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Neural Networks Applications in Pavement Engineering: A Recent Survey

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Abstract: The use of neural networks (NNs) has increased tremendously in several areas of engineering over the last three decades. This paper is intended to provide a state-of-the-art survey of NN applications in pavement engineering over the last three decades. The reported studies are briefly summarized under eight different categories: (1) prediction of pavement condition and performance, (2) pavement management and maintenance strategies, (3) pavement distress forecasting, (4) structural evaluation of pavement systems, (5) pavement image analysis and classification, (6) pavement materials modeling, and (7) other miscellaneous transportation infrastructure applications. To maintain consistency, the review was primarily based on archival journal publications although novel application-oriented NN implementations published in peer-reviewed conference proceedings and edited books were also considered. Recent publications focusing on the development and use of hybrid neural systems in pavement engineering were also included in the review. The increasing number of publications in this area of research in combination with other soft computing techniques every year definitely indicates that more and more students, researchers, and practitioners are interested in exploring the use of NNs in the study of pavement engineering problems.

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Introduction

Over the past three decades, there has been an increased interest in the use of neural networks (NNs) in civil engineering fields such as structural, environmental and water resources, traffic, geotechnical as well as pavement engineering. NNs represent a class of robust, non-linear, computationally intelligent models applicable to a wide variety of problems. NNs have been found to be useful tools for solving pavement engineering problems, which deal with highly nonlinear functional approximations.

Pavement engineering encompasses a broad spectrum of study including issues related to design, analysis, evaluation, performance, maintenance, rehabilitation, and management of both highway and airport pavements. The NN-related studies reviewed in this paper focus on three major pavement types: flexible or asphalt pavements, rigid or concrete pavements, and composite pavements.

Neural networks are information processing computational tools in which highly interconnected processing neurons work in harmony to analyze and solve complex problems in a nontraditional manner. This power of the NNs, emulating the biological nervous system, lies in the tremendous number of interconnections as they provide notable advantages in learning and generalizing from examples, producing meaningful and cost-effective solutions to various problems even when input data contain errors or are incomplete, adapting solutions over time to compensate for changing circumstances and processing information quite rapidly often in real time.

The adoption and use of NN modeling techniques in the Mechanistic-Empirical Pavement Design Guide/Pavement ME Design [1] has especially placed the emphasis on the successful use of neural nets in geomechanical and pavement systems [2-3]. Yet, many pavement engineering practitioners may not be fully aware of the benefits of using NNs and other computational intelligence systems. These obstacles can be overcome by providing the engineering practitioners with a better understanding through necessary background information and documentation of successful NN applications in pavement engineering.

This paper presents a review of neural network techniques and applications used in pavement engineering over the last three decades in eight major categories: (1) predictions of pavement performance and pavement condition, (2) pavement management and maintenance strategies, (3) pavement distress forecasting, (4) structural evaluation of pavement systems, (5) pavement distress image analysis and classification, and (6) other miscellaneous pavement applications. Similar articles focusing on the use of NNs in civil and transportation engineering applications have been published previously [4-9]. However, these publications did not specifically concentrate on pavement engineering. The aim of this paper is to fill the gap in this area and present an up-to-date comprehensive review on the use of neural networks in the field of pavement engineering. The use of the term 'neural networks (NNs)' is more prevalent in recent literature compared to that of 'artificial neural networks (ANNs)' and the same nomenclature is followed in this paper. The use of NNs in pavement materials modeling and characterization will not be discussed in this paper as it has been recently reviewed by the authors elsewhere [10].

Overview of Neural Networks

Imitating the biological nervous system, neural networks are information processing computational tools capable of solving nonlinear relations in a specific problem [11-14]. Like humans, they have the flexibility to learn from examples by means of interconnected elements, namely neurons. Neural network

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architectures, arranged in layers, involve synaptic connections amid neurons which receive signals and transmit them to the other via activation functions. Each connection has its own weight and the network 'learns' by adjusting the weight between neurons to minimize error between the predicted and expected values. Also, in the learning process node biases are also adjusted in addition to the connection weights. Since interconnected neurons have the flexibility to adjust the weights, neural networks have powerful capacities in analyzing complex problems. Neural networks motivated by the neuronal architecture and operation of the brain can contribute to a better understanding of several complex, non-linear pavement engineering problems with various pavement and soil variables.

The basic element in the NN is a processing element, called as artificial neuron or node (see Fig. 1). Each neuron contains a very limited amount of local memory and performs basic mathematical operations on data passing through them. These neurons are highly interconnected in layers such as an input layer, an output layer and one or more hidden layers. The computational power of NN comes from this interconnection which makes input data concurrently processed in artificial neurons [15].

An artificial neuron receives information (signal) from other neurons, processes it, and then relays the filtered signal to other neurons [12]. The receiving end of the neuron has incoming signals (x_1, x_2, x_3…. and x_n). Each of them is assigned a weight (w_{ji}) that is based on experience and likely to change during the training process. The summation of all the weighted signal amounts yields the combined input quantity (I_j) which is sent to a preselected transfer function (f), sometimes called an activation function. A filtered output (y_j) is generated in the outgoing end of the artificial neuron (j) through the mapping of the transfer function. The parameters can be written as per the following equations:

$$I_j = \sum_{i=1}^{n} w_{ji} x_i \tag{1}$$

$$y_j = f(I_j) \tag{2}$$

There are several types of transfer functions that can be used, including sigmoid, threshold, and Gaussian functions. The transfer function most often used is the sigmoid function because of its differentiability. The sigmoid function can be represented by the following equation:

$$f(I_j) = \frac{1}{1+\exp(-\varphi I_j)} \tag{3}$$

Where φ = positive scaling constant, which controls the steepness between the two asymptotic values 0 and 1 [12].

The NN performs two major functions: learning (training) and testing. A training data set and an independent testing data set are prepared for these functions. Inputs from a training data set are presented to the input layer to start the propagation of data. Inside the network, weights are adjusted when data pass between artificial neurons along the connections. Since interconnected neurons have the flexibility to adjust the weights, NN has the ability to analyze complex problems. It uses a learning rule to find a set of weights such that the error is minimum. This process is called "learning" or "training". The following are the three broad types of learning in neural network technology [15]:

- Supervised learning: system/weight is adjusted by comparing the network output with a given or desired output
- Unsupervised training: the network is trained to form categories based on similarity among the data and identify irregularities in data
- Reinforcement learning: the network attempts to learn the input-output vectors by trial and error through maximizing a performance function. The system can identify whether a given output is correct or not but cannot estimate the exact output

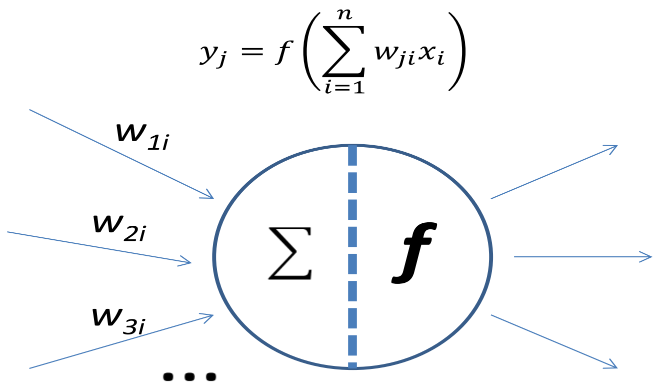

Fig. 1. Schematic of a Simple Model Neuron.

Once the training phase of the model has been successfully accomplished, the network performance is verified by presenting independent testing datasets to the NN. This process is called "testing." Details regarding the theory and mathematics behind the NN is available in several sources [12, 16-18] and is beyond the scope of this paper.

There are different types of neural network types such as back-propagation algorithms (BP), radial basis function network (RBF), probabilistic neural networks (PNN), and generalized regression neural networks (GRNN). Computing abilities of neural networks have been proven in the fields of prediction and estimation, pattern recognition, and optimization [12, 16, 17, 19, 20]. The best-known example of a neural network training algorithm is *back-propagation* [12, 21-23] which is based on a gradient-descent optimization technique. A typical multi-layer perceptron back-propagation architecture with 2 hidden layers is illustrated in Fig. 2. The back-propagation algorithm is described in many textbooks [12, 16-18].

Advantages and Limitations of Neural Networks

NNs provide an analytical alternative to conventional techniques which are often limited by strict assumptions of normality, linearity, variable independence etc. Because a NN can capture many kinds of relationships, it allows the user to quickly and relatively easily model phenomena which otherwise may have been very difficult. Neural networks offer a number of advantages, including requiring less formal statistical training, ability to implicitly detect complex nonlinear relationships between dependent and independent

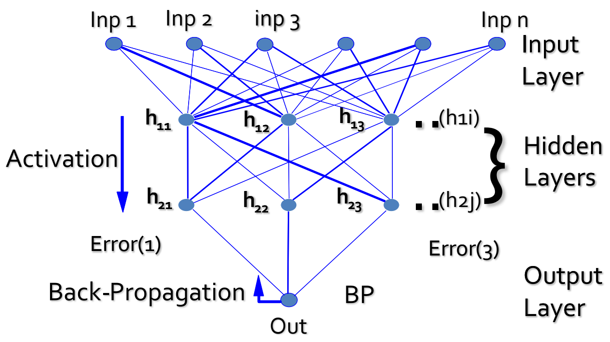

Fig. 2. A Typical Multi-layer Perceptron Back-propagation Neural Network Architecture with Two Hidden Layers.

variables, ability to detect all possible interactions between predictor variables, and the availability of multiple training algorithms.

Despite their good performance in many situations, neural networks suffer from a number of shortcomings. For example, neural networks cannot explain results using conventional methods. In problems where explaining rules may be critical, neural networks are not the tool of choice. They are the tool of choice when acting on the results is more important than understanding them. Even though neural networks cannot produce explicit rules, sensitivity analysis does enable them to explain which inputs are more important than others. This analysis can be performed inside the network, by using the errors generated from back propagation, or it can be performed externally by poking the network with specific inputs. Secondly, neural networks usually converge on some solution for any given training set. Unfortunately, there is no guarantee that this solution provides the best model of the data. Therefore, the test set must be utilized to determine when a model provides good enough performance to be used on unknown data [12, 16, 17]. Karlafitis and Vlahogianni [24] provide a nice discussion on the differences and similarities between statistical methods and neural networks and some insights for selecting the appropriate approach within the context of transportation research.

Prediction of Pavement Condition and Performance

The presence of undesirable crack, rut, and ride conditions determine the overall pavement surface condition which is generally associated with an index such as the International Roughness Index (IRI), pavement condition rating (PCR), etc. Neural networks have been found to be very powerful and versatile computational tools for determining and predicting the future condition and performance of the existing pavement systems.

Attoh-Okine [25] applied a back-propagation type NN to develop a pavement roughness progression model. A neural network model was trained using synthetically generated roughness data with an empirical simulation model which accounted for several influencing factors such as pavement structural deformation, incremental traffic loadings, extent of cracking and thickness of surface layer, incremental variation of rut depth, surface defects such as patching and potholes, and environmental and other non-traffic-related variables such as road age. The NN prediction results were found to be more satisfactory when the pavement condition database considered was large enough. However, it was reported that NN model may not produce as good results with real data sets as it gave for the simulated data set. Chou *et al*. [26] used the fuzzy enhancement algorithm, the thresholding based on the maximum fuzzy entropy, the moment invariant features, and the neural networks successfully to classify pavement cracks.

A NN system for the condition rating of rigid pavements was developed and implemented by Eldin and Senouci [27]. The Oregon State DOT condition rating scheme, based on the cracking and rutting indices, was used as the basis for the development of NN models. A backpropagation neural network with one hidden layer was used in this study consisting of 15 inputs corresponding to 15 distresses and the output was a pavement condition index ranging between 0.1 and 0.5. The proposed NN model showed good generalization capability and unlike the Oregon State DOT condition rating model, the NN also showed a good fault-tolerance capability at high level of noise. A more comprehensive model with 22 input nodes was also developed [28]. In a related study, Eldin and Senouci [29] also presented a successful application of feed-forward NN for the condition rating of flexible pavements.

Attoh-Okine [30] employed NN to predict the area of indexed cracks in flexible pavements based on modified structural number, incremental traffic loadings, and environmental mechanisms. The performance of non-overlaid thick asphalt pavements having a thickness of more than 152.4 mm (6 in.) was studied by Owusu-Ababio [31] using NN. The pavement condition, represented by the Pavement Distress Index (PDI), was predicted based on the pavement surface thickness, pavement age, traffic level, base thickness, and roadbed condition. The author reported that the NN model outperformed the multiple-linear regression (MLR) model in terms of the standard error and the coefficient of multiple determination (R^2).

In another study, Owusu-Ababio [32] investigated the effect of the neural network architecture on flexible pavement cracking prediction. The author concluded that a MLP-BP network with one hidden layer may be sufficient to satisfactorily predict the cracking in flexible pavements based on pavement surface thickness, pavement surface age, and equivalent single axle load.

Van der Gryp *et al*. [33] introduced a one-hidden layer feed-forward NN model to estimate the overall pavement condition based on the visual condition index (VCI) that ranges from 0 to 10, where 0 indicates worst and 10 indicates excellent pavement surface condition. The analysis was based on the severity and extent of various types of distresses including failure, surface cracks, longitudinal cracks, transverse cracks, patching, potholes, bleeding, and pumping. The reported simulations made it difficult to conclude on the effectiveness of the NN.

George at al. [34] developed NN models to estimate the Pavement Condition Rating (PCR) index of flexible, rigid, as well as composite pavements based on Mississippi DOT database. Attoh-Okine [35] used real pavement condition and traffic data from Kansas DOT to investigate the effect of learning rate and momentum term (in backpropagation algorithm neural network) on flexible pavement performance prediction. Rutting, faulting, transverse cracking, block cracking, and equivalent axle loads were used as input variables in this study to predict the International Roughness Index (IRI). Based on the study findings, the author suggested that a learning rate (η) of around 0.2 to 0.5 and a momentum (α) magnitude of around 0.4 to 0.5 seem to provide the best combination for the pavement performance prediction.

Shekharan [36] demonstrated the use of NN for condition prediction of five different types of pavements: original flexible, overlaid flexible, composite, jointed, and continuously reinforced concrete pavements (CRCP). A hybrid Genetic Adaptive Neural Network Training (GNNT) algorithm was employed to predict PCR based on pavement structure, history, and traffic volume inputs. Attoh-Okine [37] used NN self-organizing maps for the grouping of pavement condition variables in developing pavement performance models for prediction and evaluation purposes.

Lin *et al*. [38] developed a MLP-BP NN (14 input nodes, 2 hidden layers with 6 nodes each, and one output node) to predict IRI based on pavement distresses. Choi *et al*. [39] trained a backpropagation neural network algorithm to predict the performance of flexible pavements (IRI) using the Long Term Pavement Performance (LTPP) database. A hybrid NN-Finite Element Method (FEM) was employed by Gajewski and Sadowski [40] to investigate cracking behavior in asphalt pavements.

Pavement Management and Maintenance Strategies

Pavement management and maintenance issues must be considered very seriously in the selection of an economical treatment for rehabilitation of a deteriorated pavement section. In order to preserve or improve pavement condition, there are many maintenance and rehabilitation treatments that have to be carefully selected due to societal, environmental, and financial constraints. There are several articles summarized in this section in which the neural networks were utilized as a computational tool to decide which maintenance and rehabilitation actions should be performed on deteriorated pavement sections.

Hajek *et al*. [41] compared two different techniques, rule-based system and neural networks, for selecting and recommending routing and sealing (R&S) maintenance treatments. There were about 40 different variables and factors such as width of cracks, crack type, pavement serviceability, pavement structure and age, raveling, flushing, and rutting influencing the R&S decisions. Fwa and Chan [42] investigated the feasibility of the using NNs for priority assessment of highway pavement maintenance needs concluded that the use of neural networks had several significant advantages over the aggregated condition index.

Taha *et al*. [43] developed a hybrid NN-GA model for selecting the optimal maintenance strategy for flexible pavements and attributed the improvement in performance to hybridization. Flintsch *et al*. [44] developed and implemented NN models as part of an automatic procedure for preliminary screening and recommending roadway sections for pavement preservation at the Arizona DOT (ADOT).

A combined NN-knowledge-based expert systems (KBES) approach was employed by Goh [45] for choosing proper rehabilitation schemes of deteriorated pavement sections. The effectiveness of the NN was not clearly demonstrated in this study. Alsugair and Al-Qudrah [46] developed NN models for determining the appropriate maintenance and repair (M&R) actions based on comprehensive visual inspection data from Riyadh road network in Saudi Arabia.

Abdelrahim and George [47] used a genetic adaptive NN training (GANNT) algorithm with a single hidden layer to predict the optimum maintenance strategy based on realistic (noisy) data for the rehabilitation of a deteriorated pavement section.

Sundin and Braban-Ledoux [48] summarize applications of NNs, fuzzy logic, GAs, KBES, and hybrid systems in pavement management. Karwa and Donnell [49] employed NN to model the degradation of pavement marking reflectivity as a function of initial reflectivity, age of the markings, traffic flow, pavement marking type, and route location information using data from North Carolina engineering districts. Josen [50] utilized NN for network-level pavement performance and management study in Connecticut using asphalt pavement cracking data.

Pavement Distress Forecasting

NN-based pavement distress forecasting models have been proposed as a cost-effective approach to accurately predict the future condition of a pavement section. Schwartz [51] developed NN models for forecasting the infrastructure condition of pavement sections as a function of time, current and historical condition, loading, inventory materials, and other data elements. Roberts and Attoh-Okine [52] developed and compared the results of two different NN types, a dot product NN (using backpropagation algorithm) and a quadratic function NN (a generalized adaptive feed-forward neural network that combined supervised and self-organizing learning), for predicting the IRI of PCC overlaid HMA, full-depth HMA, and partial-design HMA. The authors concluded that the quadratic function NN model performed better than the dot product NN model.

Huang and Moore [53] used NN models (MLP-BP with one hidden layer) to predict the roughness distress level probability at some future time for flexible pavements. La Torre *et al*. [54] applied MLP-BP NNs to predict the IRI of flexible pavement sections for four years into the future. Sundin [55] predicted the progression of rut depth in road pavements using NNs. Two studies report development of NN models to forecast the pavement crack condition using the FDOT pavement condition database.

Yang *et al*. [56] summarized the results of a research study to implement an overall pavement condition prediction methodology using NNs for Florida DOT (FDOT). Three individual NN models were trained and tested using the FDOT pavement condition database to predict the crack rating, ride rating, and the rut rating up to a future period of five years. Najjar and Felker [57] used dynamic NNs based on backpropagation algorithm to develop a time-dependent roughness (IRI) prediction model for newly constructed Jointed Plain Concrete Pavements (JPCP) in Kansas. The data were obtained from the Kansas pavement condition database. The authors suggested that it was imperative to annually update such a model based on newly acquired data.

Saghafi *et al*. [58] were able to predict faulting in jointed concrete pavements using NN by considering base layer conditions and pavement age. Thube [59] implemented a NN-based pavement condition prediction methodology to forecast cracking, raveling, rutting and roughness for Low Volume Roads (LVR) in India.

Structural Evaluation of Pavement Systems

Several studies report use of NN for predicting the elastic moduli, layer thicknesses, coefficient of subgrade reaction, and shear wave velocities of the pavement layers, and pavement surface deflections.

Attoh-Okine [60] used a MLP-BP NN to interpret the Ground Penetrating Radar (GPR) thickness profile output from non-destructive pavement thickness and structure surveys. Heiler *et al*. [61] employed NNs for automatic detection of asphalt thickness and depth to reinforcement in composite pavements from GPR data.

Williams and Gucunski [62] developed MLP-BP and general regression NN models to predict the elastic moduli and layer thicknesses of pavements from the Spectral-Analysis-of-Surface-Waves (SASW) test results. With the same objective, Gucunski and Krstic [63] trained two sets of NN models, one on the basis of the average dispersion curve and the other based on the individual receiver spacing dispersion curve approach. The results showed that both models were capable of predicting the shear wave velocities and thicknesses of all the layers with high accuracy, except the thickness of the subbase, d_3.

Meier and Rix [64] were the first to develop a NN-based layered elastic analysis (LEA) approach for backcalculation of pavement layer moduli from falling weight deflectometer (FWD) deflection basins. The developed NN models were 1,500 to 2,200 times faster than the conventional backcalculation algorithmic programs in use at that time. In another study, Meier *et al*. [65] augmented the WESDEF backcalculation program with trained NN models to compute pavement surface deflections as function of pavement layer moduli for a wide range of three-layered flexible pavements. The authors noted that the NN-augmented WESDEF can successfully backcalculate pavement layer moduli 42 times faster than it did before.

Khazanovich and Roesler [66] implemented a NN-based backcalculation computer program (called as DIPLOBACK) for three-layered HMA overlaid PCC pavements. The DIPLOMAT forward model [67] was used to generate the theoretical deflection basins which were used in training the DIPLOBACK NN models.

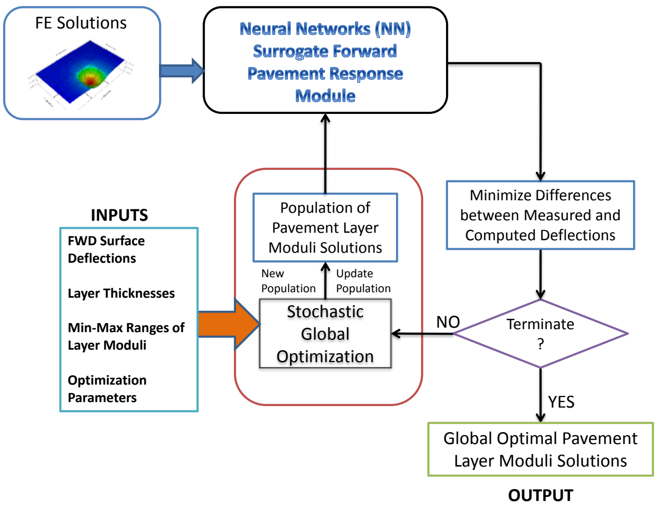

Fig. 3. Schematic of Neural Network Based Global Optimization Approach for Backcalculation of Pavement Layer Moduli [68].

Kim and Kim [68] used Hankel transforms as a forward model and NNs as inverse model for the prediction of layer moduli from FWD test data and surface wave measurements.

Several studies have reported on the ability of NNs to compute surface deflections as well as lateral and longitudinal tensile stresses at the bottom of jointed concrete airfield pavements as a function of type, level, and location of the applied gear load, slab thickness, slab modulus, subgrade support, pavement temperature gradient, and the load transfer efficiencies of the joints [3, 70, 71]. The training sets were developed using the ILLI-SLAB finite element program for prescribed gear and temperature loads. Fig. 1 displays the accuracy of best-performance NN architecture in predicting the critical pavement responses under the simultaneous aircraft and temperature loading [71].

The use of NNs for rapid backcalculation of non-linear, stress-dependent pavement layer moduli and forward calculation of critical pavement responses based on Finite Element (FE) based ILLI-PAVE synthetic database was demonstrated by Ceylan *et al*. [72] for highway flexible pavements with unbound aggregate layers, by Ceylan *et al*. [73] for full-depth asphalt pavements and by Gopalakrishnan and Thompson [74] for airport flexible pavements. Fig. 2 displays the prediction performance of NN model at 10,000 learning cycles [72]. Fig. 3 shows the comparison of results from FE-based regression algorithms and NN predictions. Similar NN-based backcalculation studies have been reported with changes in the forward model employed [75-77], dataset used [78, 79], pavement type [80], as well as hybridization of NN-based surrogate forward pavement response model with Genetic Algorithms (GAs) [81-84], Particle Swarm Optimization (PSO) [69], Co-variance Matrix Adaptation Evolution Strategy (CMAES) [85, 86], and Shuffled Complex Evolution (SCE) [87, 88], etc. A schematic of the NN based stochastic global optimization hybrid approach proposed by Gopalakrishnan [87] for pavement backcaculation is depicted in Fig. 3. Tarawneh and Nazzal [89] employed NN to optimize the prediction of subgrade resilient modulus design input from FWD test results. More recently, Gopalakrishnan *et al*. [90] attempted to backcalculate the asphalt concrete dynamic modulus master curve coefficients from FWD deflection-time history data.

The rapid prediction ability of the NN backcalculation models makes them perfect evaluation tools for analyzing the FWD deflection data, and thus assessing the condition of the pavement sections, in real time for both project specific and network level FWD testing. The efforts of the authors and their colleagues have resulted in a suite of NN-based pavement layer backcalculation models for flexible, rigid, and composite pavements, referred to as I-BACK, which is currently being used on a routine basis at the Iowa Department of Transportation (DOT) [91]. A screenshot of the Excel-based I-BACK pavement backcalculation software tool is shown in Fig. 4.

Pavement Distress Image Analysis/Classification

Quantification of pavement crack data is one of the most important criteria in determining optimum pavement maintenance strategies. Over the years, a significant amount of effort has been spent on developing methods to objectively evaluate the condition of pavements. In this section, various studies reporting the application of NNs for classification of cracks from digital pavement images are summarized.

Kaseko and Ritchie [92] employed MLP-BP NN to segment and classify 8-bit grayscale pavement digital images collected using the ROADRECON instrumentation vehicle. The authors used mean, standard deviation of gray scale level histogram of the image and a co-occurrence parameter as input variables. The threshold value was assumed as the output of the NN model and images were classified into four different categories according to the nature of cracks: "transverse", "longitudinal", "alligator", and "block cracking".

Kaseko *et al*. [93] developed a NN-based methodology for processing video images for automated detection, classification, and quantification of cracking on pavement surfaces and compared the performance of NN classifiers with those of Bayesian and k-nearest-neighbor classifiers. The authors were able to demonstrate that the NN classifiers had a significant advantage in real-time applications with high computation rates required in pattern-recognition problems.

The classification of pavement distresses from digital images using the radial basis function (RBF) NN was investigated by Nallamothu and Wang [94]. Cheng *et al*. [95] presented an approach to pavement cracking detection based on NN and CVPRIP (computer vision, pattern recognition, and image processing) techniques. This approach is based on the assumption that the crack pixels in pavement images are darker than their surroundings and crack pixels can be separated from the background using the threshold approach.

Lee and Lee [96] developed an integrated NN based crack imaging system to classify crack types of digital pavement images. Three different types of neural networks were used in the analyses: image-based neural network (INN), histogram-based neural network (HNN), and proximity-based neural network (PNN). Based on the analysis, the authors concluded that the proximity-based neural networks produced results with a very high success rate. All NN-based models achieved a high accuracy of 95% or higher for the training sets and relatively low accuracy of 70% or higher for the testing sets. Salari *et al*. [97] used NN in designing an image processing based pavement inspection system for the assessment of highway surface conditions. An expert system based on wavelet transform and radon neural network (WRNN) was proposed by Nejad and Zakeri [98] for classification of pavement distresses from images.

Other Miscellaneous Pavement Applications

Other NN related applications in pavement engineering are summarized in this section. Owusu-Ababio [99] presented a NN model for predicting skid resistance on flexible pavements containing no overlays for assessing the future rehabilitation needs for the Connecticut DOT pavement performance study results were used in the study. The pavement age, the location, the accumulated average annual daily traffic, and the posted speed limit were the four input variables and the skid number was the output variable. The results of the NN model and regression models were compared.

Wang [100] investigated the feasibility of using a specially designed and programmable neural net chip, Ni1000, in a PC to conduct real-time processing for pavement surface distress survey. Faghri and Hua [101] tried to predict the average annual daily traffic (AADT) using NN as a function of seasonal factors, 48 hours traffic counts, annual traffic pattern, and road attributes. Ioannides *et al*. [102] used MLP-BP NN for assessing the deflection and stress load transfer efficiencies of concrete pavement joints and for backcalculating joint parameters.

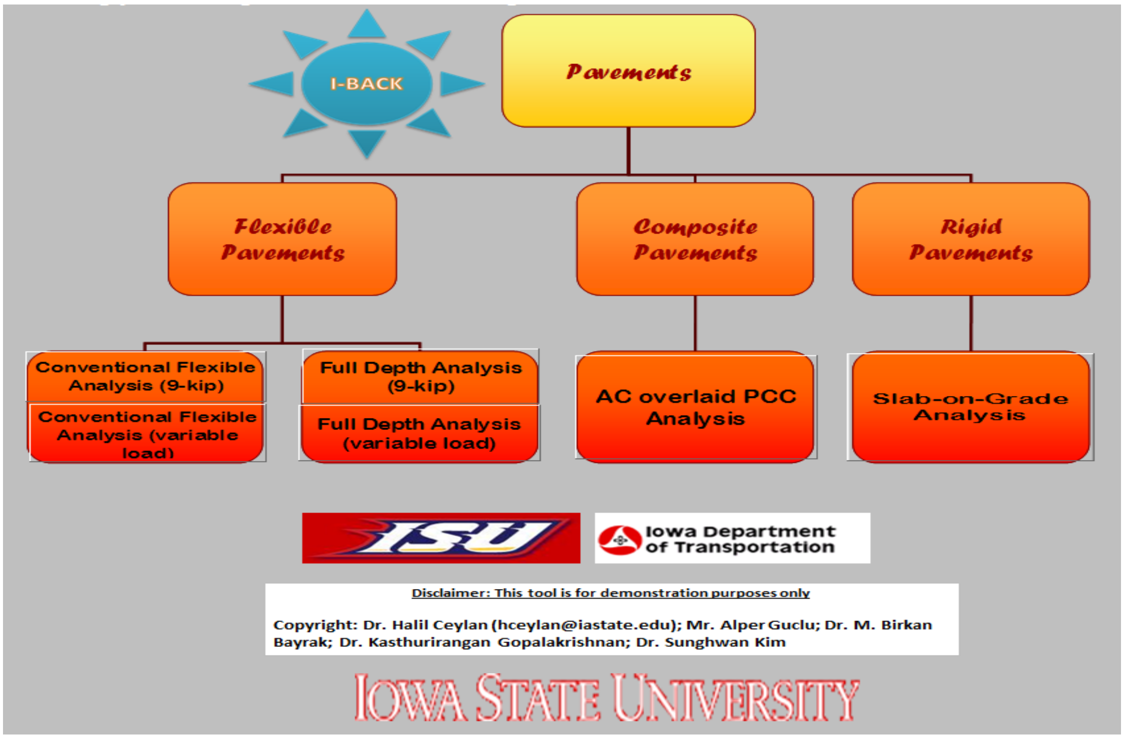

Fig. 4. Screenshot of Excel-based I-BACK Neural Networks Pavement Backcalculation Software Tool.

Other miscellaneous pavement applications involving the use of NN have also been reported by Dougherity [5] and Adeli [4]. Banan and Hjelmstad [103] re-examined the AASHO road test data using a Monte Carlo Hierarchical Adaptive Random Partitioning (MC-HARP) based NN approach. Mei *et al*. [104] developed a NN model to estimate the load related shallow crack depths and surface-initiated fatigue cracks in asphalt pavements based on crack-surface geometry and pavement and traffic characteristics. Ceylan *et al*. [105] and Wu *et al*. [106] employed the NN methodology to model the stress growth in asphalt concrete overlays due to load and thermal effects which substantially reduced the overall computer run time for a 20-year reflection cracking prediction of a typical overlay.

Summary

Neural Network (NN) models are useful complements to more-traditional numerical and statistical methods such as regression. Once fully trained or developed, NNs provide engineers with sophisticated, real time analysis and prediction tools with no complex analysis input requirements, such as those of finite element numerical solution techniques, and no large computer resources needed. They do not provide "a priori" function such as one generated by regression analysis, yet, they are not meant to be "black boxes" for practitioners either. NNs commonly outperform their traditional modeling counterparts in solving complex engineering problems.

NN modeling has shown great promise as a useful and nontraditional computing tool for analyzing too complex, non-linear problems inherent to pavement engineering. NNs have the potential to investigate, properly model and, as a result, better understand some of the complex pavement engineering mechanisms that have not been well understood and formulated yet. This is especially possible with the vastly powerful and nonlinear interconnections provided in the network architecture that enables an NN to even model very sophisticated finite element method numerical solutions as the state-of-the-art pavement structural analysis results. As an example, the Mechanistic-Empirical Pavement Design Guide (MEPDG) utilizes an NN model to analyze rigid concrete pavements and solve for concrete pavement critical responses under environmental and traffic loading conditions.

Several successful NN applications were reviewed in this paper for solving various pavement engineering problems in the areas of prediction of pavement performance and condition, pavement management and maintenance strategies, pavement distress forecasting, pavement structural evaluations, pavement distress image analysis and classification. Most of the studies reported in this regard utilized the backpropagation type neural network models, which is one of the most common NN models. Backpropagation NNs are indeed very powerful and versatile networks that can be taught a mapping from one data space to another using a representative set of pattern/examples to be learned. NN models were also noted to be able to rapidly present the required solutions by analyzing the pavement data in real time. This aspect becomes especially important in data collection and processing in real time for pavement condition and performance studies.

The use of NN in pavement engineering has significantly increased in the past twenty years. An issue that needs some attention in the future development of NNs is to include treatment of uncertainties associated with pavement engineering parameters. More recently, hybrid NN approaches, in combination with global optimization techniques or other machine learning techniques, have become popular in addressing complex pavement engineering issues. One of the main motivations for this paper is to enable the use of NN more widespread and common among both researchers and practitioners in the field of pavement engineering. Overall, despite the limitations of NNs, they have a number of significant benefits that make them a powerful and practical tool for solving many problems in the field of pavement/geotechnical engineering.

References

1. NCHRP (2004). Guide for Mechanistic-Empirical Design of New and Rehabilitated Pavement Structures, *NCHRP 1-37A Final Report*. Available at: http://onlinepubs.trb.org/onlinepubs/archive/mepdg/guide.htm [Accessed December 6, 2010].
2. Khazanovich, L., Selezneva, O.I., Yu, H.T., and Darter, M.I. (2001). Development of rapid solutions for prediction of critical continuously reinforced concrete pavement stresses. *Transportation Research Record*, No. 1778, pp. 64-72.
3. Ceylan, H. (2002). *Analysis and design of concrete pavement systems using artificial neural networks*. Ph.D. Dissertation. University of Illinois at Urbana-Champaign, Urbana, IL, USA.
4. Adeli, H. (2001). Neural Networks in Civil Engineering: 1989-2000. *Computer-Aided Civil and Infrastructure Engineering*, 16(2), pp. 126-142.
5. Dougherty, M. (1995). A review of neural networks applied to transport. *Transportation Research Part C: Emerging Technologies*, 3(4), pp. 247-260.
6. Flood, I. (2008). Towards the next generation of artificial neural networks for civil engineering. *Advanced Engineering Informatics*, 22(1), pp. 4-14.
7. Flood, I. and Kartam, N. (1994). Neural Networks in Civil Engineering. I: Principles and Understanding. *Journal of Computing in Civil Engineering*, 8(2), pp. 131-148.
8. Flood, I. and Kartam, N. (1994). Neural Networks in Civil Engineering. II: Systems and Application. *Journal of Computing in Civil Engineering*, 8(2), pp. 149-162.
9. Vanluchene, R.D. and Sun, R. (1990). Neural Networks in Structural Engineering. *Computer-Aided Civil and Infrastructure Engineering*, 5(3), pp. 207-215.
10. Kim, S., Gopalakrishnan, K., and Ceylan, H. (2009). Neural Networks Application in Pavement Infrastructure Materials. In K. Gopalakrishnan, H. Ceylan, and N.O. Attoh-Okine, eds. *Intelligent and Soft Computing in Infrastructure Systems Engineering: Recent Advances*. Studies in Computional Intelligence. Springer, pp. 47–66, Heidelberg, Berlin, Germany.
11. Funahashi, K.-I. (1989). On the approximate realization of continuous mappings by neural networks. *Neural Networks*, 2(3), pp. 183-192.
12. Haykin, S.S., 1999. *Neural networks: a comprehensive foundation*, Prentice Hall, Upper Saddle River, New Jersey,

USA.

13. Hornik, K., Stinchcombe, M., and White, H. (1989). Multilayer feedforward networks are universal approximators. *Neural Networks*, 2(5), pp. 359-366.
14. Mohiuddin, K.M., Jain, A.K., and Mao, J. (1996). Artificial neural networks: a tutorial. *Computer*, 29(3), pp. 31-44.
15. TRB (1999). *Use of Artificial Neural Networks in Geomechanical and Pavement Systems*, Transportation Research Board, Washington, DC, USA.
16. Adeli, H. and Hung, S.-L. (1995). *Machine learning: neural networks, genetic algorithms, and fuzzy systems*, Wiley, Hoboken, New Jersey, USA.
17. Mehrotra, K., Mohan, C.K., and Ranka, S. (1997). *Elements of artificial neural networks*, MIT Press, Cambridge, Massachusetts, USA.
18. Hegazy, T., Fazio, P., and Moselhi, O. (1994). Developing Practical Neural Network Applications Using Back-Propagation. *Computer-Aided Civil and Infrastructure Engineering*, 9(2), pp. 145-159.
19. Golden, R.M. (1996). *Mathematical methods for neural network analysis and design*, MIT Press, Cambridge, Massachusetts, USA.
20. Adeli, H. and Park, H.S. (1998). *Neurocomputing for design automation*, CRC Press, Boca Raton, Florida, USA.
21. Rumelhart, D.E., Hinton, G.E., and Williams, R.J. (1986). Learning internal representations by error propagation. In D. E. Rumelhart, ed. *Parallel distributed processing: Explorations in the Microstructure of Cognition*. MIT Press, Cambridge, MA, USA, pp. 318-362.
22. Fausett, L.V. (1994). *Fundamentals of neural networks: architectures, algorithms, and applications*, Prentice-Hall, Upper Saddle River, New Jersey, USA.
23. Patterson, D.W., 1996. *Artificial neural networks: theory and applications*, Prentice Hall, Upper Saddle River, New Jersey, USA.
24. Karlafitis, M. G. and Vlahogianni, E. I. (2014). Statistical methods versus neural networks in transportation research: Differences, similarities and some insights. *Transportation Research Part C: Emerging Technologies*, 19(3), pp. 387-399.
25. Attoh-Okine, N.O. (1994). Predicting roughness progression in flexible pavements using artificial neural networks. In *Third International Conference on Managing Pavements*. pp. 55–62.
26. Chou, J.C., O'Neill, W.A., and Cheng, H.D. (1994). Pavement distress classification using neural networks. In *Humans, Information and Technology: 1994 IEEE International Conference on Systems, Man, and Cybernetics*. San Antonio, TX, USA, pp. 397-401.
27. Eldin, N.N. and Senouci, A.B. (1995). Condition rating of rigid pavements by neural networks. *Canadian Journal of Civil Engineering*, 22(5), pp. 861-870.
28. Eldin, N.N. and Senouci, A.B. (1995). Use of neural networks for condition rating of jointed concrete pavements. *Advances in Engineering Software*, 23(3), pp. 133-141.
29. Eldin, N.N. and Senouci, A.B, (1995). A pavement condition-rating model using backpropagation neural networks. *Computer-Aided Civil and Infrastructure Engineering*, 10(6), pp. 433–441.
30. Attoh-Okine, N.O. (1996). Predicting cracking index in flexible pavements: Artificial neural network approach. In *Reflective Cracking in Pavements*. Third International RILEM Conference. London, England: E & FN Spon, pp. 153-160.
31. Owusu-Ababio, S. (1998). Application of Neural Networks to Modeling Thick Asphalt Pavement Performance. In N. O. Attoh-Okine, ed. *Artificial Intelligence and Mathematical Methods in Pavement and Geomechanical Systems: Proceedings of the International Symposium, Miami, Florida, USA, November 5-6, 1998*. CRC Press, pp. 23-30.
32. Owusu-Ababio, S. (1998). Effect of neural network topology on flexible pavement cracking prediction. *Computer-Aided Civil and Infrastructure Engineering*, 13(5), pp. 349–355.
33. van der Gryp, A., Bredenhann, S.J., Henderson, M.G., and Rohde, G.T. (1998). Determining the visual condition index of flexible pavements using artificial neural networks. In *Fourth International Conference on Managing Pavements*. Durban, South Africa, pp. 115–129.
34. George, K.P., El-Rahim, A.M.A., and Shekharan, A. R. (1998). Updates of pavement performance modeling. In *Third International Conference on Road and Airfield Pavement Technology*. Beijing, China, pp. 402-410.
35. Attoh-Okine, N.O. (1999). Analysis of learning rate and momentum term in backpropagation neural network algorithm trained to predict pavement performance. *Advances in Engineering Software*, 30(4), pp. 291-302.
36. Shekharan, A. R. (2000). Pavement performance prediction by artificial neural network. In N. O. Attoh-Okine, ed. *Computational Intelligence Applications in Pavement and Geomechanical Systems: Proceedings of the 2nd International Workshop*. A.A. Balkema, pp. 89-98.
37. Attoh-Okine, N.O. (2001). Grouping Pavement Condition Variables for Performance Modeling Using Self-Organizing Maps. *Computer-Aided Civil and Infrastructure Engineering*, 16(2), pp. 112-125.
38. Lin, J.D., Yau, J.T., and Hsiao, L.H. (2003). Correlation analysis between international roughness index (IRI) and pavement distress by neural network. In *CD-ROM Proceedings of the 82nd annual meeting of the Transportation Research Board*. Washington, DC, USA.
39. Choi, J., Adams, T.M., and Bahia, H.U. (2004). Pavement roughness modeling using back-propagation neural networks. *Computer-Aided Civil and Infrastructure Engineering*, 19(4), pp. 295–303.
40. Gajewski, J. and Sadowski, T. (2014). Sensitivity analysis of crack propagation in pavement bituminous layered structures using a hybrid system integrating Artificial Neural Networks and Finite Element Method. *Computational Materials Science*, 82, pp. 114-117.
41. Hajek, J.J., Chong, G.J., Phang, W.A., and Haas, R.C.G. (1987). ROSE: A knowledge-based expert system for routing and sealing. In *Proceeding of the 2nd North American Pavement Management Conference*. Toronto, Canada, pp. 301-341.
42. Chan, W.T. (1993). Priority rating of highway maintenance needs by neural networks. *Journal of Transportation Engineering*, 119, p.419.

43. Taha, M.A. and Hanna, A.S. (1995). Evolutionary neural network model for the selection of pavement maintenance strategy. *Transportation Research Record*, No. 1497, pp. 70–76.
44. Flintsch, G., Zaniewski, J., and Delton, J. (1996). Artificial Neural Network for Selecting Pavement Rehabilitation Projects. *Transportation Research Record*, No. 1524, pp. 185-193.
45. Goh, A.T.C. (1997). A hybrid neural network based pavement management system. *Road and Transport Research*, 6, pp. 62–71.
46. Alsugair, A.M. and Al-Qudrah, A.A. (1998). Artificial Neural Network Approach for Pavement Maintenance. *Journal of Computing in Civil Engineering*, 12(4), pp. 249-255.
47. Abdelrahim, A. and George, K. (2000). Artificial Neural Network for Enhancing Selection of Pavement Maintenance Strategy. *Transportation Research Record*, 1699(1), pp.16-22.
48. Sundin, S. and Braban-Ledoux, C. (2001). Artificial Intelligence-Based Decision Support Technologies in Pavement Management. *Computer-Aided Civil and Infrastructure Engineering*, 16(2), pp. 143-157.
49. Karwa, V. and Donnell, E. T. (2011). Predicting Pavement Marking Retroreflectivity Using Artificial Neural Networks: Exploratory Analysis. *Journal of Transportation Engineering*, 137(2), pp. 91–103.
50. Josen, R. S. (2012). Network-level pavement performance and management study in Connecticut. M.S. Theses. University of Connecticut, Storrs, Connecticut, USA.
51. Schwartz, C.W. (1997). Infrastructure condition forecasting using neural networks. *NDT & E International: Independent Nondestructive Testing and Evaluation*, 30(5), pp. 334–334.
52. Attoh-Okine, N.O. (2002). Combining use of rough set and artificial neural networks in doweled-pavement-performance modeling: A hybrid approach. *Journal of transportation engineering*, 128(3), p.270–275.
53. Huang, Y. and Moore, R.K. (1997). Roughness level probability prediction using artificial neural networks. *Transportation Research Record*, No. 1592, pp. 89–97.
54. La Torre, F., Domenichini, L., and Darter, M.I. (1998). Roughness Prediction Based on the Artificial Neural Network Approach. In *Proceedings of the Fourth International Conference on Managing Pavements*. pp. 599-612.
55. Sundin, S. (1998). Predicting rut depth in pavements using artificial neural networks. In *Proceedings of Nimes '98 Conference on Complex Systems, Intelligent Systems, & Interfaces*. La Lettre de l'IA Nimes 98. France, pp. 263-266.
56. Yang, J., Lu, J.J., Gunaratne, M., and Xiang, Q. (2003). Overall pavement condition forecasting using neural networks—an application to Florida Highway Network. In *82nd Annual Meeting of the Transportation Research Board,* Washington, DC, USA.
57. Najjar, Y. and Felker, V. (2003). Modeling the time-dependent roughness performance of Kansas PCC pavements. In *Intelligent Engineering Systems through Artificial Neural Networks*. Artificial Neural Networks in Engineering (ANNIE). pp. 883–888.
58. Saghafi, B., Hassani, A., Noori, R., and Bustos, M. G. (2009). Artificial neural networks and regression analysis for predicting faulting in jointed concrete pavements considering base condition. *International Journal of Pavement Research and Technology*, 2(1), pp. 20-25.
59. Thube, D. T. (2012). Artificial Neural Network (ANN) Based Pavement Deterioration Models for Low Volume Roads in India. *International Journal of Pavement Research and Technology*, 5(2), pp. 115-120.
60. Attoh-Okine, N. O. (1993). Using Neural Network to Identify Pavement Structure Based on Radar Output. In *Proceedings of Pacific Rim TransTech Conference*. Pacific Rim TransTech Conference. Seattle, WA: American Society of Civil Engineers (ASCE), pp. 450-456.
61. Heiler, M., McNeil, S., and Garrett, J.H. (1995). Ground-penetrating radar for highway and bridge deck condition assessment and inventory. In *Conference Proceedings of SPIE (Society of Photo-optical Instrumentation Engineers)*, p. 195.
62. Williams, T.P. and Gucunski, N. (1995). Neural networks for backcalculation of moduli from SASW test. *Journal of Computing in Civil Engineering*, 9(1), pp. 1–8.
63. Gucunski, N. and Krstic, V. (1996). Backcalculation of pavement profiles from spectral-analysis-of-surface-waves test by neural networks using individual receiver spacing approach. *Transportation Research Record*, No. 1526, pp. 6–13.
64. Meier, R.W. and Rix, G.J. (1995). Backcalculation of flexible pavement moduli from dynamic deflection basins using artificial neural networks. *Transportation Research Record*, No. 1473, pp. 72–72.
65. Meier, R.W., Alexander, D.R., and Freeman, R.B. (1997). Using artificial neural networks as a forward approach to backcalculation. *Transportation Research Record*, No. 1570(-1), pp. 126–133.
66. Khazanovich, L. and Roesler, J. (1997). DIPLOBACK: Neural-network-based backcalculation program for composite pavements. *Transportation Research Record*, No. 1570, pp. 143–150.
67. Khazanovich, L. and Ioannides, A.M. (1995). DIPLOMAT: analysis program for bituminous and concrete pavements. *Transportation Research Record*, No. 1482, p.52–60.
68. Kim, Y. and Kim, Y.R. (1998). Prediction of layer moduli from falling weight deflectometer and surface wave measurements using artificial neural network. *Transportation Research Record*, No. 1639, pp. 53–61.
69. Gopalakrishnan, K. (2010). Neural Networks-Swarm Intelligence Hybrid Nonlinear Optimization Algorithm for Pavement Moduli Backcalculation. *Journal of Transportation Engineering*, 136(6), pp. 528-536.
70. Ceylan, H., Tutumluer, Erol, and Barenberg, E.J. (2000). Effects of Simultaneous Temperature and Gear Loading on the Response of Concrete Airfield Pavements Serving the Boeing B-777 Aircraft. In *The 2020 Vision of Air Transportation: Emerging Issues and Innovative Solutions*. 26th International Air Transportation Conference. San Francisco, California, USA, pp. 25-44.
71. Ceylan, H., Tutumluer, E. and Barenberg, E. (1999). Artificial Neural Networks for Analyzing Concrete Airfield Pavements

Serving the Boeing B-777 Aircraft. *Transportation Research Record*, No. 1684, pp. 110-117.

72. Ceylan, H., Gopalakrishnan, K., and Kim, S. (2014). I-BACK: Iowa's Intelligent Pavement Backcalculation Software. Geo-Congress 2014 Technical Papers, *Geo-Technical Special Publication (GSP)*, No. 234, pp. 2952-2959.
73. Ceylan, H., Guclu, A., Tutumluer, E., Thompson, M.R., and Gomez-Ramirez, F. (2004). Neural network-based structural models for rapid analysis of flexible pavements with unbound aggregate layers. In *Pavements unbound*. Sixth Interantional Symposium on Pavements Unbound (UNBAR 6). Nottingham, England: Taylor & Francis, pp. 139-147.
74. Gopalakrishnan, K. and Thompson, M. R. (2004). Backcalculation of airport flexible pavement non-linear moduli using artificial neural networks. In *Proceedings of the Seventeenth International Florida Artificial Intelligence Research Society (FLAIRS) Conference*. Miami Beach, FL, USA. The AAAI Press.
75. Sharma, S. and Das, A. (2008). Backcalculation of pavement layer moduli from falling weight deflectometer data using an artificial neural network. *Canadian Journal of Civil Engineering*, 35(1), pp. 57–66.
76. Saltan, M., Uz, V.E., and Aktas, B. (2013). Artificial neural networks–based backcalculation of the structural properties of a typical flexible pavement. *Neural Computing and Applications*, 23(6), pp. 1703-1710.
77. Hassani, A., Bahreininejad, A., and Moaveni, M. (2008). Kenlayer based pavement backcalculation moduli using artificial neural networks. *International Journal of Pavement Research and Technology*, 1(4), pp. 155-160.
78. Ceylan, H., Guclu, A., Bayrak, M. B., and Gopalakrishnan, K. (2007). *Nondestructive Evaluation of Iowa Pavements: Phase I*, Ames, IA: Institute for Transportation, Iowa State University, Ames, Iowa, USA.
79. Ceylan, H., Gopalakrishnan, K., and Guclu, A. (2007). Advanced Approaches to Characterizing Nonlinear Pavement System Responses. *Transportation Research Record*, No. 2005, pp. 86-94.
80. Miradi, M., Molenaar, A.A.A., and Ven, M.F.C. van de (2009). Knowledge Discovery and Data Mining Using Artificial Intelligence to Unravel Porous Asphalt Concrete in the Netherlands. In K. Gopalakrishnan, H. Ceylan, & N.O. Attoh-Okine, eds. *Intelligent and Soft Computing in Infrastructure Systems Engineering: Recent Advances*. Studies in Computional Intelligence (SCI). Springer, pp. 107-176, Heidelberg, Berlin, Germany.
81. Nune, R., Jain, A.K., Reddy, M.A., and Reddy, K.S. (2006). Artificial neural networks—genetic algorithm based model for backcalculation of pavement layer moduli. *International Journal of Pavement Engineering*, 7(3), pp. 221–230.
82. Pekcan, O., Tutumluer, E., and Ghaboussi, J. (2010). Soft Computing Methodology to Determine Pavement Thickness from Falling Weight Deflectometer Testing. In D. Fratta, A. J. Puppala, & B. Muhunthan, eds. *Proceedings of the GeoFlorida 2010 Conference*. GeoFlorida 2010: Advances in Analysis, Modeling, and Design. West Palm Beach, Florida: ASCE, p. 266.
83. Goktepe, A.B., Agar, E., and Hilmi Lav, A. (2006). Advances in backcalculating the mechanical properties of flexible pavements. *Advances in Engineering Software*, 37(7), pp. 421–431.
84. Gopalakrishnan, K., Ceylan, H., and Guclu, A. (2009). Airfield pavement deterioration assessment using stress-dependent neural network models. *Structure and Infrastructure Engineering: Maintenance, Management, Life-Cycle Design and Performance*, 5(6), p. 487.
85. Gopalakrishnan, K. and Manik, A. (2010). Co-Variance Matrix Adaptation Evolution Strategy for Pavement Backcalculation. *Construction and Building Materials*, 24, pp. 2177-2187.
86. Kargah-Ostadi, N. and Stoffels, S.M. (2014). Backcalculation of Flexible Pavement Structural Properties Using a Restart Covariance Matrix Adaptation Evolution Strategy. *Journal of Computing in Civil Engineering*, DOI: 10.1061/(ASCE)CP.1943-5487.0000309.
87. Gopalakrishnan, K. and Kim, S. (2010). Global Optimization of Pavement Structural Parameters during Backcalculation Using Hybrid Shuffled Complex Evolution Algorithm. *Journal of Computing in Civil Engineering*, 24(5), pp. 441-451.
88. Ceylan, H. and Gopalakrishnan, K. (2014). Finite Element based Hybrid Evolutionary Optimization Approach to Solving Rigid Pavement Inversion Problem. *Engineering with Computers*, 30, pp. 1-13.
89. Tarawneh, B. and Nazzal, M. D. (2014). Optimization of resilient modulus prediction from FWD results using artificial neural network. *Periodica Polytechnica*, 58(2), pp. 143-154.
90. Gopalakrishnan, K., Kim, S., Ceylan, H., and Kaya, O. (2014). Development of Asphalt Dynamic Modulus Master Curve Using Falling Weight Deflectometer Measurements. Final Report. In Trans Project 13-471. Institute for Transportation, Iowa State University, Ames, IA, USA.
91. Ceylan, H., Gopalakrishnan, K., and Kim, S. (2014). I-BACK: Iowa's Intelligent Pavement Backcalculation Software. Geo-Congress 2014 Technical Papers, *Geo-Technical Special Publication (GSP)*, No. 234, pp. 2952-2959.
92. Kaseko, M.S. and Ritchie, S.G. (1993). A neural network-based methodology for pavement crack detection and classification. *Transportation Research Part C: Emerging Technologies*, 1(4), pp. 275–291.
93. Kaseko, M.S., Lo, Z.-P., and Ritchie, S.G. (1994). Comparison of Traditional and Neural Classifiers for Pavement-Crack Detection. *Journal of Transportation Engineering*, 120(4), pp. 552-569.
94. Nallamothu, S. and Wang, K.C.P. (1996). Experimenting with recognition accelerator for pavement distress identification. *Transportation Research Record*, No. 1536, pp. 130–135.
95. Cheng, H.D., Wang, J., Hu, Y. G., Glazier, C., Shi, X. J., and Chen, X.W. (2001). Novel approach to pavement cracking detection based on neural network. *Transportation Research Record*, No. 1764, pp. 119–127.
96. Lee, B.J. and Lee, H. (2004). Position-Invariant Neural Network for Digital Pavement Crack Analysis. *Computer-Aided Civil and Infrastructure Engineering*, 19(2), pp. 105–118.
97. Salari, E., Chou, Y. J., Lynch, J., and Dutta, U. (2010).

Advanced Road Scene Image Segmentation and Pavement Evaluation Using Neural Networks. Final Report. Report No. MIOH UTC TS 18p3 2010-Final. Michigan Ohio University Transportation Center, Detroit, MI, USA.

98. Nejad, F. M. and Zakeri, H. (2011). An expert system based on wavelet transform and radon neural network for pavement distress classification. *Expert Systems with Applications*, 38(6), pp. 7088-7101.
99. Owusu-Ababio, S. (1995). Modeling skid resistance for flexible pavements: a comparison between regression and neural network models. *Transportation Research Record*, No. 1501, pp. 60–71.
100. Wang, K.C.P. (2005). Feasibility of Applying Embedded Neural Net Chip to Improve Pavement Surface Image Processing. In *Computing in Civil Engineering*. ASCE, pp. 589-595.
101. Faghri, A. and Hua, J. (1995). Roadway seasonal classification using neural networks. *Journal of Computing in Civil Engineering*, 9(3), pp. 209–215.
102. Ioannides, A.M., Alexander, D.R., Hammons, M.I., and Davis, C.M. (1996). Application of artificial neural networks to concrete pavement joint evaluation. *Transportation Research Record*, No. 1540, pp. 56–64.
103. Banan, M.R. and Hjelmstad, K.D. (1996). Neural Networks and AASHO Road Test. *Journal of Transportation Engineering*, 122(5), pp. 358-366.
104. Mei, X., Gunaratne, M., Lu, J.J., and Dietrich, B. (2004). Neural network for rapid depth evaluation of shallow cracks in asphalt pavements. *Computer-aided Civil and Infrastructure Engineering*, 19(3), pp. 223–230.
105. Ceylan, H., Gopalakrishnan, K., and Lytton, R. L. (2011). Neural Networks Modeling of Stress Growth in Asphalt Overlays due to Load and Thermal Effects during Reflection Cracking. *Journal of Materials in Civil Engineering*, 23(3), pp. 221-229.
106. Wu, Z., Hu, S. and Zhou, F. (2014). Prediction of stress intensity factors in pavement cracking with neural networks based on semi-analytical FEA. *Expert Systems with Applications*. 41(4), pp. 1021-1030.