A Proposed Model for the Structural Evaluation of Flexible Pavements: In Relation to the Future of Artificial Neural Networks

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Abstract-- As input patterns are presented to ANN networks, output patterns are produced. ANN’s neurons constitute layers: the output layer, one or more hidden layers, and the input layer. Hence, information flows to the output layer from the input layer via the hidden layer, with the latter forming a platform for input-output layer association (Meier & Rix, 1994). One of the findings in the study by Nazzal and Tatari (2013), who used ANN for backcalculation of flexible pavement moduli, it was observed that ANN exhibits the capability of predicting layer moduli values of pavements with success; with FWD-enabled field deflection measurements on focus. Similarly, it was noted that ANN adoption yields a significant reduction in computation time while simplifying the backcalculation process.

Keywords— ANN, backcalculation, FWD.

1. Background

These findings concurred with those established by Meier and Rix (1995), who affirmed that from the perspective of speed, ANN models’ rapid prediction ability imply that they are able to analyze 100,000 FWD deflection profiles in mini and micro seconds. The eventuality is the provision of a significant advantage to pavement engineers who end up assessing transportation infrastructure conditions nondestructively and in real time (Saltan & Terzi, 2008). Despite this promising nature of ANN to foster the backcalculation of flexible pavement moduli in real time, Goktepe, Agar and Lav (2005) cautioned that a number of considerations need to be made. For instance, it was suggested that the accuracy of ANN-led outcomes is dependent on the integrity and quality of FWD deflection data that the operators collect from the field. Hence, the need to define FWD reporting requirements, data analysis approach, and testing requirements while seeking to assure ANN outcome accuracy cannot be overemphasized. Accurate information regarding layer thickness (at the testing points of FWD) has also been documented to play a crucial role in steering successful backcalculation of the stiffness of layers or predict maximum deflections, strains, and stresses, which constitute critical pavement responses (Saltan, Uz & Aktas, 2013). The implication is that the degree of accuracy of the FWD data obtained at the testing points determines then level of success achieved in ANN-led backcalculation of flexible pavement moduli. Figure 1 illustrates the structure of ANN.
2. Structural Evaluation In Relation To Flexible Pavements

The development of ANN as an intelligent software is attributed to the convergence of learning and adaptation. Through the latter processes, variable and complex systems are modeled. According to Gopalakrishnan and Thompson (2004), the solving of problems via ANN is dependent on prior knowledge in such a way that new information is incorporation in the entire evolving learning procedure, ensuring that the forecasting capabilities of ANNs are increased. It has also been established that ANN yields algorithmic developments responsible for mimicking the manner in which humans think. In turn, the software treats nonlinear and more complex problems in a manner deemed to be rational, following the development of regression computations’ multivariate models. Therefore, it is evident that the human brain’s efficiency and complex pattern forms an inspiration of the ANN technique. Specifically, a high degree of connectivity characterizing a number of neurons translates into intelligence. As the neurons of ANN transmit, process, and receive information or signals to related neurons to which it is connected, the resultant and individual links exhibit unique and associated values referred to as weights (Kim, Kim & Mun, 2010). As these weights are fitted, they end up simulating certain behaviors or features. A representation of these weights is shown in figure 4.
Figure 2: A representation of ANN weights

It is also worth noting that the outcomes obtained after applying ANN to establish the layer moduli of flexible pavements is dependent on the nature of interconnection or architecture between neurons. In a related observation, Mehta and Roque (2003) documented that the ANN modeling outcomes are also determined by the strength values characterizing weight values (or connections). The implication is that multi-dimensional and non-linear problems are more likely to arise in situations where complex structures are present. In the study by Meier and Rix (1994), it was asserted that ANN system’s typical elements include transfer functions, input functions, error functions, and the learning rules. Hence, the need to establish definitions of these elements via trial-and-error procedures cannot be overemphasized. Imperative to note further is that the ANN development procedure constitutes two leading steps. During the training stage, input-output sets of data enhance the learning process. In situations where the desired outputs are known, Meier and Rix (1995) documented that there is a need to reinforce the learning process. However, situations where, for the specified outputs, the desired outputs are given, it was observed that supervision needs to be embraced in relation to the learning process (Nazzal & Tatari, 2013). Apart from the training stage, the model development of ANN exhibits the testing procedure. Indeed, the importance of this stage lies in the decision to predict ANN’s capacity to produce reasonable outputs in relation to any new data. The implication is that the testing data is responsible for reporting the model’s performance statistics in its entirety (Saltan & Terzi, 2008). Upon establishing desirable outcomes in the two stages (ANN training and testing), the model produced is poised to exhibit the capability of steering reliable predictions when presented with data sets that are unknown.

3. Practical Application of ANN in Flexible Pavement Moduli Backcalculation

To illustrate the application of ANN in practice and theoretically, a sample length of the road, say 28 kilometers, is used. Some of the types of pavement systems that could characterize such a road include a four-layer system and a three-layer system. Whereas the former could feature a sub-base whose stiffness exceeds that of the granular base, the latter could be characterized by layers whose stiffness decreases with depth. To apply the ANN backcalculation procedure, the initial process is expected to entail the design and training practice using the available database of the road. The next step is expected to
constitute an assessment of forecasting capabilities. Lastly, the proposed model is verified via the
establishment of comparisons between the pavement’s actual condition and the layer moduli values
predicted.

A. The Design and Training Procedure
To achieve this process, it is important to establish the leading variables shaping the nature of input-
output data sets. Saltan, Uz & Aktas (2013) documented that pavement behavior is affected by numerous
variables. As such, an identification of variables deemed to be the most influential is appropriate and this
procedure can be achieved via sensitivity analyses. In the selected example, some of the most influential
variables could include surface pavement deflections in the respective tests, layer thickness, and the load
level. It is also worth noting that for the respective layer materials, typical values can be assumed in
relation to Poisson’s ratio. These layer materials include the lower layer, stabilized sub-base, granular
base, and the asphalt layer (Seo, Kim, Cho & Jeong, 2013). Figure 5 illustrates this sample procedure
depicting the backcalculation model.

![Diagram of the backcalculation model]  
**Figure 3: The backcalculation model highlighted**
The ANN design and training process culminates into deflection basin verification. The latter, which
constitutes sensitivity studies, holds that the transfer function represents sigmoid, the input function
represents the dot product, and the pre-processing defined by the mean standard deviation. Figure 6
illustrates these outcomes in relation to the selected sample application of ANN design and training in
practice; given the selected road.
In such a case, each interval of about 500 iterations is expected to be accompanied by an examination of the decrease in the error trend, with the error criterion MAE aiding in the evaluation of approximations between the computed EANN and the target moduli Etarget. According to Sharma and Das (2008), this step in the ANN design and training procedure yields a great enhancement of chances of achieving the adopted convergence criteria. Given that a variety of layer moduli combinations could still yield similar errors, the process of deflection basin verification is deemed ideal in fostering the selection of a set of moduli perceived to be more adequate; also achieved via ANN. Whereas target outputs are represented by the measured deflection basins, inputs are defined by the computed moduli EANN. Hence, the optimal solution becomes the option with better regression analysis indicators, as well as the least error between field-measured and predicted deflection basins. Therefore, it can be inferred that the forecasting reliability of ANN options is determined by the desirable extent to which their resultant computations tend to match field-measured deflection basins. To achieve the matching accuracy, it is expected that the measured and the computed deflections exhibit a linear regression (ARA Inc. & ERES Consultants Division, 2004).
B. Generalization capability of ANN and final verification

Upon establishing the optimum ANN, it becomes important to assess the generalization capability. According to Ceylan, Guclu, Tutumluer & Thompson, 2005), this assessment is achieved via data sets different from those utilized in designing and training the network. From the perspective of verification, the predicted layer moduli values are compared with the actual condition of the road; considering further the structural defects and material variability of the selected stretch. In situations where spatial variations of the respective moduli suggest that estimations of material such as asphalt concrete are the least, a notable attribute that could be linked to such a trend constitutes asphalt base’s lower stiffness. In a quest to establish potential reasons behind the atypical or low values of the resultant layer moduli, inclusions of the actual condition of the pavement surface are imperative. As documented by Chatti, Ji and Harichandran (2004), the surface condition affects the estimated moduli values. In stretches closer to areas with severe distresses or higher rutting and deflections, lower values are obtained (Goel & Das, 2008). On the other hand, deteriorated regions prompting special initiatives via maintenance procedures are associated with lower moduli (Goktepe, Agar & Lav, 2006).

4. Summary and Field Implications

To assess pavement systems’ structural integrity, one of the most applicable tests is the Falling Weight Deflectometer (FWD) test. Whereas a number of techniques responsible for the backcalculation of the layer moduli of flexible pavements exist, they remain inefficient from the computation perspective. Given the existence of this perceived limitation, the eventuality is that the techniques become tedious to use. Similarly, it is evident that the techniques are constrained when it comes to their utilization in the wake of the demand for relatively quick computation. The eventuality is that when these existing techniques are employed, significant errors mar the pavement moduli backcalculation process. In this paper, the main aim has been to examine the manner in which ANN can be utilized to foster real-time backcalculation of FWD data-led pavement layer moduli. Imperative to note is that ANN prompts the training process to approximate backcalculation functions via numerous volumes of synthetic test data produced by pavement response models; both dynamic and static. For pavement evaluations, the overall outcomes hold that ANN are more cost-effective, frequent, and thorough, proving to be ideal due to their capabilities to steer backcalculation in real-time.

5. References

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