# Advanced characterization of granular material behavior using artificial neural networks

## Caractérisation avancée du comportement de matériel granulaire sous l'emploi des réseaux artificiels neurologiques

E.Tutumluer – *Assistant Professor*

H.Ceylan & U.Seyhan – *Graduate Research Assistants, Department of Civil & Environmental Engineering, University of Illinois at Urbana-Champaign*

ABSTRACT: Artificial neural network (ANN) based granular material modulus models have been developed and compared for performance using the previously reported test data of Boyce (1976), Pappin (1979), and Tutumluer & Seyhan (1999). The primary goal has been to properly characterize the loading stress path dependent resilient behavior from advanced repeated load triaxial tests that can simulate in the laboratory the actual moving wheel load conditions. Due to the complex loading regimes followed in the laboratory tests, ANN characterization models that altogether considered as inputs the static and dynamic components of the applied mean and deviator stresses and the loading stress path slope produced the greatest accuracy. Such advanced models can better describe the granular material behavior under the actual field loading conditions.

RÉSUMÉ: Les modèles de module du réseau artificiel neurologique (ANN) basé sur les matériels granulaires ont été développés et comparés pour leur performance avec l'application des données des essais préalablement citées de Boyce (1976), Pappin (1979) et de Tutumluer et Seyhan (1999). Le but principal a été de bien caractériser le comportement résilient qui dépend de la voie d'accès de chargement basé sur des essais d'examens avancés et répétés à trois axes qui peuvent simuler dans le laboratoire les conditions véritables de chargement mobiles de roue. À cause des régimes complexes de chargement suivis dans les essais en laboratoire, les modèles de caractérisation de ANN qui considéraient entièrement comme données les composants statiques et dynamiques des efforts appliqués de moyen et de déviation ainsi que la pente de voie d'accès d'effort de chargement produisaient la plus grande exactitude. De tels modèles avancés peuvent mieux décrire le comportement matériel granulaire sous les conditions véritables de chargement.

## 1 INTRODUCTION

Unbound granular materials commonly used in bases/subbases of pavements serve the primary purpose of load distribution through aggregate interlock that is essential to the integrity of the pavement. The resilient (elastic/recoverable) response of these granular materials to dynamic wheel loading is typically attained in the field after a shakedown state is reached. In triaxial conditions, the resilient modulus has been best obtained from the repeated load test data when both the mean pressure $p = (\sigma_1 + 2\sigma_3)/3$ and the deviator (shear) stress $q = (\sigma_1 - \sigma_3)$ are included in the material characterization. To better characterize the behavior of unbound granular layers, however, it is important to properly simulate in the laboratory the actual field loading conditions including the effects of moving wheel loads. Recent studies on pavement analysis/modeling at the University of Illinois have recognized the effects of approaching and departing loads (rotation of

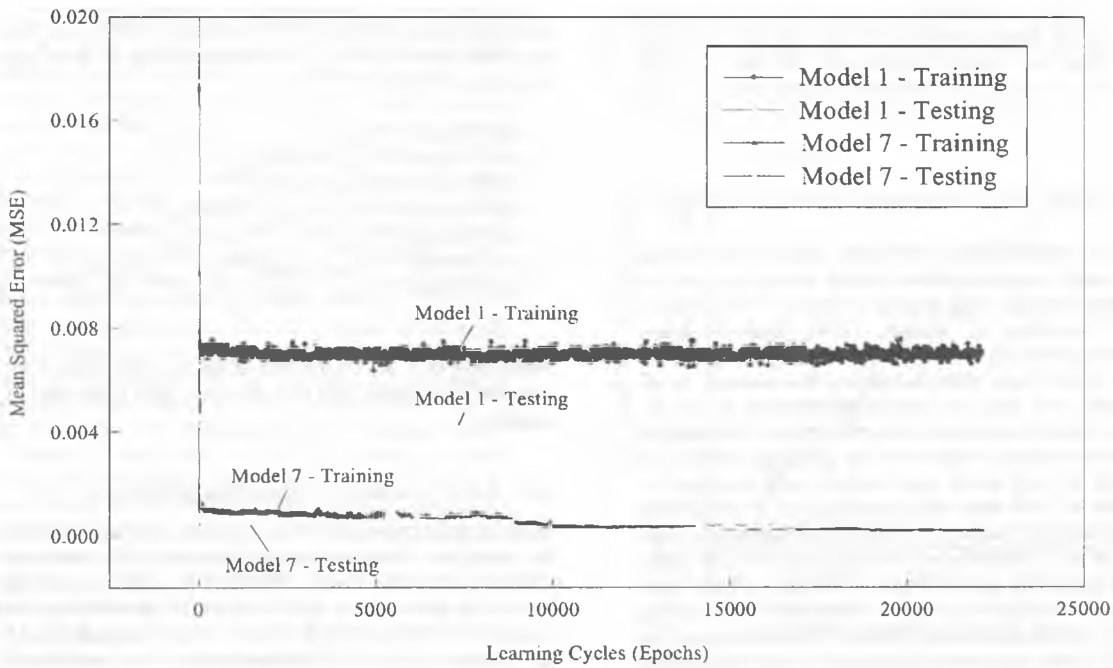


Figure 1. Training Progress Curves for ANN Models 1 and 7 for the Tutumluer & Seyhan Data

principal stresses) along with identifying directional variation (anisotropy) in material properties.

This paper presents the results of a modeling study recently undertaken at the University of Illinois to develop artificial neural network (ANN) based advanced characterization models for granular materials. The primary goal is to properly characterize the loading stress path dependent resilient behavior from advanced repeated load triaxial tests that can simulate in the laboratory the actual moving wheel load conditions. Artificial neural network (ANN) material models have been developed and compared for prediction performances using the previously reported stress path test data of Boyce (1976), Pappin (1979), and Tutumluer & Seyhan (1999). The test data are obtained from comprehensive laboratory-testing programs in which tests were conducted to apply various stress path loadings on the granular material specimens. ANN models are studied to capture the effects of static and dynamic bulk and shear stresses and the loading stress path.

## 2 FIELD AND LABORATORY STRESS STATES

The pavement in the field is usually loaded by moving wheel loads, which at any time impose varying magnitudes of vertical, horizontal, and shear stresses in the aggregate layer accompanied by the rotation of the principal stresses. This type of dynamic loading can not be ideally simulated in the laboratory by the constant (*static*) confining pressure (CCP) type repeated load triaxial tests, which have been commonly used in the United States since late 1960s and recognized as the standard procedure (AASHTO T294-94). In the CCP tests, it is only possible to apply one constant stress path ($\Delta q/\Delta p = 3$) representing those stress states that occur directly under the wheel loading. Yet, due to the moving nature of the wheel load, the major principal stress is often not aligned in the vertical direction, but rotates in the direction of the applied load. Depending upon the location, the total principal stresses on a pavement element rotate by a certain rotation angle as the wheel load passes.

The variable (*dynamic*) confining pressure (VCP) type repeated load triaxial tests, on the other hand, offer the capability to apply a wide combination of stress paths by pulsing both cell pressure and vertical deviator stress. Such stress path loading tests better simulate actual field conditions since in the pavement structure the confining stresses acting on the material are also cyclic in nature. Typically, some radial distance away from the centerline of loading, the horizontal component of the dynamic wheel load can become greater in magnitude than the vertical component. In that case, an extension type of loading can be more critical on top of the base.

## 3 STRESS PATH TESTS ON GRANULAR MATERIALS

Three sets of complete triaxial test data obtained from testing aggregates under various realistic in-situ stress paths due to moving wheel loading were analyzed (Boyce 1976, Pappin, 1979, and Tutumluer & Seyhan, 1999). Resilient (elastic/recoverable) behavior was typically determined during repeated load triaxial tests after shakedown was reached. In all of these tests, both axial and radial deformations of the repeated load triaxial specimens were measured to individually account for the resilient response of the granular materials to combinations of both radial and vertical pulse loadings. A large number of VCP tests were conducted on a well-graded crushed limestone by Boyce (1976) and subsequently by Pappin (1979) at the University of Nottingham in the UK. Samples having maximum particle sizes of 38-mm (1.5-in.) were subjected to wide ranges of static and simulated traffic loading stresses by varying stress path slopes. Tests performed by Pappin (1979) also considered the additional effects of varying moisture conditions for dry, partially saturated, and saturated states.

More recently, Tutumluer & Seyhan (1999) used an advanced triaxial testing machine, referred to as University of Illinois FastCell (UI-FastCell), for determining in the laboratory the resilient properties of a crushed aggregate. Having independent loading capabilities in the vertical and horizontal directions, the UI-FastCell is ideally suited for simulating dynamic field stresses on the sample and for studying the effects of anisotropic, stress path dependent aggregate behavior. A series of combined CCP and VCP type stress path tests were performed on a crushed aggregate using the UI-FastCell. With the major stress direction conveniently switched, both compression and extension type dynamic stress states were adequately applied on the triaxial samples. A total of six stress path tests were conducted on the crushed aggregate samples for the selected constant stress path slopes.

In general, the results of the testing revealed that the resilient strains were affected by the mean normal stresses and the ratios of the deviator stress $q_{dynamic}$ to mean normal stress $p_{dynamic}$, i.e., stress path slopes "m" selected in the testing program. The different conditions for the static (overburden) stress states defined by $p_{static}$ and $q_{static}$ were also considered by including either a hydrostatic stress state or a $K_0$ (= horizontal effective stress divided by the vertical) type condition.

## 4 NEURAL NETWORK MODELING OF RESILIENT BEHAVIOR

The resilient moduli ($M_R$) for the various stress path tests conducted by Boyce (1976) and Pappin (1979) and Tutumluer and Seyhan (1999) were computed from the measured axial and radial strains using axisymmetric stress-strain relations and assuming isotropic material properties. Considering the three-dimensional nature (3-D) of the static and dynamic stresses applied in the VCP tests, the resilient modulus ($M_R$) can be best obtained from the experimental data when both the mean pressure $p = I_1/3 = \theta/3$ ($\theta$ = bulk stress) and the shear stress $q = (3J_2)^{1/2} = (3\tau_{oct}/\sqrt{2})$ ($\tau_{oct}$ = octahedral shear stress) are included in the material characterization models. Such models, proposed previously by Lade and Nelson (1987) and Uzan et al. (1992) represent the stress dependency of the resilient granular material behavior as power functions of the 3-D stress states.

A total of seven different ANN based characterization models, which account for the static, dynamic, and total stress states and the stress path slope m, were studied and compared for performance in predicting the output, experimental $M_R$ from the works of Boyce (1976), Pappin (1979), and Tutumluer and Seyhan (1999). The input variables of these models are given as follows:

ANN Model 1: $\theta_{total}$
ANN Model 2: $\theta_{static}$ and $\theta_{dynamic}$
ANN Model 3: $\theta_{total}$ and $(\tau_{oct})^{total}$
ANN Model 4: $\theta_{static}$, $\theta_{dynamic}$, and $(\tau_{oct})^{total}$
ANN Model 5: $\theta_{total}$, $(\tau_{oct})^{static}$, and $(\tau_{oct})^{dynamic}$
ANN Model 6: $\theta_{static}$, $\theta_{dynamic}$, $(\tau_{oct})^{static}$, and $(\tau_{oct})^{dynamic}$
ANN Model 7: $\theta_{static}$, $\theta_{dynamic}$, $(\tau_{oct})^{static}$, $(\tau_{oct})^{dynamic}$, and "m"

where $\theta$ ($= \sigma_1 + 2\sigma_3$) is the bulk stress, $\tau_{oct}$ ($= \sqrt{2}/3\ q$) is the octahedral shear stress, and m is the stress path slope used in the models.

### 4.1 *Back-Propagation Artificial Neural Networks*

Back-propagation type ANN models were trained in this study by using the delta-bar-delta-bar learning rule proposed by Ochiai, et. al. (1993) using laboratory $M_R$ data. An independent testing data set was used to check the prediction performances of the different ANN models. Back-propagation ANNs are very powerful and versatile networks that can be taught a mapping from one data space to another using examples of the mapping to be learned. The term "back-propagation network" actually refers to a multi-layered, feed-forward neural network trained using an error back-propagation algorithm. The learning process performed by this algorithm is called "back-propagation learning," which is mainly an error minimization technique (Haykin, 1999; Hecht-Nielsen, 1990; Parker, 1985, Rumelhart et al., 1986; & Werbos, 1974).

As with many ANNs, the connection weights in the back-propagation ANNs 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 and the correct answers are then propagated backwards through the network and the connection weights are individually adjusted to reduce the error. After many examples (training patterns) have been propagated through the network many times, the mapping function is learned with some specified error tolerance. This is called supervised learning because the network has to be shown the correct answers for it to learn. Back-propagation networks excel at data modeling with their superior function approximation capabilities (Haykin, 1999; and Meier & Tutumluer, 1998).

### 4.2 *Neural Network Design and Training*

An adaptive method of architecture determination was employed to train the seven different ANN based characterization models (Ghaboussi et al., 1997 and Ghaboussi & Sidarta, 1998). Number of nodes in the input layers varied from 1 to 5 as given previously and $M_R$ was the only node in the output layers for all network architectures trained. Only single hidden layer networks were considered due to the not very complex nature of the function approximation (modulus characterization) performed on the laboratory data.

In the adaptive method of architecture determination, the training starts with a small number of nodes in the hidden layer. The rate of learning is monitored as the training progresses. After a certain amount of learning cycles the network approaches its capacity and new hidden nodes are added at this point to generate new connections. The new cycles of learning after the addition of new nodes are only done with changing the new connection weights while the old connection weights are kept constant. Then, the additional cycles of learning take place by allowing all the connection weights to change. This procedure is repeated each time the network reaches its capacity and the additional hidden nodes are added. The suitable network architecture is therefore automatically determined at the end of the training process. For all the seven ANN models trained in this study number of neurons in the hidden layer was started from 1 and increased up to 30 hidden neurons.

To train the ANN models, first the entire training data sets were randomly shuffled and divided into training and testing data sets. A total of 28 different data sets were used for the test data of (1) Boyce, (2 & 3) Pappin – dry & partially saturated materials –, and (4) Tutumluer & Seyhan; each used to train the 7 ANN models. The number of individual test results varied from 75 and 150 in these data sets. About 80% to 90% of the data were used in each data set to train different network architectures while the remaining patterns were used for testing to verify the prediction ability of each trained ANN model. Since ANNs learn relations and approximate functional mapping limited by the extent of the training data, the best use of the trained ANN models were achieved in interpolation.

An adaptive type back-propagation ANN program developed by Sidarta (2000) was used for the training process, which consisted of iteratively presenting training examples to the network. Each training epoch of the network consisted of one pass over the entire training data sets. The testing data sets were used to monitor the training progress. Figure 1 depicts for Tutumluer & Seyhan (1999) data the training progress curves obtained from ANN models 1 and 7 for a total of 30 different network architectures. After a certain number of learning cycles the mean squared error (MSE) values leveled off for both models and adding more nodes to the hidden layer did not help further reduce the MSE values. MSE is defined as the sum of the squares of the differences (error) between the predicted and actual moduli values for the given data set (training or testing). Figure 1 clearly shows that the more sophisticated the models get (model 7 with 5 input parameters), the lower MSE values are obtained when compared to the simpler ones (model 1 with a single input parameter). The very close MSE values obtained from the training and testing sets for model 7 (see Figure 1) is also a good indication of proper network training, in other word, the trained network actually learned the nonlinear relationship between the inputs and the output $M_R$ for the given data set.

For almost all of the ANN models trained in this study, the MSE values for both training and testing sets leveled off within the first 100 learning cycles with relatively small number of hidden nodes. For the simpler models (models 1, 2, and 3), increasing the number of hidden nodes and continuing the training until a higher number of learning cycles did not help reduce the MSE values. The MSE values decreased more gradually and then leveled off for more sophisticated models (models 5, 6, and 7).

Figure 2 depicts the prediction ability of ANN models 1 and 7 trained using Tutumluer & Seyhan data (1999). As can be clearly seen in Figure 2, $M_R$ predictions from model 7 are much closer to the line of equality than the prediction from model 1. The average absolute error (AAE) for the 15 individual test results used as the testing data set for model 7 is 4.5% while the corresponding AAE value for model 1 is up to 20.0%. The maximum absolute error (MAE) values obtained for models 7 and 1 are 13% and 65%, respectively.

Figure 3 shows the MSE values of the seven different ANN models trained in this study for each of the three different experimental studies. In all of the ANN trainings, very low values of MSEs were consistently obtained for the more sophisticated ANN models, i.e., models 6 and 7. When the bulk stresses, $\theta$, were separated into static and dynamic components only (model 2), the predictions improved for the results of all three studies. A closer look at the MSE values indicates that the octahedral shear stresses, $\tau_{oct}$, when they too were separated into static and dynamic components, typically produced expressions with greater accuracy. The models therefore revealed a trend in producing significantly better predictions (thus very low MSE values) when bulk and shear stresses, $\theta$ and $\tau_{oct}$, were both analyzed separately in static and dynamic components (model 6) rather than as a single total $\theta$ and $\tau_{oct}$. The inclusion of stress path slopes (model 7), in a way representing the direction of loading in the field, increases further the prediction performances and results in the greatest accu-

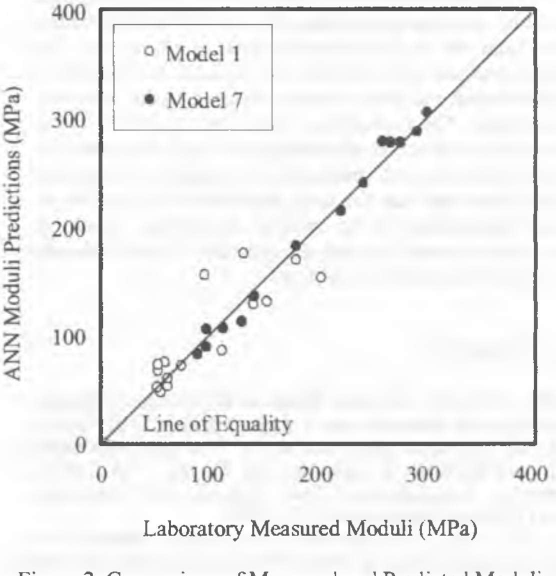


Figure 2. Comparison of Measured and Predicted Moduli for Tutumluer & Seyhan Data

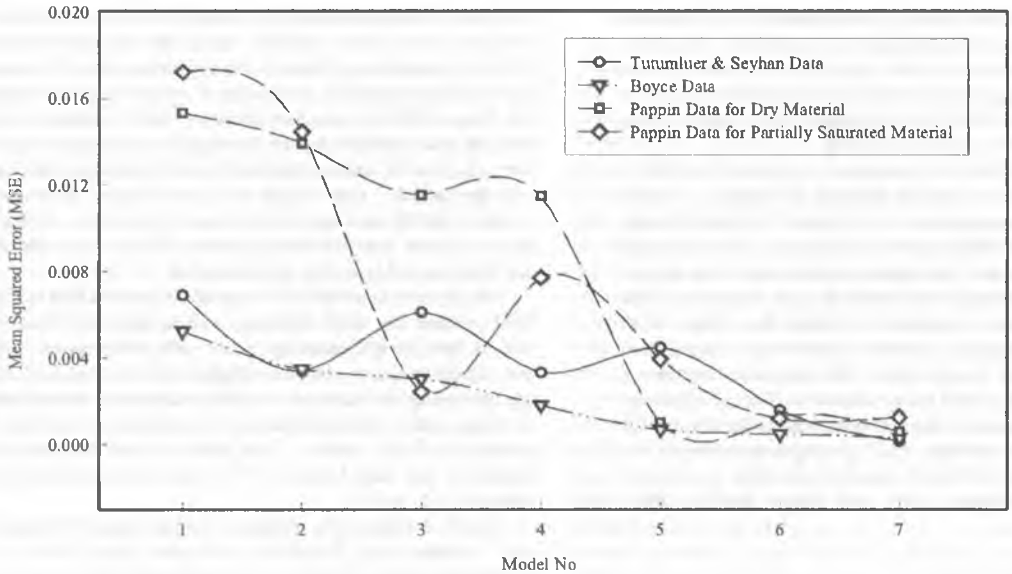


Figure 3. Comparison of the MSE Values for Different Material and Model Types

racy especially for Tutumluer and Seyhan data (1999) since changing the applied principal stress ratio has the most significant effect on the directional dependency of the resilient properties. It is also interesting to note that the MSE values for all four of the data sets matched closely for models 6 and 7. This is probably due to the fact that trained ANN model 6 could capture in its connections the various stress path slopes m, which is a dependent variable and can be expressed as a function of the dynamic components of the bulk and shear stresses.

## 5 SUMMARY/CONCLUSIONS

A modeling study has been undertaken at the University of Illinois to develop artificial neural network (ANN) models for advanced characterization of granular materials used in the base and subbase courses of flexible pavements. The primary goal has been to properly characterize the loading stress path dependent resilient behavior from advanced repeated load triaxial tests that can simulate in the laboratory the actual moving wheel load conditions. The ANN modulus models were developed using the previously reported stress path test data of Boyce (1976), Pappin (1979), and Tutumluer & Seyhan (1999); comprehensive laboratory-testing programs in which tests were conducted to apply various stress path loadings on the granular material specimens. Due to the complex loading regimes followed in the laboratory tests, ANN models that analyzed simultaneously the static and dynamic components of the applied mean and shear stresses produced significantly better predictions. The inclusion of stress path slopes, in a way representing the direction of loading in the field, increased further the prediction performances since changing the applied principal stress ratio has the most significant effect on the directional dependency of the resilient properties. Such advanced models better describe the granular material behavior under actual field loading conditions.

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