# Artificial Neural Network Applications in Transportation Infrastructure Asset Management

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## SYNOPSIS

Transportation officials are faced every day with competing investment demands, and they must distribute limited resources so that the transportation infrastructure is maintained in the best possible condition. Thus, they have resorted to the use of asset management tools to support their decisions. Since transportation infrastructure management decisions are often based on data that is uncertain, ambiguous, and incomplete, soft computing techniques, such as neural networks, are gaining widespread applications. This paper reviews the application of artificial neural networks in transportation infrastructure asset management, highlighting their advantages over traditional approaches.
Artificial neural networks imitate, to a small extent, some of the operations perceived in biological neurons: they can be trained to assess an observed function when its shape is unknown. The main advantages of neural networks are their learning capabilities and their distributed architecture that allows for highly parallel implementation. These computational algorithms have excellent pattern recognition capabilities, can make generalizations, and are particularly appropriate in those cases in which there is a significant amount of examples available.
Within the transportation asset management field, artificial neural networks have been used successfully for condition assessment, deterioration modeling, performance prediction, project and treatment selection, and prioritization. As an example, two practical applications are presented in the paper. The first application describes the development of a neural network-based project screening procedure developed for a state highway agency in the U.S. The second application describes a pavement friction prediction model developed for an Italian motorway. The review conducted suggests that artificial neural networks hold great promise for supporting infrastructure management decisions, especially in the areas of modeling deterioration, performance prediction and project selection.

# Artificial Neural Network Applications in Transportation Infrastructure Asset Management

## INTRODUCTION

Transportation infrastructure asset management is a particularly complex and articulated process, which must be the result of a global analysis that takes into account the agency's objectives and the existing constraints that may affect the final result. Transportation officials are faced every day with competing investment demands, and they must distribute limited resources so that the transportation infrastructure is maintained in the best possible condition. Therefore, It is important that decision makers have access to valid, efficient, and robust asset management tools, which are mathematically reliable and can support the optimization of maintenance interventions and support the policies at all decisional levels. These tools are particularly important because transportation infrastructure management decisions are often based on data that is uncertain, ambiguous, and incomplete.

Within this context, emerging technologies, such as artificial intelligence techniques, provide efficient alternatives to the traditional mathematical approaches. In particular, this paper reviews the application of artificial neural networks in transportation infrastructure asset management.

Within the transportation asset management field, artificial neural networks have been used successfully for supporting condition assessment (Pant et al. 1993, Eldin et al. 2003, Lee and Lee 2003, Sadek et al. 2003), deterioration modeling and performance prediction (Huang and Moore 1997, La Torre et al. 1998, Owusu-Abadia 1998, Shekharan 1998, Van der Gryp et al. 1998, Abdelrahim and George 2000, Luo et al. 2001, Farias et al 2003, Felker et al. 2003, Yang et al. 2003), project and treatment selection (Hajek and Hurdal 1993, Fwa et al. 1997, Lee et al. 2002), prioritization (Fwa and Chan 1993, Fwa et al.2002), and optimization (Razaqpur et al. 1996).

This paper presents some basic background about neural networks and then illustrates the practicality of this approach through two practical applications. The first application uses neural networks to develop a network-level pavement rehabilitation project screening procedure. The second application uses neural networks to develop a pavement friction prediction model.

## ARTIFICIAL NEURAL NETWORKS

Artificial neural networks simulate the structure and the functioning of biological neurons. These powerful models are composed of many simulated neurons or simple computational units that are connected in such a way that they are able to learn in a manner similar to people (Lawrence, 1994). This distributed architecture makes neural networks particularly appropriate for solving nonlinear problems and input-output mapping problems.

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; it also allows the establishment of particular rules, with consequent time saving, simplification of the phenomenon analysis for the programmer, and simplicity of utilization for the final user. If they are correctly organized and "instructed," neural networks allow the cause-effect relationships that are at the basis of complex multivariable systems to be reconstructed; they can make generalizations, and are particularly appropriate in those cases in which there is a significant amount of examples available.

Neural networks, or connectionist systems, have experienced a resurgence of interest in recent years as a paradigm of computational and knowledge representation (Garrett et al., 1990). After a first surge of attempts to simulate the functioning of the human brain using artificial neurons in the 1950s and 1960s, this artificial intelligence sub-discipline was put on hold until recently. The resurgence has been due mainly to the appearance of faster digital computers that can simulate large networks and the discovery of new neural network architectures and more powerful learning mechanisms. The new network architectures, for the most part, are not meant to duplicate the operation of the human brain, but rather to receive inspiration from known facts about how the brain works. These architectures are characterized by the following features:

1. A large number of very simple neuron-like processing elements, sometimes called artificial neurons, that maintain only one piece of information or level of activation, and are capable of a few simple computations.
2. A large number of weighted connections between the elements. The weights on the connections encode the knowledge of a network.
3. Highly parallel, distributed control.
4. An emphasis on learning internal representations automatically.

There are different types of neural networks. 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. In this type of network, there are generally three distinct types of neurons organized in "layers." The input layer contains the input variables. The hidden neurons, which are contained in one or more "hidden" layers, process 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" that controls the output of each one.

Neural networks train through adaptation of their connection weights based on examples provided in a training set. The 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 that is used to propagate the error back to the hidden layerand to the input layer in order to modify the weights. This iterative procedure is carried out until the error at the output layer is reduced 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 that must be organized beforehand in an efficient and aimed manner. Validation of the performance of a neural network 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 practical applications.

## PROJECT SCREENING PROCEDURE

One of the first applications of neural networks was for infrastructure rehabilitation project selection. Flintsch et al. (1996) used artificial neural networks to develop an automatic procedure for screening and recommending roadway sections for pavement preservation. The neural network was used to "learn" the knowledge from past project selections. It was trained using examples that illustrated the pavement condition and characteristics at the time of selection and the sections selected for the pavement preservation program for several years.

The Arizona Department of Transportation's (ADOT) has operated a pavement management system (PMS) since 1980. The PMS uses a network optimization system to determine the optimum budget needs and allocation for ADOT's pavement network. The network-level optimization system recommends the miles of pavement in each road functional category, traffic level, and design region that should receive each rehabilitation action, as well as the budget required for these actions (Wang et al, 1994). The application discussed here screens potential candidate sections and recommends roadway sections for ADOT's pavement preservation program.

The neural network simulator learned the knowledge previously applied by the PMS staff by studying the relationship between the pavement condition and characteristics at the time of programming and the sections finally selected for the pavement preservation program. The output of the neural network is a list of candidate roadway sections that should be considered for rehabilitation.

Commercial artificial neural network software was used for the training phase. Several types of artificial neural network types were considered, and the use of a commercial software package was weighted against the possibility of developing a specific neural network simulator. Based on the literature reviewed, a back-propagation neural network appeared to be the most appropriate type for this sort of application (Flintsch et al. 1996).

The training examples were prepared with sections that had been programmed during past pavement preservation programs, as well as with those that had not been programmed. The Pavement Preservation Programs from 1990 to 1996 were used to prepare the examples for training and testing the neural network. A longer period of time could have been used. However, it was felt that the selection criteria and/or the roadway conditions could have changed significantly. A database with all the projects programmed from 1990 to 1996 and a sample of similar size of non-programmed sections was compiled. The variables considered included: road classification, region, Structural Number, percent cracking (programming year and 1, 2 and 3 years before), smoothness (programming year and 1, 2 and 3 years before), surface friction,

rutting, percent patching, flushing, Average Daily Traffic (ADT), maintenance cost (average for the last three years), and rate (a dimensionless condition index). If no data for a particular indicator was available for any milepost in the section, an average value was assigned trying to avoid any effect on the results. An output variable *prog* was added to the database to indicate if the section was programmed or not. The variable was assigned a value of 1 if the section was programmed and 0 if it was not. As a result, a total of 418 examples were available for training and testing. Seventy-five percent of these examples were used for training, and 25% were reserved for testing. The percentage of testing cases is probably higher than usual, but it was selected to have a good estimate of the network's ability to generalize. This is very important to ensure a good performance of the network in the future. The training and testing examples were separated randomly.
The most appropriate network architecture and training parameters were then defined concurrently using a designed experiment. A fractional factorial experiment was used for this purpose. The objectives of the experiment were to identify the neural network design factors that significantly affect the network performance, as well as the levels at which these factors should be used. The two factors that have a significant effect on the artificial neural network performance were further studied to determine their more appropriate settings. Several network architectures, with variable number of hidden neurons and stratification schemes with different number of levels and break-down values, were studied.
The best trained artificial neural network was selected and implemented for screening and recommending candidate sections using information regarding the current condition of the pavement sections in the network. An artificial neural network that performed the best had 27 hidden neurons, used a stratified input, and trained with a low training tolerance and a low learning rate. This network was able to learn 99 % of the training facts and to predict a correct output for 75 % of testing examples with a testing tolerance of 0.5. This performance was considered acceptable, especially if we consider that not all the reasons for selecting the projects for the pavement preservation program are directly inherited from the information in the PMS database. Once the weights of the connections were determined, the simulation of the artificial neural network was implemented through a computer program. Figure 1 shows the scheme for the implemented artificial network simulator. For each pavement section, an input processor computes the input values for each field and passes them to the artificial neural network simulator. The simulator uses the neural network architecture defined and computes a *prog* number for each section in the network. This *prog* value is then translated to a recommendation regarding wheter or not the pavement section should be considered for inclusion in the pavement preservation program. The simulation is repeated for each uniform pavement section in the database to prepare the recommended list of sections for the preservation program.

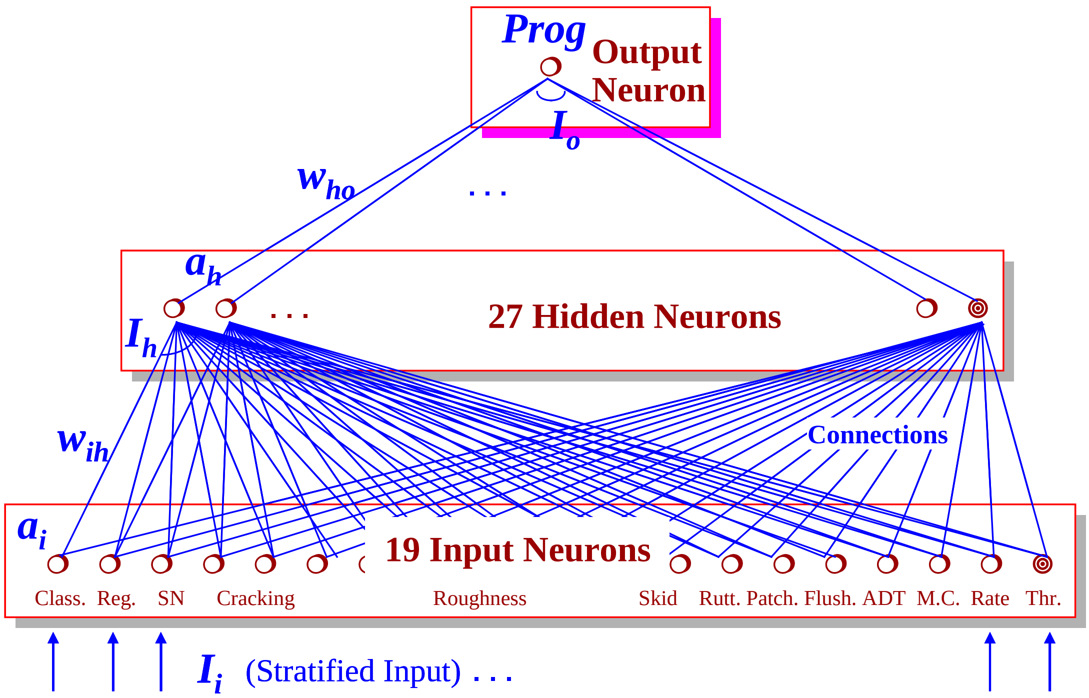


**Figure 1: Scheme of the Artificial Neural Network Developed**

## PERFORMANCE PREDICTION MODELING

The knowledge of the pavement deterioration curve is fundamental to the optimal planning of maintenance activities. While inaccurate models may lead to the selection of non-optimal maintenance strategies, well developed models will contribute to the selection of the optimum maintenance plan. However, there are many difficulties associated with the measurements and 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 and generalizing the defined models. Significant research has been done in the past few years regarding pavement deterioration models; AASHTO (2001) presents a good overview of available techniques and models. Neural networks models are particularly appropriate for these types of predictions. Bosurgi et al. (2004) used artificial neural networks to develop a Sideway Force Coefficient (SFC) prediction model. In particular, they defined this prediction model for the pavement of the motorway A18 which expands along the eastern coast of Sicily (Italy).

In the examined infrastructure, a series of instrumental check-ups concerning friction (Grip Tester) and roughness (ARAN) were carried out in the past (1994 and 1997). For research purposes, these measurements were complemented with three additional measurement surveys in 2001, 2002 and 2003 using the Grip Tester equipment. The grip number values were transformed in SFC values using conversion equations [Croney et al. (1997)].

Pavement sections rehabilitated with the same thickness of the layers and the same materials before September 1997 were considered. This was done to select homogeneous pavement on which to make friction deterioration evaluations. These additional measurements allowed having, for each selected pavement section (50 meters), the following four SFC values:

- SFC values measured in September 1997 after the maintenance interventions;
- SFC values measured in December 2001;
- SFC values measured in October 2002;
- SFC values measured in October 2003;

The friction data was integrated with information about the cumulative traffic in the period of time elapsed between the two SFC measurements analyzed, resulting in 735 examples, which were used to train and test the neural network. To ensure the best possible performance of the developed model, the data set was divided into two groups: the training set (65% of the data) and the test set (remaining 35% of the data).

The following step consisted of a careful 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 with at least one hidden layer. The network architecture selected (Figure 2) consisted of a network composed of three layers: an input layer composed of two neurons (SFC 1997 and cumulative traffic), a hidden layer, and an output layer with one neuron (the SFC measured on 2001, 2002, or 2003).

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, activation functions, and training algorithms. After training 200 neural networks, the best results were obtained using three neurons in the hidden layer, a symmetric sigmoid transfer function ($f(x) = \tanh(x)$) and the Levenberg-Marquardt method as minimization algorithm.

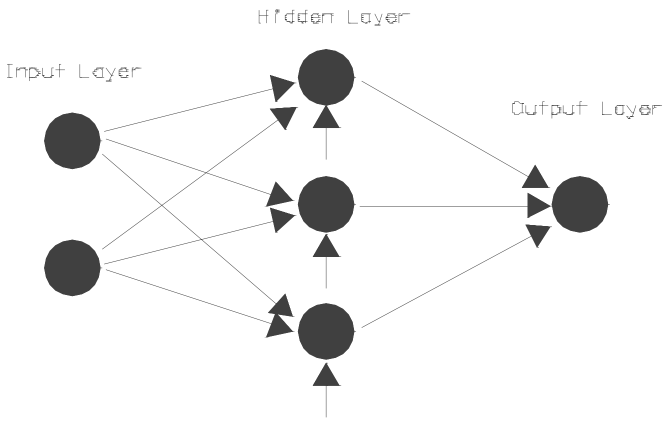


**Figure 2: Architecture of the network**

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;
- Representation of the error histogram;
- Representation of the error autocorrelation curve in the two phases.

The residue error variance was 0,0055 in the training phase and 0,0082 in the testing phase, which was considered appropriate. The trend of the error histogram came close to a Gaussian curve in the two phases and the trend of the error autocorrelation closely resembled a white noise in the two phases. Therefore, the results obtained confirmed that the neural network was able to interpret the phenomenon and that it managed to capture the internal correlations existing between the variables [Trifirò (2003)].
Moreover, in order to be able to judge the acceptability of the result, the percentage errors for predicting the SFC values of the two phases were evaluated. An error lower than 8% was observed in 88% of the cases in the training phase (Figure 3) and in 84% of the cases in the testing phase (Figure 4), which confirms the goodness of the model and of the procedure used.

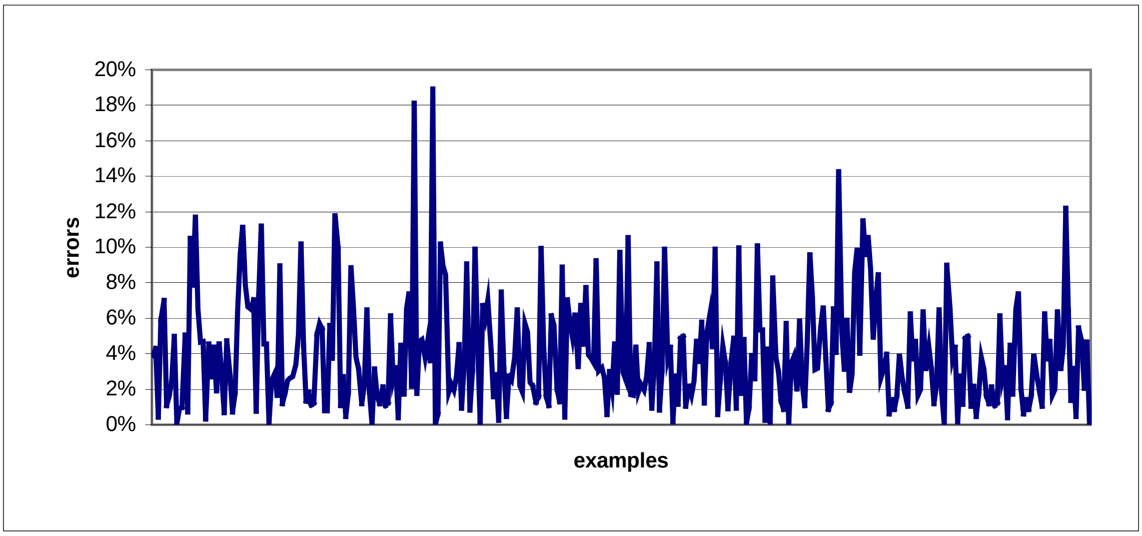


**Figure 3: Trend of the error per cent in the training phase**

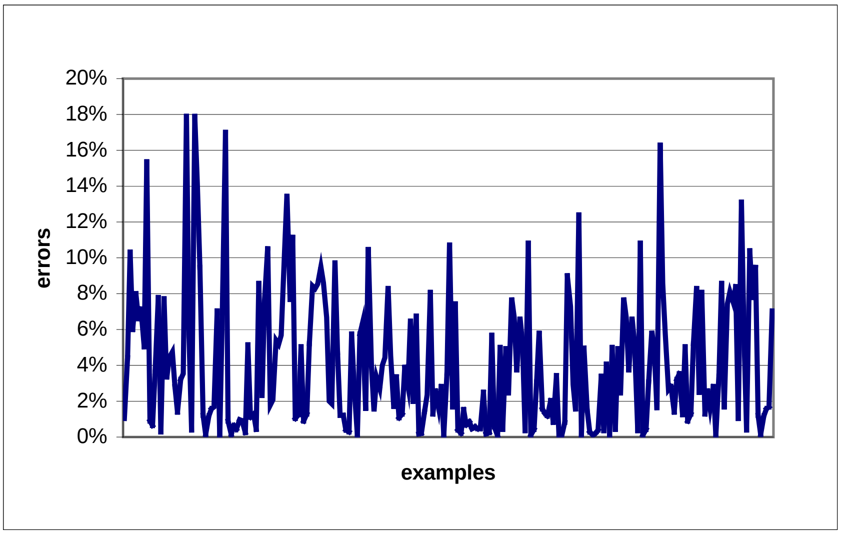


**Figure 4: Trend of the error per cent in the testing phase**

## CONCLUSIONS

In this paper it has been put in evidence the applicability and the potential of the artificial neural networks to develop analytical tools to support transportation infrastructure asset management. After a description of the structure of this computational technique, highlighting its advantages over traditional approaches, two practical applications have been presented.

The first application used neural networks to develop a pavement rehabilitation project screening procedure for the Arizona Department of Transportation. The second application used neural networks to predict pavement friction on an Italian motorway. These applications illustrate the efficacy of the neural networks in the analysis of important road problems and their ability to support infrastructure management decisions, especially in the areas of pavement performance prediction and project selection.

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