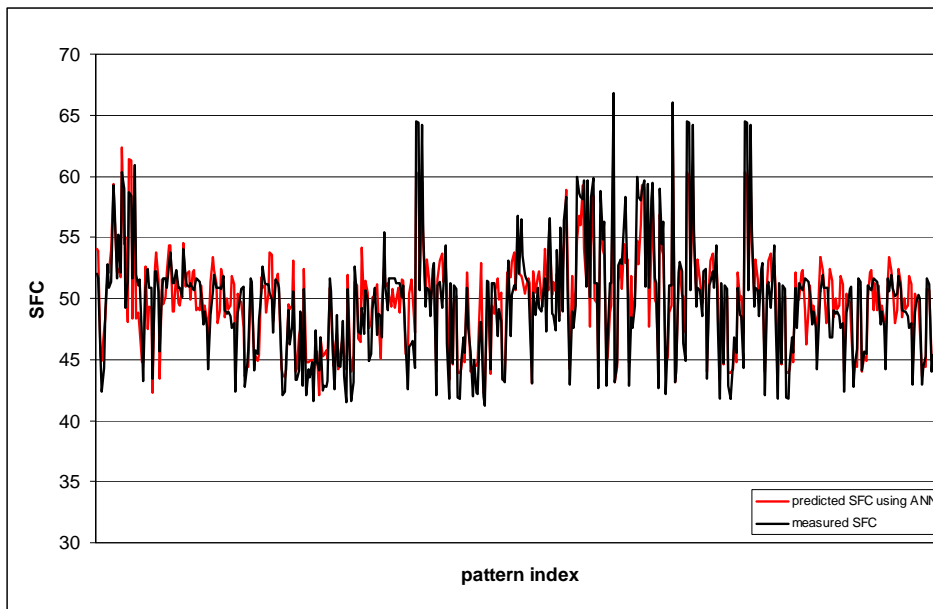
Figure 5 Training Data Set - Comparison between Measured and Predicted SFC Values
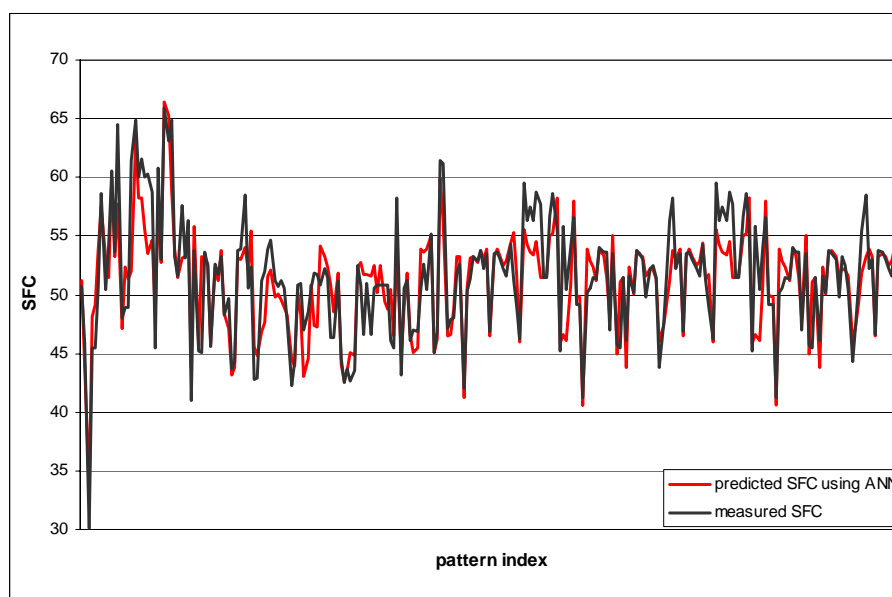

Figure 6 Testing Data Set - Comparison between Measured and Predicted SFC Values
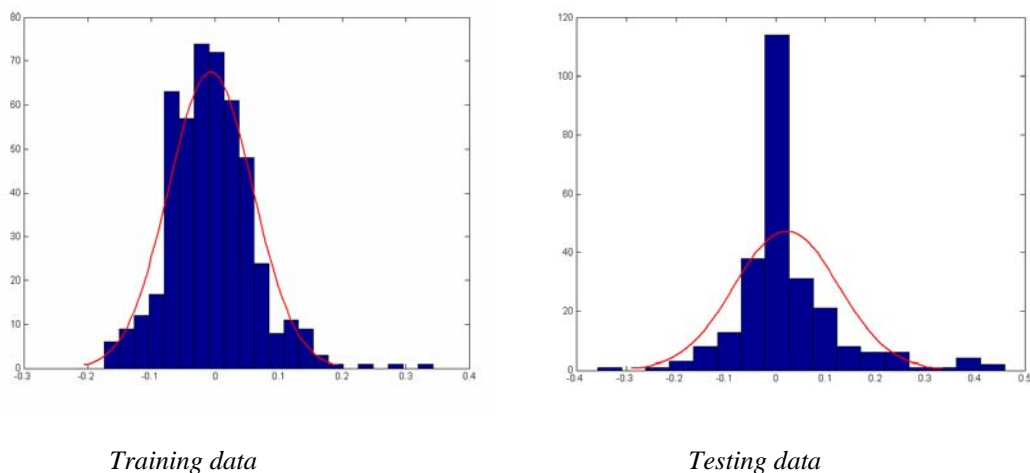
The residual histograms are reported in Figure 7.

Training data   *Testing data*

Figure 7 Residual Histograms

Residual autocorrelations on the training and testing data are reported in Figure 8.

Training data   *Testing data*
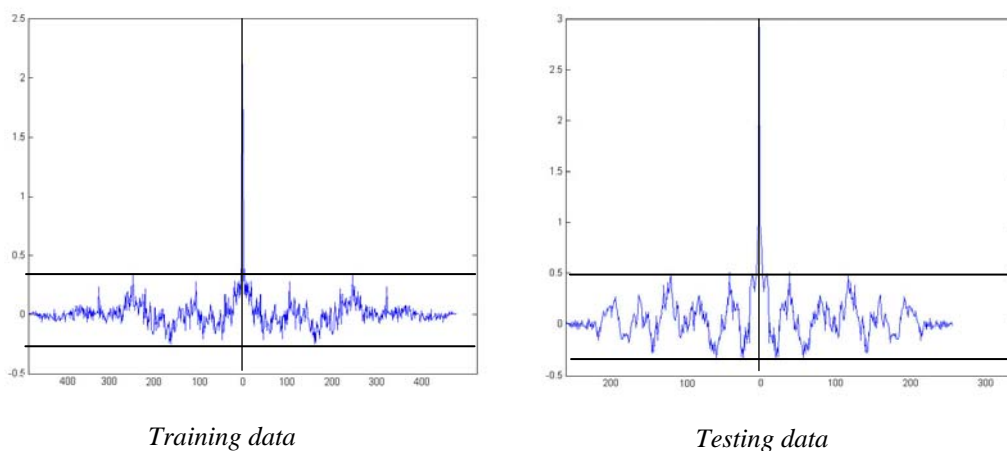
Figure 8 Residual Autocorrelation Function

A good agreement between measured and predicted SFC values can be observed analyzing the previous figures.

Moreover, the percentage errors for predicting the SFC values of the two phases were evaluated. An error lower than 7% was observed in 91% of the cases in the training data and in 86% of the cases of the testing data. This confirms the suitability of the model and of the procedure.

The obtained results are very good in comparison with those obtained using linear regression and considering the difficulties associated with the measurements and precise estimations of the inputs involved in the deterioration models and the uncertainty in the determination of these and other factors. However a further improvement in model performance could be obtained in the future by using a lager set of experimental data.

CONCLUSIONS

In this paper it has been put in evidence the suitability of ANNs in prediction of pavement conditions, and in particular in the prediction of SFC values.

After a description of the application of this technique in this field, a practical application has been presented regarding the prediction of Sideway Force Coefficient values for an italian motorway.

The obtained results have been compared with those obtained using a LMS technique used by the road agency which manages the analyzed motorway, and have put in evidence the efficacy of the ANN in the solution of this important road problem.

So, neural networks have showed to be able to give a considerable contribution for supporting management decisions for the analyzed infrastructure, in particular in the area of pavement performance prediction. In fact, as mentioned in the paper, pavement condition assessment and deterioration is an integral part of all successful pavement and infrastructure management systems. Therefore the carried out model could be used from the Transportation officials for the optimal planning of maintenance activities.

However, some agencies and transportation practitioners have reservations about implementing such technique. So it is necessary to facilitate acceptance of ANN. A solution could be to insert models based on ANN as alternative to the traditional analysis tool in all the available PMS packages. Then, the user may begin to test the new technologies and then adopt them if they prove to be more effective than the traditional tools for a practical application.

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