USE OF NEURAL NETWORKS IN THE PREDICTION OF BEARING CAPACITY OF PAVEMENT STRUCTURES

V Venayagamoorthy and D Allopi

Department of Civil Engineering and Surveying, Durban University of Technology,
P O Box 1334, Durban, 4000; E-mail : swetha@absamail.co.za/allopid@dut.ac.za

ABSTRACT

Roads have formed the basic infrastructure of commerce. There is an increasing growth of road transportation nowadays in the modern world. Roadways are very large, in volume, in extent, and in value. They deteriorate over time primarily due to accumulated damage from vehicles. Pavements are designed for an expected service life and require some form of maintenance before they come to the end of their service life. The increasing complexity of road transportation need advanced techniques for effective pavement design and maintenance of roads. An intelligent technique based on Artificial Neural Networks is applied for the prediction of bearing capacity of road pavement structures under different loading conditions.

1. INTRODUCTION

Pavements are complex systems involving the interaction of numerous variables. A pavement is a structure consisting of superimposed layers of selected and processed materials placed on a subgrade whose primary function is to support the applied traffic loads and distribute them to the subgrade soil. The structural behaviour of a road pavement during its expected structural life is dependent on the interaction between the strength of the pavement layers and the repeated traffic stresses imposed on the pavement structure. The strength of the structural layers of the pavement is dependent on the properties of the materials used in their construction. The classifications of the pavement structures are based on the different type of materials and their respective layer thickness. The estimation of the bearing capacity and the load equivalency factor of a road depend on the type of the pavement structures used in the construction (Venayagamoorthy *et al*, 2004).

Neural networks are valuable intelligent tools that have significantly increased in engineering applications where conventional methods are difficult to pursue or show inferior performance (Fwa and Chan, 1993). Artificial Neural Networks (ANNs) have proved to outperform traditional modelling counterparts in solving various complex engineering problems. ANNs are applied in pavement design for backcalculation of pavement moduli (Meier,1995). ANNs are intelligent systems that are based on simplified computing models of the biological structure of the human brain (Venayagamoorthy *et al*, 2002). The highly connected, distributed nature of the neural networks lends a high degree of noise immunity, fault tolerance and generalization capability.

This paper primarily focuses on the development of an intelligent technique based on neural networks to predict the bearing capacity of the different types of road pavement structures under different loading conditions used for South African roads. The catalogue

Proceedings of the 26th Southern African Transport Conference (SATC 2007) 9 - 12 July 2007
ISBN Number: 1-920-01702-X Pretoria, South Africa
Produced by: Document Transformation Technologies cc Conference organised by: Conference Planners

in the TRH4 manual (Committee of Land Transport Officials, 1996) is used as a guide to select the types of pavement structures. The TRH14 manual (Committee of State Road Authorities, 1985) is used as a guide to select 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. 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 (Theyse,*et al, 1995*).

The main objectives of the research are to increase the efficiency of pavement designs by avoiding complicated and time consuming input file preparation, to extend pavement evaluation to highways with high volumes of heavy traffic and to bring advanced intelligent techniques for pavement designs into practical use. Thus, neural networks are invaluable tools to the pavement engineer.

Granular based pavement structures for the higher road category (Category A) in wet region are selected in this paper for the design of the neural network estimator and the TRH 4 guideline is used for the selection of pavement types.

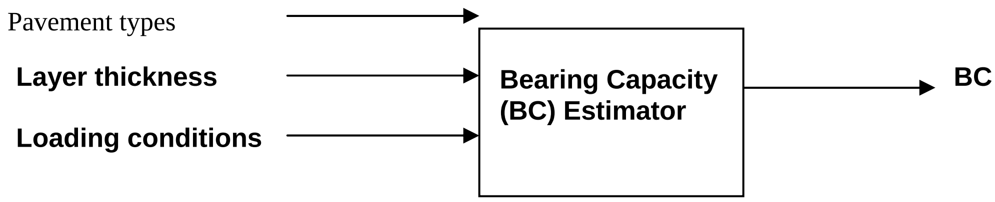


Figure 1. Block diagram for estimation of bearing capacity.

2. 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 time consuming finite element input file preparation for routine design applications.

Neural networks have become very popular for data analysis over the past two decades. They 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 (Haykin, 1994). The self-learning ability of neural networks 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.

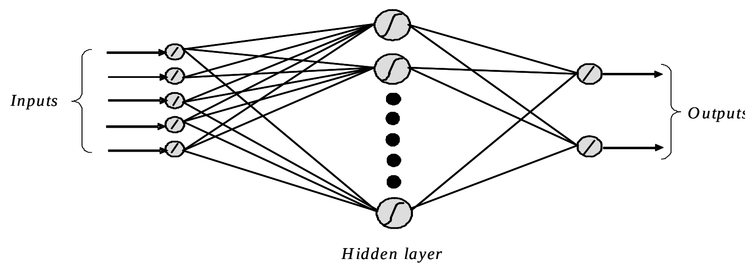


Figure 2. A multilayer feedforward neural network.

Typically, in a Multilayer Feedforward Neural Network (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 activity of the input units represents the raw information that is fed into the network. The activity of each hidden unit is determined by the activities of the input units and the weights on the connections between the input and the hidden units. The behaviour of the output units depends on the activity of the hidden and output units. The different layers structure allows a neural network to be flexible, capture more information and identify relationships between variables.

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).

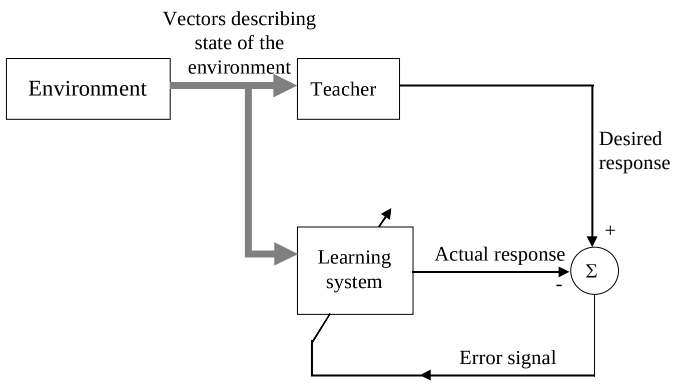


Figure 3. Block diagram for supervised learning.

3. NEURAL NETWORK TRAINING AND RESULTS

For the application described in this paper i.e. estimation of bearing capacity of pavement structures, the multilayer feedforward neural network (MLFNN) is proposed. The MLFNN (Figure 4) is trained with the backpropagation algorithm (Werbos, 1974) to estimate the bearing capacitity for granular pavement structures for higher road category in the wet region, according to TRH 4 (Committee of Land Transport Officials, 1996). There are three input variables, pavement types (five material types and thicknesses) and two loading conditions. The output is the bearing capacity for the pavement structures. The neural network output layer transfer function is a linear one with the range of 0 and 1.

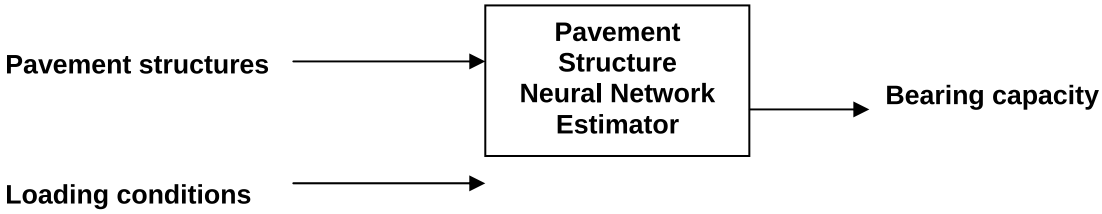


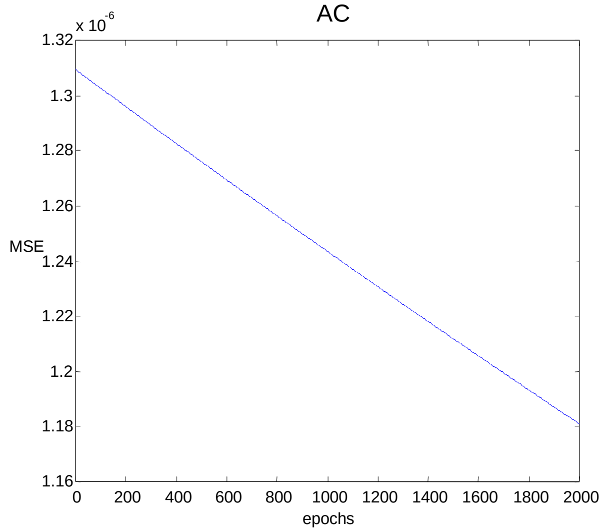
Figure 4. Inputs and outputs of the neural network estimator.

Table 1 shows a typical layout of pavement structure Type 1. Basically there are four major pavement composition types used in Southern African road designs, the granular, cemented, hot-mix asphalt and concrete base pavements. The types of pavement material are according to the South African Material Classification in TRH 14 (Committee of State Road Authorities, 1985). The catalogue for different pavement types (Committee of Land Transport Officials, 1996) 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. The pavement structure shown in Table 1 consists of a continuously graded asphalt surfacing (AC); a graded crushed stone granular base (G1), a cemented crushed subbase (C3) and a gravel/soil subgrade (G7-G10).

Table 1: Typical layout of a pavement structure Type 1 (Granular base, wet region and road category A)

No. of Layers	Material Type	Layer Thickness
1^{st} layer	Asphalt surfacing: AC	30 mm
2^{nd} layer	Graded crushed stone: G1	150 mm
3^{rd} layer	Stabilized Material: C3	200 mm
4^{th} layer	Gravel/soil: G7-G10	150 mm
5^{th} layer	Gravel/soil subgrade: G9 – G10	150 mm

The neural network is trained for several epochs and the training error plots for the bearing capacity of each material type and the critical bearing capacity (lowest BC) in the pavement structure are given in the Figures 5, 6, 7, 8, 9 and 10 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 numbers of epochs were increased. The performance of the trained neural network estimator was tested for different pavement types in the training set.



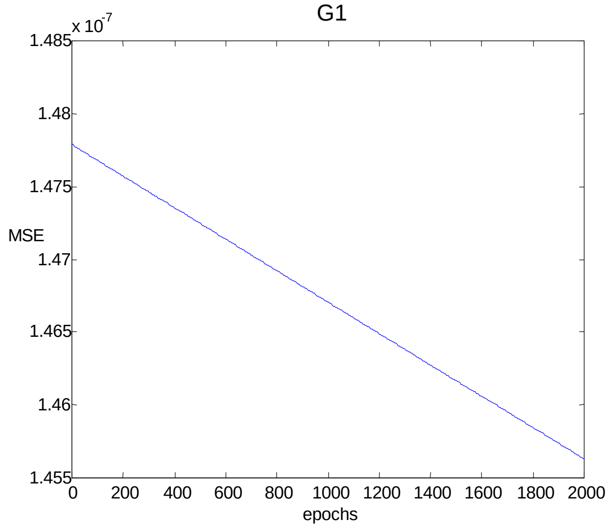
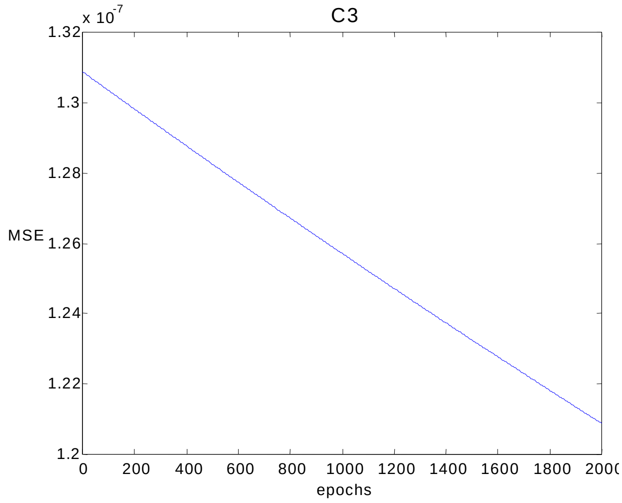


Figure 5: Neural network training error plot for AC.

Figure 6: Neural network training error plot for G1.



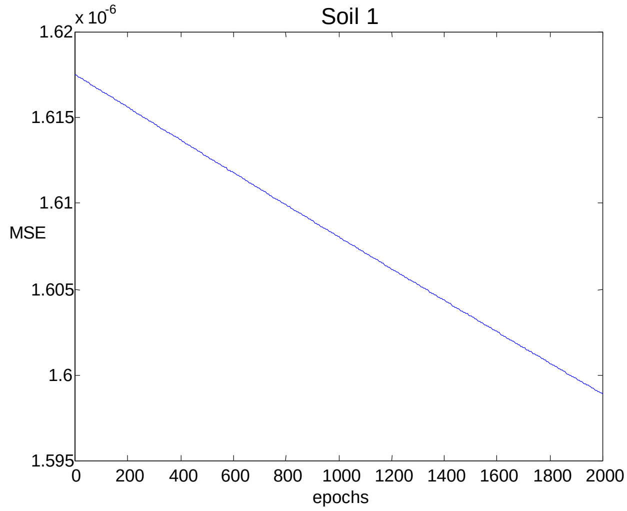
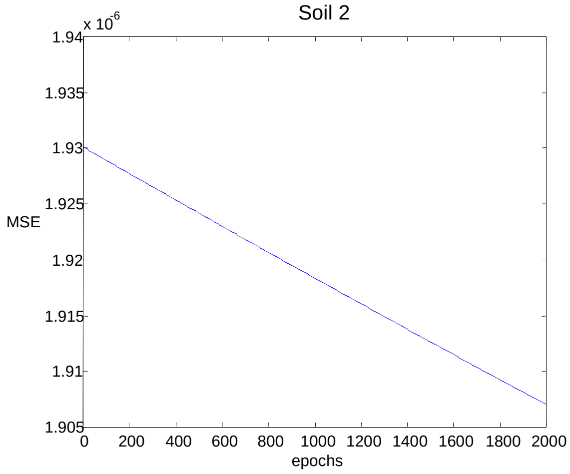


Figure 7: Neural network training error plot for C3.

Figure 8: Neural network training error plot for Soil 1.



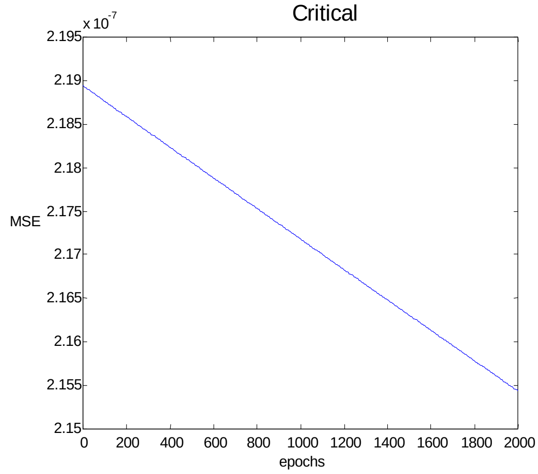


Figure 9: Neural network training error plot for Soil 2.

Figure 10: Neural network training error plot for Critical BC

Data sets were normalised between the values 0 and 1. The bearing capacities from the SAMDM (target/desired values) and ANN (actual/modelled values) are calculated in the range of 0 and 1, i.e. normalised values. Target values were obtained from the SAMDM.

Table 2 shows the desired/target normalised values (SAMDM) for bearing capacities of each material type and the critical one in the pavement structure Type 1, for loading range from 20 – 140 kN and contact pressure of 400 – 520 kPa for dual axle wheel loads at 350mm spacing.

Table 3 indicates the actual/modelled results from the neural network estimator in normalised values. In comparison to the desired values the neural network predicted the bearing capacities with tolerable error. Figure 11 shows the plot for desired/target against actual/modelled bearing capacities. The desired values are indicated by series 1 to 6 and actual values by series 7 to 12.

Table 2: Normalised desired (SAMDM) bearing capacities for Type 1 pavement structure.

Loading (kN)	Contact pressure (kPa)	Layer 1 (AC)	Layer 2 (G1)	Layer 3 (C3)	Layer 4 (SOIL1)	Layer 5 (SOIL2)	Critical BC
20	400 (Dual axle tyre at 350 mm spacing)	0.0000	1.0000	0.0000	1.0000	1.0000	1.0000
60		0.0000	0.0732	0.0497	0.0001	0.0000	0.0580
80		0.0006	0.0300	0.0209	0.0000	0.0000	0.0188
100		0.0080	0.0141	0.0130	0.0000	0.0000	0.0068
140		1.0000	0.0032	0.0097	0.0000	0.0000	0.0009
20	520	0.0000	0.9222	1.0000	0.8566	0.9439	0.9699
60		0.0000	0.0491	0.0392	0.0001	0.0000	0.0441
80		0.0000	0.0168	0.0155	0.0000	0.0000	0.0122
100		0.0001	0.0066	0.0084	0.0000	0.0000	0.0036
140		0.0051	0.0000	0.0061	0.0000	0.0000	0.0000

Table 3: Normalised actual (ANN) bearing capacities for Type 1 pavement structure.

Loadings (kN)	Contact pressure (kPa)	Layer 1 (AC)	Layer 2 (G1)	Layer 3 (C3)	Layer 4 (SOIL1)	Layer 5 (SOIL2)	Critical BC
20	400 (Dual axle tyre at 350 mm spacing)	0.0001	1.0000	0.0000	1.0000	1.0000	1.0000
60		0.0014	0.0729	0.0495	0.0006	0.0006	0.0576
80		0.0020	0.0308	0.0213	0.0012	0.0013	0.0197
100		0.0095	0.0137	0.0127	0.0008	0.0009	0.0063
140		0.9998	0.0032	0.0098	0.0001	0.0001	0.0009
20	520	0.0000	0.9222	1.0000	0.8566	0.9439	0.9699
60		0.0002	0.0487	0.0396	0.0015	0.0016	0.0435
80		0.0001	0.0171	0.0147	0.0029	0.0032	0.0125
100		0.0007	0.0071	0.0086	0.0017	0.0018	0.0041
140		0.0057	0.0004	0.0062	0.0001	0.0001	0.0004

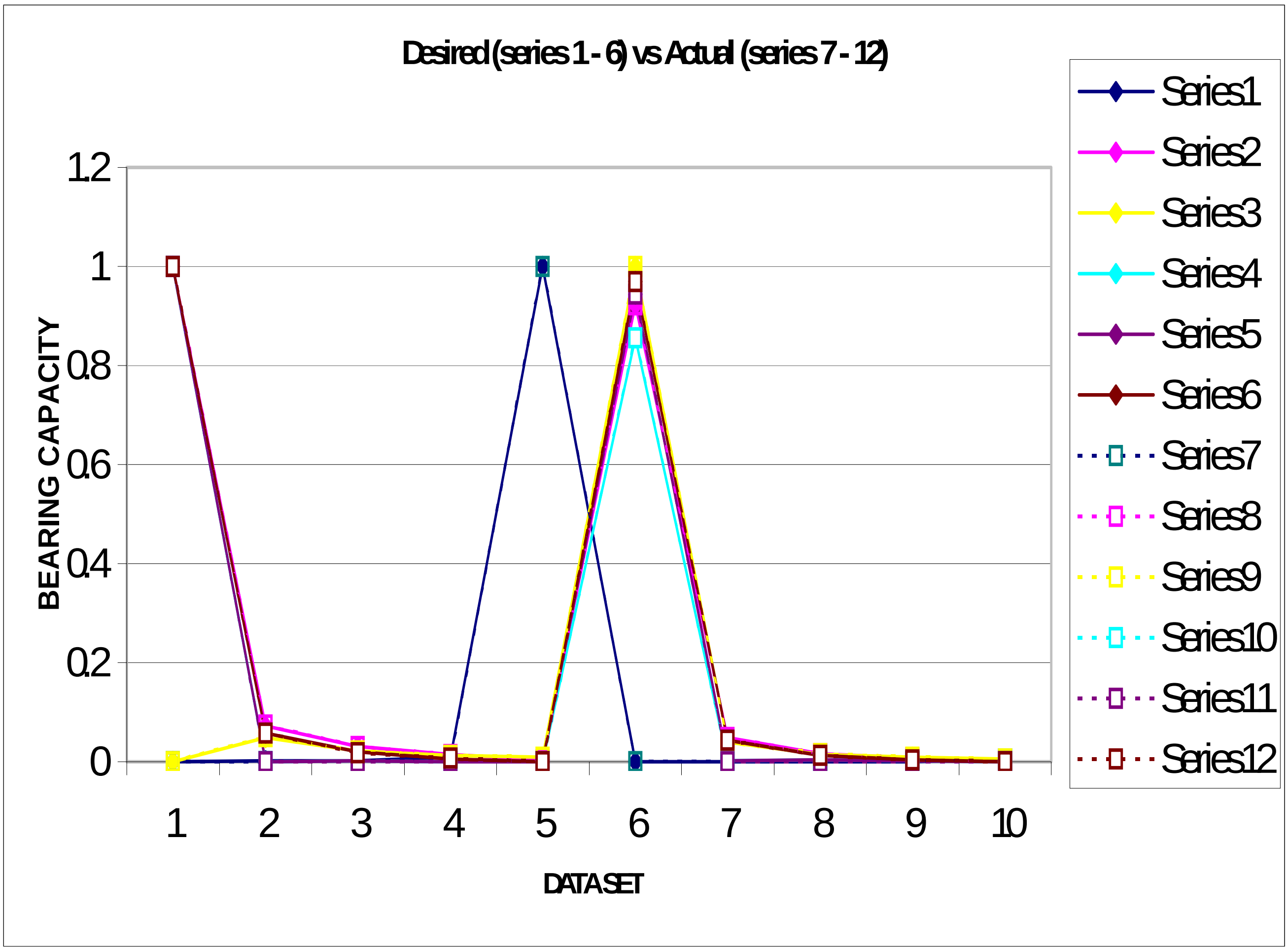


Figure 11: Desired (SAMDM) against Actual (ANN) bearing capacities.

4. CONCLUSION

This paper proposed a potential solution using an intelligent technique based on neural networks to predict the bearing capacities of different pavement structures under various loading conditions. The neural network model was trained with granular based pavement structures for higher road category in wet region under different loading conditions, for roads in South Africa. The model successfully estimated the bearing capacities for a granular based pavement structure type (shown in Table 1, 2 and 3) under different loading conditions for road Category A in wet region with negligible torelance error. The neural network model currently demonstrated for this work can be further applied for other pavement structure types prevailing under varying loading conditions and other factors. The merits of the neural network are the ability to detect complex nonlinear relationships between dependent and independent variables and to detect the possible interaction between predictor variables and the training algorithms. The performance of the model relies on the training data sets generated. Therefore to have an expert model, a lot of training data sets based on current and predictable/future trends need to be generated.

ANN models have been developed for pavement engineering applications in the modelling of pavements for the backcalculation of pavement moduli and the prediction of stresses.

The model currently to be developed would increase the efficiency of pavement designs by avoiding complicated and time consuming input file preparation and to extend pavement evaluation to highways with high volumes of heavy traffic loadings for different pavement structures, and finally to bring advanced intelligent techniques for pavement designs into more practical use in South Africa. One of the benefits to the practitioner is that the number of inputs is reduced when using the ANN model. Thus, neural networks are invaluable tools to the pavement engineer.

5. REFERENCES

[1] Committee of Land Transport Officials, Draft TRH4, 1996. "Structural design of flexible pavements for inter-urban and rural roads", Department of Transport, Pretoria.

[2] Committee of State Road Authorities, TRH14, 1985. "Guidelines for road construction materials", Department of Transport, Pretoria.

[3] Fwa, T. F., Chan, W. T., 1993. Priority rating of highway maintenance needs by neural networks. ASCE Journal of Transportation Engineering. vol. 119, p. 419-422.

[4] Haykin, S., Neural Networks, 1994. A Comprehensive Foundation, New York, NY: Macmillan.

[5] Meier, R. W., 1995. Backcalculation of flexible pavement moduli from falling weight deflectometer data using artificial neural networks. Ph.D. Dissertation, Georgia Institute of Technology, School of Civil and Environmental Engineering, Atlanta.

[6] Theyse, H. L., De Beer, M., Rust, F. C., 1996. Overview of the South African mechanistic pavement design method. Transportation Research Board, National Research Council. 1539, p. 6-17.

[7] Venayagamoorthy, V., Allopi, D., Venayagamoorthy, G. K., 2002, Using artificial neural network as a design tool for flexible pavement design. Proceeding of the IPET International Conference on Engineering Technology Research, p. 58-61.

[8] Venayagamoorthy, V., Allopi, D., Venayagamoorthy, G. K., 2004. Neural network based classification for pavement structures. Proceeding of the International Conference on Intelligent Sensing and Information Processing, India, p. 295-298.

[9] Werbos, P., 1974. Beyond regression: New tools for prediction and analysis in the behavioural sciences. PhD Dissertation, Harvard University, MA, USA.