

Mechanistic-Based Characterization of Non-Linear Pavement Mechanical Properties with Evolving Intelligent Information Processing Systems

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Abstract

The backcalculation methodology is an inverse process to determine in-situ materials stiffness of pavement layer from Non-Destructive Test (NDT) surface deflections using iterative optimization or more recently, computational intelligence techniques. Intelligent Information Systems (IIS) have been developed with the idea of dealing with information in a way a human expert would by incorporating abilities to learn fast from a large amount of data, dynamically create new modules, connections and neurons, accommodate imprecise or uncertain knowledge, etc. Evolving Connectionist Systems (ECOS) are IIS created with such requirements in mind. This paper explores the feasibility of applying an ECOS methodology, namely Dynamic Evolving Neuro-Fuzzy Inference System (DENFIS), to backcalculation of non-linear pavement mechanical properties and real-time non-destructive condition evaluation of flexible pavements.

Introduction

Pavement road infrastructure systems deteriorate during service times due to distresses (cracking, faulting, punch-outs, etc.) caused by a combination of traffic loads, materials related distresses and weather conditions. The utilization of deflection measurements from non-destructive assessment techniques like Falling Weight Deflectometer (FWD) tests is a standardized method to assess structural conditions of in-situ pavements. Using the FWD deflection measurements, the in-situ material stiffness of each layer in the pavement structure is computed through a

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procedure known as backcalculation or inverse analysis. Over the years, several traditional as well as non-traditional backcalculation approaches have been developed. Non-traditional approaches involve intelligent and soft computing techniques and are attractive alternatives owing to their ability to better handle imprecision and uncertainty and still provide superior prediction accuracies. A representative cross-section of state-of-the-art non-traditional methodologies and studies in pavement backcalculation can be found in TRB (1999) and more recently in Gopalakrishnan et al. (2010).

This paper focuses on exploring the applications of Evolving Connectionist Systems (ECOS) to the study of conventional flexible pavement condition evaluation and backcalculation of non-linear mechanical properties. Two popular ECOS methods developed by Kasabov (1998) include DENFIS (Dynamic Evolving Neuro-Fuzzy Inference System) and EFuNN (Evolving Fuzzy Neural Networks). ECOS can be considered as open architecture Artificial Neural Networks (ANN) in which the neurons are added to their structures and the connection weights are modified as the system evolves based on a continuous input data stream in an adaptive, life-long, modular way (Watts 2004; Kasabov and Song 2002).

It is advantageous to employ ECOS networks for analyzing complex engineered systems such as pavement systems in real-time since ECOS networks are resistant to catastrophic forgetting, have the ability to adapt to and learn new data as soon as they become available, do not have a limit to the amount of knowledge they can store and learn the examples very quickly compared to traditional Multi-Layered Perceptron BackPropagation Neural Networks (MLP-BP NN).

Intelligent Information Processing Systems

ECOS networks are intelligent information processing systems created with specific requirements such as the ability to learn large data from fast one-pass training, be memory-based, manifest introspection, etc. The overall ECOS learning algorithm is based on accommodating new training examples within the evolving layer, either through modification of evolving neuron connection weights, or by adding new neuron to that layer (sees Figure 1).

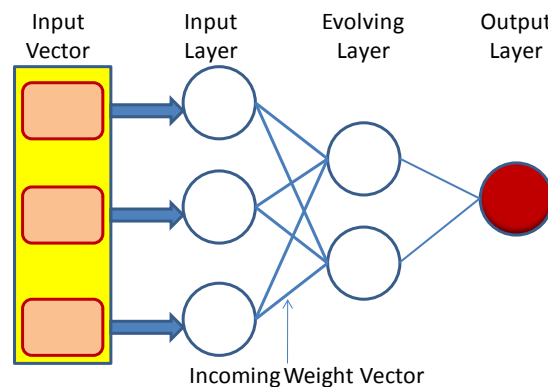


Figure 1. Overall schematic of ECOS learning algorithm.

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DENFIS is a Takagi-Sugeno type of Fuzzy Inference System (FIS) with a Backpropagation (BP) algorithm (Kasabov and Song 2002) developed for both on-line and off-line learning. The DENFIS model forms a FIS dynamically for calculating the output depending on the input vector position in the input space. The dynamically formed FIS is based on fuzzy rules created during the past learning process. The DENFIS model for offline learning in batch mode was used in this paper in attempting to develop an effective tool for rubblized pavement layer moduli backcalculation.

Two DENFIS models for offline learning were developed by (Kasabov and Song 2002): (1) a linear model, model I, and (2) a Multi-Layer Perceptron (MLP) based model, model II. A first-order Takagi-Sugeno type fuzzy inference engine is employed in model I while model II employs an extended high-order Takagi-Sugeno fuzzy inference engine. In model II, several small-size, two-layer (the hidden layer consists of two or three neurons) MLPs are used to realize the function in the consequent part of each fuzzy rule instead of using a predefined function.

The seminal ECOS network proposed by Kasabov (Kasabov 1998; Watts 2009), EFuNN, contains fuzzy logic elements that transform the input variables into 'fuzzy' representations, which then maps these fuzzy input values to the target fuzzy output values. The EFuNN training algorithm works in such a way that rule neurons exist only if they are needed. Starting with a very small number of neurons initially, additional neurons are added to the network as more training examples are presented to it based on user-defined sensitivity threshold and error threshold values. Although EFuNN has been applied widely, it has certain disadvantages related to its fuzzification and defuzzification operations (Watts, 2009). In this paper, only the DENFIS methodology was considered.

ECOS Flexible Pavement Backcalculation Approach

Database Generation

The proposed backcalculation approach is to develop ECOS models to predict the in-situ non-linear stiffness properties (moduli) of conventional flexible pavement layers using FWD deflection measurements. First, a comprehensive synthetic database covering wide ranges of pavement layer thicknesses and moduli values were generated using an Finite Element (FE) pavement response model (Raad and Figueroa, 1980) which was then used for off-line learning in batch mode using the ECOS models.

The Elastic Layered Programs (ELPs) used in the analysis and design of flexible pavements consider the pavement as an elastic multi-layered media, and assume that pavement materials are linear-elastic, homogeneous and isotropic. However, the unbound granular materials and fine-grained subgrade soils, referred to as pavement geomaterials, do not follow a linear-stress-strain behaviour under repeated traffic loading. The non-linearity or stress-dependency of resilient modulus for unbound granular materials and cohesive fine-grained subgrade soils has been well established (Garg et al., 1998).

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A generic three-layer flexible pavement structure consisting of Hot-Mix Asphalt (HMA) surface layer, unbound aggregate base layer, and subgrade layer was modeled using the FE response model. The top surface HMA layer was characterized as a linear elastic material with Young's Modulus, E_{HMA} , and Poisson ratio, ν . The K- θ model (Hicks and Monismith, 1971) was used as the non-linear characterization model for the unbound aggregate layer ($E_R = K\theta^n$; where E_R is the resilient modulus, θ is bulk stress, and K and n are regression parameters and are related through a regression equation).

Fine-grained soils were considered as "no-friction" but cohesion only materials and modeled using the commonly used bi-linear model (Thompson and Elliot 1985) for resilient modulus characterization. As indicated by Thompson and Elliot (1985), the value of the resilient modulus at the breakpoint in the bilinear curve, E_{Ri} , can be used to classify fine-grained soils as being soft, medium or stiff. The E_{Ri} is the main input for subgrade soils in the FE model. The bilinear model parameters were set to default values. The 40-kN (9-kip) wheel load was applied as a uniform pressure of 552 kPa (80 psi) over a circular area of radius 152 mm (6 in) simulating the FWD loading. The HMA layer thicknesses (T_{HMA}) and base layer thicknesses (T_b) were varied between 75 to 380 mm (3 to 15 in.) and 100 to 560 mm (4 to 22 in.), respectively. The E_{HMA} values were varied in the range of 0.7 to 41.5 GPa, K in the range of 21 to 82 MPa, and E_{Ri} in the range of 7 to 105 MPa.

After generating the synthetic database, the next step is to determine the optimal architecture for ECOS models to maximize prediction accuracy. From a comprehensive database comprising over 25,000 records, 7,500 random data vectors were extracted as training data sets for ECOS and another 1,000 independent data sets were extracted as testing data sets for ECOS.

ECOS Implementation

The eight inputs to the ECOS models are: (1) HMA layer thickness (T_{HMA}); (2) base layer thickness (T_b); (3) D0 - FWD deflection measured at a radial offset of 0-mm (0-in.) from the center of the loading plate; (4) D300 - FWD deflection measured at a radial offset of 300-mm (12-in.); (5) D600 - FWD deflection measured at a radial offset of 600-mm (24-in.); (6) D900 - FWD deflection measured at a radial offset of 900-mm (36-in.); (7) D1200 - FWD deflection measured at a radial offset of 1200-mm (48-in.); and (8) D1500 - FWD deflection measured at a radial offset of 1500-mm (60-in.). The desired outputs include HMA layer moduli (E_{HMA}), non-linear unbound granular base layer moduli parameter (K), and non-linear subgrade moduli (E_{Ri}). Separate models were developed for each of the desired outputs as the ECOS models are designed for only one output at a time. The overall framework in which ECOS is implemented for flexible pavement condition evaluation is illustrated in Fig. 2.

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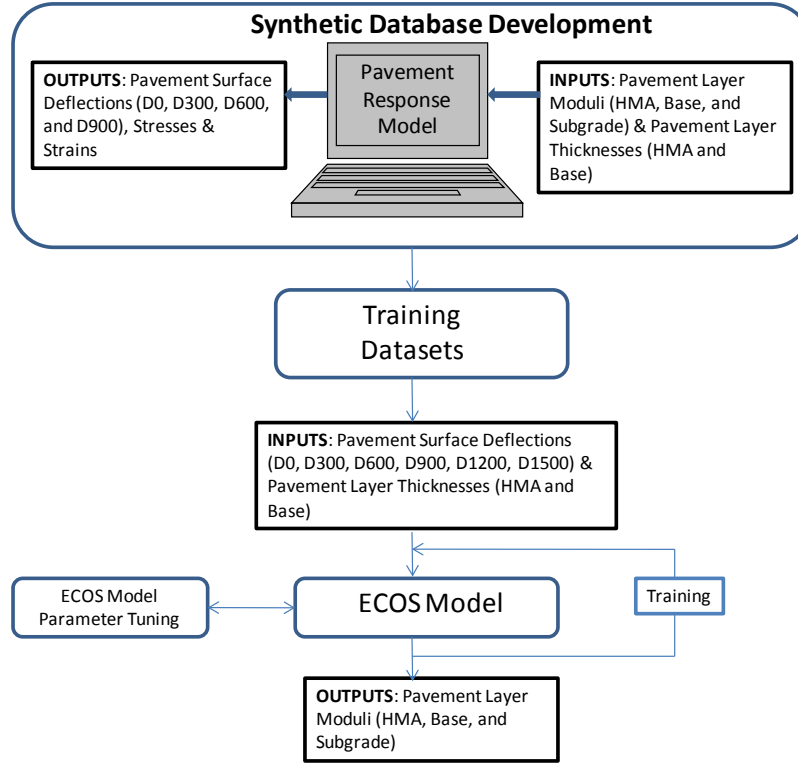


Figure 2. ECOS implementation for pavement moduli backcalculation.

The *NeuCom*® v0.919 software developed at the Knowledge Engineering and Discovery Research Institute (KEDRI), Auckland University of Technology, New Zealand was used for developing, training, and testing the ECOS models for flexible pavement backcalculation. *NeuCom*® is self-programmable, learning and reasoning computer environment based on connectionist modules. The software has user-ready options to develop DENFIS and EfuNN ECOS models. All data points were normalized between 0.1 and 0.9 for increased ease of model development and prediction.

ECOS Networks Optimization

First, several runs were conducted to optimize the parameter settings for DENFIS-based backcalculation models. The parameters to be optimized in the DENFIS model include: (1) *Dthr* - Distance Threshold which determines the maximum radius of the rule nodes in this network; (2) *M-of-N* - this determines the number of nodes which are referenced to estimate the output of the current sample; and (3) *Epochs* - the number of epochs used to train or retrain the network originally. To estimate the accuracy of predictions, the DENFIS model outputs three result parameters: (1) *NumRn* - number of Rule Nodes (RNs) in the network; (2) *NDEI* - Non-Dimensional Error Index; and (3) *RMSE* - Root Mean Squared Error. In addition, the system also outputs the CPU time (seconds) taken for training the network.

Table 2 summarizes the DENFIS model parametric sensitivity analysis results for E_{HMA} prediction. The default DENFIS parametric settings are: $Dthr = 0.1$; $M-of-N$

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= 3; and Epochs = 2. It is seen that the default DENFIS settings already yielded a high prediction accuracy ($R^2 = 0.95$; RMSE = 0.0570) for the backcalculation problem although the highest E_{HMA} prediction accuracy is achieved with a distance threshold (Dthr) of 0.03. No significant increase in prediction accuracy was achieved by increasing the number of epochs which confirms the ability of ECOS to learn large datasets through one-pass fast training. In developing the best-performance DENFIS-based backcalculation models, the DENFIS parameter settings highlighted in the table were utilized.

Table 1 ECOS network parametric optimization runs for predicting E_{HMA}

Dthr	M-of-N	Epochs	Training Time (s)	Fuzzy Rules	Training NDEI	Training RMSE	Testing NDEI	Testing RMSE	Testing R^2
0.1	3	2	87	77	0.223	0.052	0.242	0.057	0.950
0.1	3	4	148	77	0.217	0.050	0.231	0.054	0.954
0.1	3	6	605	77	0.280	0.065	0.290	0.068	0.928
0.05	3	2	245	436	0.132	0.031	0.168	0.039	0.974
0.04	3	2	408	738	0.109	0.025	0.159	0.037	0.978
0.03	3	2	808	1337	0.093	0.022	0.132	0.031	0.983
0.03	3	4	1107	1337	0.091	0.021	0.131	0.031	0.983

Discussion of Results

A scatterplot for each pair of variables used in developing ECOS models is displayed in a matrix arrangement and compiled in Figure 3. A 95% bivariate normal density ellipse is imposed on each scatterplot. If the variables are bivariate normally distributed, this ellipse encloses approximately 95% of the points. The correlation of the variables is seen by the collapsing of the ellipse along the diagonal axis. If the ellipse is fairly round and is not diagonally oriented, the variables are uncorrelated. The correlation strength (r) of the linear relationships between each pair of variables is calculated using the Restricted (or Residual) Maximum Likelihood (REML) method. In contrast to conventional maximum likelihood estimation, REML can produce unbiased estimates of variance and covariance parameters. As seen from the scatterplot, the HMA pavement layer moduli are strongly correlated to surface deflections nearer to loading center whereas the subgrade pavement layer moduli are strongly correlated to farther deflections, as expected. The base layer moduli parameter, K , is poorly correlated to the deflections and therefore it is expected that it will be the hardest to predict as confirmed by previous studies.

As mentioned previously, the optimal DENFIS parameter settings were identified from runs summarized in Table 1 as that with the highest prediction accuracy and lowest computational expense (highlighted in black). Using these optimal model parameter settings, separate DENFIS based predictions models were developed for predicting K and E_{Ri} . As mentioned previously, K was the hardest to predict since K is not correlated to any of the deflections directly. As a result, poor prediction accuracy was achieved ($R^2 = 0.326$) with only the thicknesses and deflections as the inputs. Alternatively, as suggested by previous studies, when the

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first four deflections (D0, D300, D600, and D900) together with the predicted E_{HMA} and E_{Ri} and pavement layer thicknesses (T_{HMA} and T_b) were used as inputs for predicting K , significantly higher prediction accuracy ($R^2 = 0.819$) was achieved although at the cost of increased number of fuzzy rules. These results are summarized in Table 2.

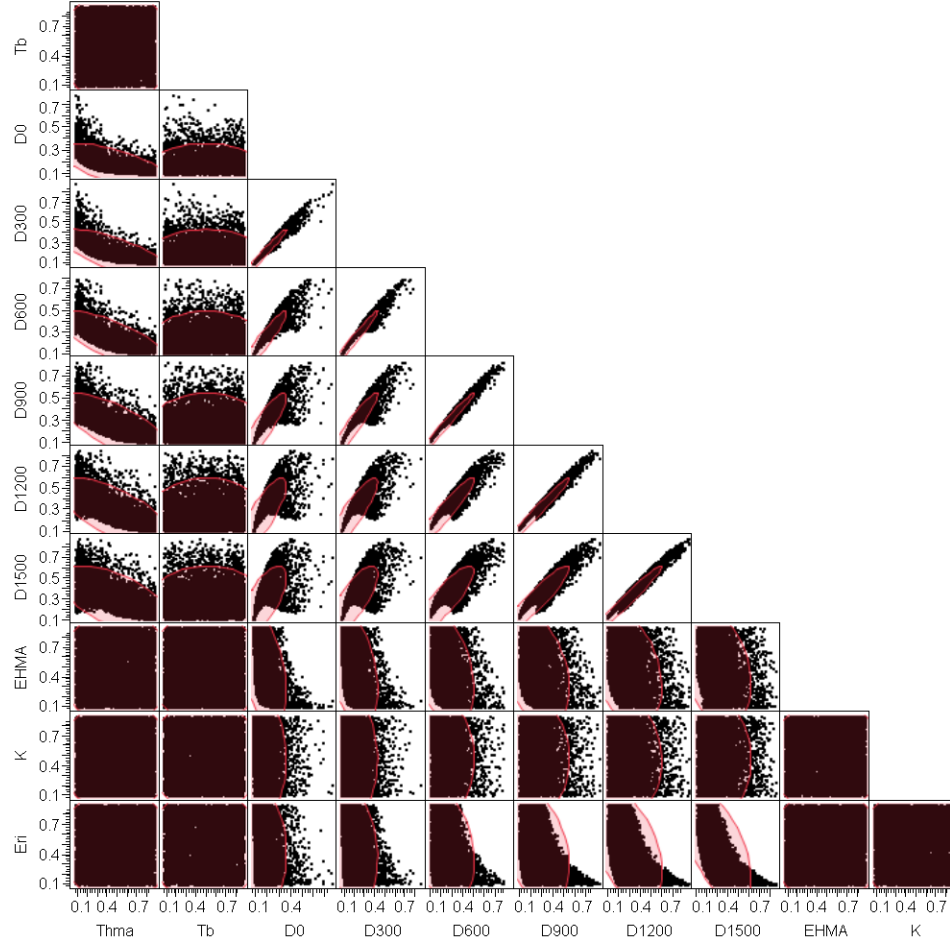


Figure 3. Scatterplot matrix of inputs and outputs.

Table 2 ECOS models for predicting E_{Ri} and K

Output	Training Time (s)	Fuzzy Rules	Training NDEI	Training RMSE	Testing NDEI	Testing RMSE	Testing R^2
E_{Ri}	773	1337	0.093	0.021	0.129	0.031	0.984
K	800	1337	0.625	0.145	0.9691	0.229	0.326
K	5006	4276	0.296	0.068	0.434	0.102	0.819

Figure 4 displays DENFIS predicted iso- E_{HMA} and iso- E_{Ri} contour lines as functions of deflections and HMA layer thickness. Note that the normalized values of the variables are used in these plots. Such 2-D contour plots are helpful in graphing three dimensional data in two dimensions and extracting useful information and

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visualizing equipotential curves. The regions between the shaded contours are colored to different intensities to indicate their relative magnitude. The major contours are also labeled with the corresponding values.

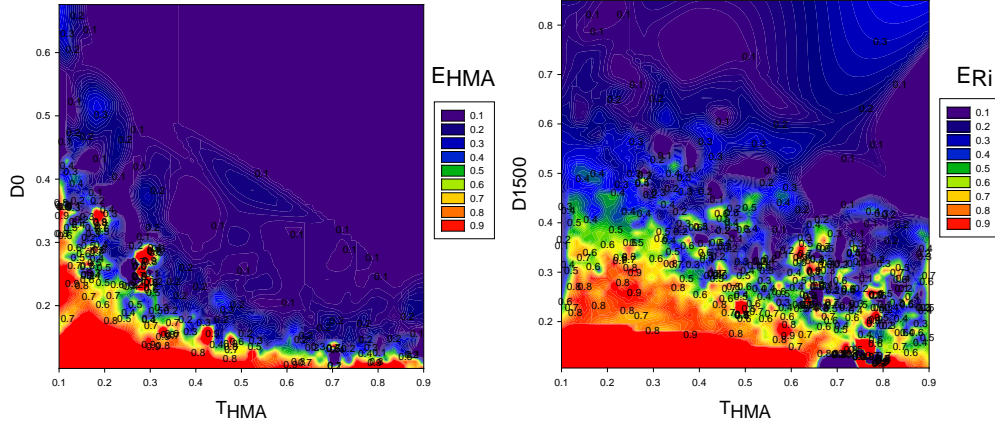
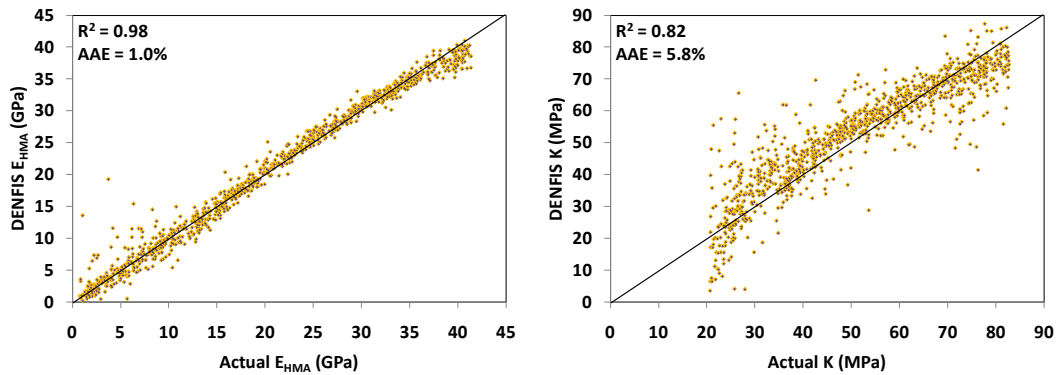


Figure 4. DENFIS predicted pavement layer moduli as function of HMA layer thickness and deflections.

Figure 5 depicts the prediction ability of the DENFIS based pavement layer moduli backcalculation modes. Average absolute errors (AAEs) were calculated as sum of the individual absolute errors divided by the 1,000 independent testing patterns. The AAE for the HMA layer moduli was a low 1.0% while the AAE for the non-linear base layer moduli parameter, K, and non-linear subgrade breakpoint moduli, E_{Ri} , were 2.2% and 5.8%, respectively. Note that the HMA moduli is strongly related to the maximum FWD surface deflection, D_0 , while the subgrade moduli is largely a function of FWD surface deflection at offsets greater than 900 mm (36 in.). Note that the magnitude of FWD surface deflections decreases with increasing radial offsets and so does the relative accuracy of measurements. As a result, the prediction accuracy for HMA moduli is generally higher compared to subgrade moduli.



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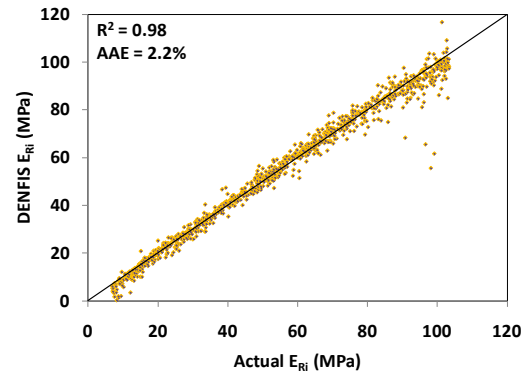


Figure 5. Prediction performance of DENFIS based backcalculation models.

Conclusions

This study investigated the feasibility of applying an ECOS methodology, namely Dynamic Evolving Neuro-Fuzzy Inference System (DENFIS), to backcalculation of non-linear pavement mechanical properties and real-time non-destructive condition evaluation of conventional flexible pavements. ECOS can be considered as open architecture Artificial Neural Networks (ANN) in which the neurons are added to their structures and the connection weights are modified as the system evolves based on a continuous input data stream in an adaptive, life-long, modular way. First, a comprehensive Finite Element (FE) based synthetic database was generated to train and test the ECOS models. DENFIS model parametric analysis was conducted to identify the optimal parameter settings for solving the backcalculation problem. DENFIS based backcalculation models were successfully developed for HMA layer moduli, non-linear, stress-dependent base layer moduli and subgrade moduli. It is advantageous to employ ECOS networks for analyzing complex engineered systems such as pavement systems in real-time since ECOS networks are resistant to catastrophic forgetting, have the ability to adapt to and learn new data as soon as they become available, do not have a limit to the amount of knowledge they can store and learn the examples very quickly compared to traditional Multi-Layered Perceptron BackPropagation Neural Networks (MLP-BP NN) with minimal model parameters to be fine-tuned.

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