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Neural Network Based Classification of Road Pavement Structures

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Abstract
Roads have formed the basic infrastructure of commerce since flints and other tools and artifacts were first exchanged along the trade routes of prehistory. Roadways are very large, in volume, in extent, and in value. They also wear out, and their useful life is directly proportional to their initial strength and inversely proportional to the number of heavy goods vehicles using them. Therefore, the increasing complexity of road transportation need advanced techniques for effective design of pavements. This paper proposes an intelligent technique using neural networks to classify different types of road pavement structures, which is essential in estimating bearing capacities and load equivalency factors of pavements under different loadings.

Keywords
Pavement structure; Neural networks; Bearing capacity; Load equivalency factor.

INTRODUCTION

Pavements are complex systems involving the interaction of numerous variables. The structural behavior of a road pavement during its expected structural life is dependent on the interaction between the strength of the various pavement layers and the repeated traffic stresses imposed on the pavement structure. Moreover, in a given environment the strength of the structural layers of the pavement is dependent on the properties of the materials used in their construction. Pavement structures are classified based on the different type of materials and their respective layer thicknesses. The estimation of the bearing capacity and the load equivalency factor of a road depend on the type/class of the pavement structures used in the construction [1].

The use of neural network offers potential solution to the complexity and uncertainty in material constitutive behavior and the nonlinear traffic loading for pavement analysis and design. Artificial neural networks are intelligent tools that have gained strong popularity in a rather large array of engineering applications where conventional analytical methods are difficult to pursue or show inferior performance [2, 3, 4] for nonlinear problems. This paper primarily focuses on the development of a neural network based classifier for the different pavement structures used in South African roads. The pavement structure classifier output can be used by a second neural network (estimator) to estimate the bearing capacity and load equivalency factor (LEF) of a road pavement under given base loads and loading conditions as shown in Figure 1 below.

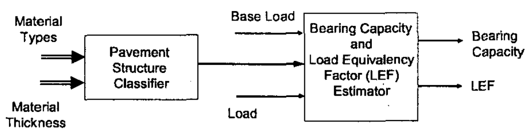

Figure 1. Block diagram for bearing capacity and load equivalency factor estimation.

The South African Mechanistic Design Method (SAMDM) has been used for new and rehabilitation pavement design since the 1970s. The latest version of the SAMDM has been used to develop standard pavement designs for different road categories contained in a catalogue for the design of interurban and rural roads on a national level and has been calibrated against the experience of road engineers from various road authorities in South Africa [5]. The catalogue in the TRH4 [6] manual is used as a guide to select the type of pavement structure. The TRH14 manual [7] gives the recommended standards for materials, which may be considered during the structural design of pavements. Materials used in the structural layer of the pavement can be selected according to criteria of availability, economic factors and previous experience.

Thirty types of pavements are selected in this paper for the design of the neural network classfier and the TRH 4 manual is used as a guide for the selection of pavement types.

NEURAL NETWORK

Neural networks are valuable computational tools that are increasingly being used to model resource intensive complex nonlinear problems as an alternative to using more traditional techniques, such as the finite element method. They are suitable for multi-variable applications, where they can easily identify the interactions and patterns between inputs and outputs. The neural network models do not require any complicated and timeconsuming finite element input file preparation for routine design applications.

Neural networks have become very popular for data analysis over the past two decades. Neural networks are intelligent systems that are based on simplified computing models of the biological structure of the human brain, whereas traditional computer logic – based systems require comprehensive programming in order to perform a given task. Neural networks are inherently able to infer what needs to be done by simply observing data that is representative of the underlying process to be implemented [8]. The self-learning ability of neural network s is particularly useful where the comprehensive models that are required for conventional computing methods are either too large or complex to represent accurately, or simply does not exist at all. The highly connected, distributed nature of the neural networks also lends a high degree of noise immunity, fault tolerance and generalization capability.

An ANN consists of a number of nonlinear computational processing elements (called neurons) arranged in several layers connected by weighted connections between layers, shown in Figure 2. Typically in a MLFNN, there is an input layer, one or more intermediate layers called the hidden layers and an output layer which outputs the network's response to its inputs. The different layers structure allows a neural network to be flexible, capture more information and identify relationships between variables.

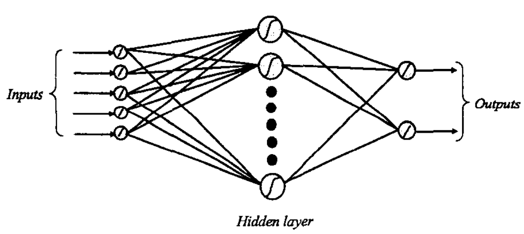

Figure 2. A multilayer feedforward neural network.

As with many neural networks, the connection weights in the MLFNN are initially selected at random. Inputs from the mapping examples are propagated forward through each layer of the network to emerge as outputs. The errors between those outputs (actual response) and the correct answers (desired responses) are propagated backwards through the network and the connection weights are individually adjusted so as to reduce the error. After many examples have been propagated through the network many times, the mapping function is "learned" to within some error tolerance/goal specified by the designer. This is called supervised learning because the neural network (learning system) has to be shown the correct desired responses in order for it to learn (Figure 3).

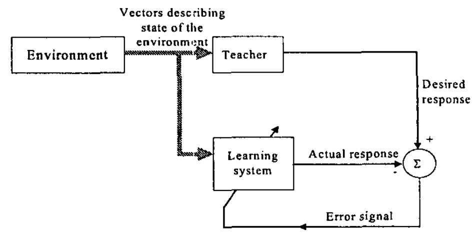

Figure 3. Block diagram of supervised learning.

NEURAL NETWORK TRAINING AND RESULTS

For the application described in this paper, classification of pavement structures, the multilayer feedforward neural network (MLFNN) is proposed. The MLFNN (Figure 4) is trained with the backpropagation algorithm [9] to classify a selected thirty road pavement types from TRH 4 [6]. There are ten input variables (five material types and five material thickness for the five layers) are used in the input layer. The four outputs are the pavement type, base type, road category and traffic class. A neural network with five hidden layer sigmoidal neurons is chosen for this application. The neural network output layer transfer function is a linear one with the range of 0 and 1.

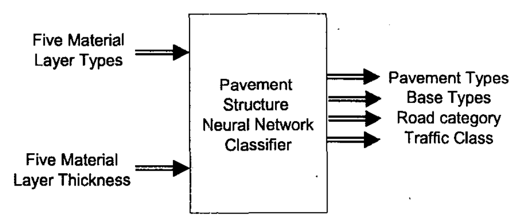

Figure 4. Inputs and outputs of the neural network classifier for pavement types.

Table 1 shows typical layouts of pavement structure types – Type 1 and Type 6. Basically there are four major pavement composition types used in Southern African road designs, the granular, cemented, hot-mix asphalt and concrete base pavements [5]. The types of pavement material are according to the South African Material Classification in TRH4. The catalogue for different pavement types [5] is used as a guide for pavement type selection. The material codes are used to identify the material types in each layer as indicated in Table 1 and 2. The pavement structure shown in Table 1 and 2 consists of a continuously graded asphalt surfacing (AC), a graded crushed stone granular base (G1 and G2), a cemented crushed or gravel subbase (C3 or G6 and G7) and a gravel/soil subgrade (G9-G10).

The neural network is trained for several epochs (100, 500 and 1200 epochs) and the training error plots are given in the Figures 5, 6 and 7 respectively. One epoch means one forward propagation and one backward propagation. The performance of the neural network depends on the initial values of the connection weights, which were randomly selected. The training converged (the average approximation error decreased) as the number of epochs were increased. The approximation error goal of 0.001 was attained at 1131 epochs and the training was terminated. The performance of the trained neural network classifier after 100, 500 and 1200 epochs were each tested for different pavement types in the training set and outside the training set. The percentage of correct and false classifications is shown in Table 3.

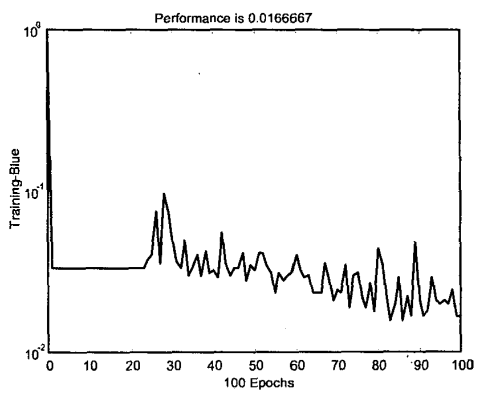

Figure 5. Neural network training error plot showing the error goal of 0.01667 attained in 100 epochs.

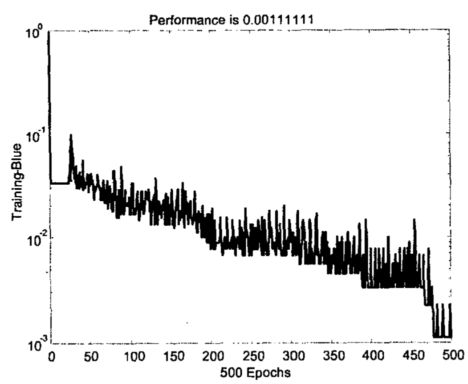

Figure 6. Neural network training error plot showing the error goal of 0.00111 attained in 500 epochs.

CONCLUSION

This paper has proposed a potential solution using neural networks for classification of different pavement structures and is can be used for the estimation of bearing capacities and load equivalency factories of the pavement structures under different loadings. The neural network model was trained with thirty-selected pavement structures and it classified successfulyy the types of pavement structures (belonging to certain road category, traffic class and type of base), with a zero percent error. The neural network model currently developed for this work will result in both a drastic reduction in computation time and a simplification of the input and output requirements over the SAMDM or other traditional methods which are currently needed for routine practical design. Thus, neural networks are invaluable tools to the pavement engineer. Specific areas for future work which follow on from the work of this paper are the estimation of bearing capacities for the different types of pavements, and hence the load equivalency factors by using neural networks.

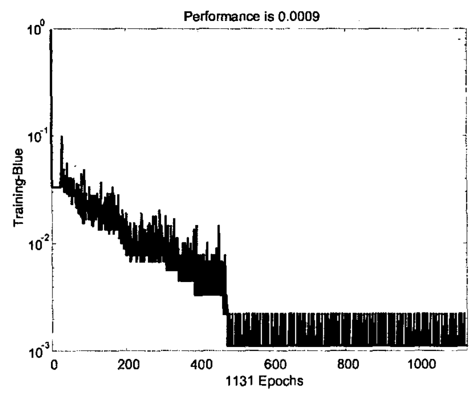

Figure 7. Neural network training error plot showing the error goal of 0.001 attained in 1134 epochs.

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Table 1. Typical layout of a pavement structure -Type 1: Grannular base, Road category A and Traffic class ES3

Layers: material type	Material type	Layers: material thickness
1st layer - AC	Asphalt Surfacing	40 mm
2nd layer – G2	Graded crushed stone	125 mm
3rd layer - C3	Crushed cement	150 mm
4th layer – G7	Gravel	150 mm
5th layer - G9 – G10	Gravel/soil subgrade	Semi infinite (taken to be 300 mm)

Table 2. Typical layout of a pavement structure -Type 6: Grannular base, Road category B and Traffic class ES10

Layers: material type	Material type	Layers: material thickness
1st layer – AC	Asphalt Surfacing	20 mm
2nd layer – G2	Graded crushed stone	125 mm
3rd layer – G5	Natural gravel	150 mm
4th layer – G7 – G10	Gravel/soil	Semi infinite (taken to be 300 mm)
5th layer -	Not applicable	Not applicable

Table 3. Average testing performance for neural network trained for different number of epochs on the thirty pavement structures

Number of Training Epochs	100	500	1200
Correct Classifications	43.3%	96.7%	100%
False Classifications	56.7%	3.3%	0%