Artificial Neural Network Approach for Overlay Design of Flexible Pavements

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Abstract: *Pavements are constructed to deteriorate because of many factors such as traffic loading, material related factors, climate, and other environmental factors. In order to preserve these investments, a maintenance program should be carried out at right time and right places. One of the most important maintenance activities is asphalt overlays. Designing an overlay is more challenging since it restricts the pavement design engineer to a vast number of boundary conditions that must be observed and designed for. The most important factor in this process is the assessment of the existing pavement structural capacity, and relating it to the new overlay. The process becomes more complicated when considering environmental changes of the pavement materials. Such process should be implemented using a computer model to overcome complexity procedures, repeated tasks and time consuming. An artificial neural network approach can be used for the elimination of this drawback. This study presents an attempt to apply artificial neural network to recommend pavement overlay thickness based on learning from Mechanistic-Empirical overlay design cases. Results of this study reveal that artificial neural network is appropriate for implementation in calculating flexible overlay thickness based on mechanistic-based design procedure.*

Keywords: *Overlay, ANN, pavement design, neural network, mechanistic-empirical, flexible pavements.*

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1. Introduction

Highway pavements consist of several flexible layers. The common layers are Asphaltic Concrete (AC) wearing course on the top followed by base and/or sub-base layers in which they are rested on subgrade layer. Generally, pavements are constructed to fail due to many factors that affect on the serviceability of the pavement such as traffic loading and weather conditions. To preserve these investments achieving the design life, Maintenance Rehabilitation (MR) activities should be applied through a timely maintenance plan. It is important that the maintenance activities be done at the right time and right places [19].

One of the most popular M and R activities is Hot Mix Asphalt (HMA) overlays. They provide a relatively fast, cost-effective means of correcting existing surface deficiencies, restoring user satisfaction and adding structural load-carrying capacity depending on the designed thickness. There are many overlay design methods that consider many design construction factors. These factors should be addressed by the design engineer, if early failure is to be avoided and maximum performance achieved [17, 20].

A Mechanistic-Empirical (M-E) overlay design procedure offers a more defined engineering approach, to most of the current subjective methods, where it relates the pavement performance to actual stress-strain state of the pavement structure. The mechanistic-based design process considers many design factors to calculate the required thickness. These factors include the expected future traffic, the structural capacity of each pavement layer, and the variation of the pavement material properties due to seasonal environmental changes, especially the temperature and moisture variations [5, 3]. Due to the complexity of such a design system, its procedure should be implemented in a computer model to overcome complexity procedures, and time consuming.

On the other hand, the following quote from [18] highlights the importance of a powerful and versatile computational tool in solving complex procedures: "over the past two decades, there has been an increased interest in a new class of computational intelligence systems known as Artificial Neural Networks (ANNs). This type of networks have been found to be powerful and versatile computational tools for organizing and correlating information in ways that have proved useful for solving certain types of problems too complex, too poorly understood, or too resource-intensive to tackle using more-traditional computational methods. ANNs have been successfully used for many tasks including pattern recognition, function approximation, optimization, forecasting, data retrieval, and automatic control [18]."

This paper investigates the feasibility of applying ANN approach to recommend appropriate pavement overlay thickness based on learning from M-E overlay design cases. This is particularly promising for developing countries where such applications can play an effective role in offsetting the lack of decision tools and other related factors, which is often apparent.

2. M-E Overlay Design Procedure

2.1. M-E Concept

From an engineering point of view, there is much to be desired about a mechanistic approach to pavement design. In general, the application of the principles of engineering mechanics refers to "Mechanistic" term that can be used in calculating critical stress, strain, or deflection in the pavement, which leads to a rational design process. While, "empirical" term refers to prediction of resulting damages by some empirical failure criteria. That is why it is called M-E design approach, as shown in Figures 1 and 2 presents the elements of M-E design system [15].

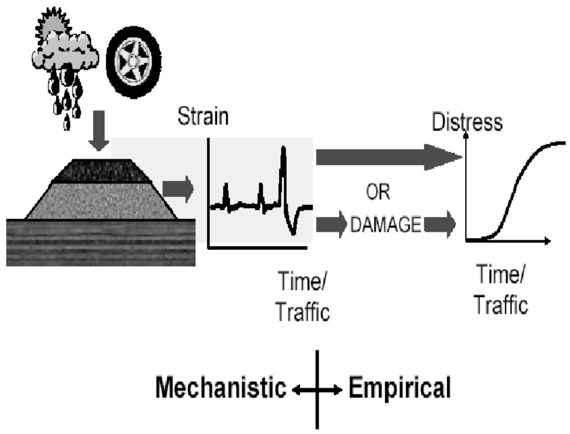

Figure 1. Concept of M-E design procedure.

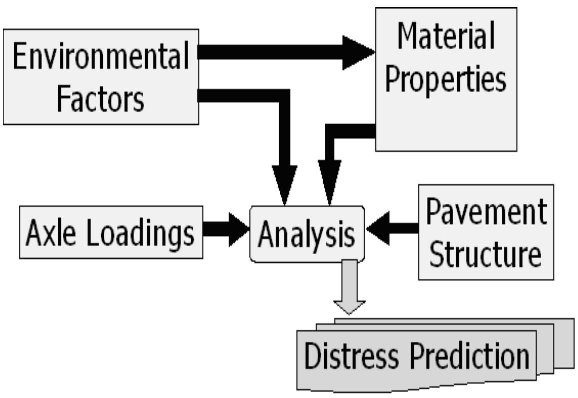

Figure 2. Elements of M-E design system.

Although the mechanistic approach to pavement design is much more rational than the current empirical approach, it necessitates high level of technical and computation requirements. Today, advent of high-speed computers overwhelms this difficulty [15].

Detailed description of the M-E design procedure is out of scope of this paper, while it can be found in references [5, 15, 21]. However, the following sections present overview on the M-E overlay design procedure.

2.2. Outline of M-E Overlay Design Procedure

In M-E overlay design procedure, the pavement layer thicknesses are calculated so that the damages in either the existing pavement or the new overlay will be within the allowable limits. This procedure considers many design factors to calculate the required thickness. These factors include the axle loading, environmental factors, and pavement material properties. It takes into consideration the effect of seasonal variation on the change of pavement layer properties and accounts for non-linearity of material properties. The main features of the method include: determination of design inputs, modeling pavement response, and damage analysis [5, 6].

2.2.1. Design Inputs

A layered elastic model requires a minimum number of inputs to adequately characterize a pavement structure and its response to loading. These inputs are as follow [21, 6]:

- Material properties of each layer (Modulus of elasticity, poisson's ratio, pavement layer thicknesses).
- Traffic and loading conditions.
- Environmental effects.

Material properties: since the pavement has been regarded as a multi-layered elastic system, the elastic moduli and Poisson rations must be specified. Because The Poisson's ratio has a relatively small effect on the pavement response, it is customary to assume reasonable values for design rather than determining from actual tests [9]. Pavement layer moduli are predicted from deflection data using back-calculation techniques. Several programs have been developed that perform the back-calculation [10, 16, 4].

Traffic and loading conditions: traffic data is one of the key elements required for the structural design and analysis of pavement structures. It is required for estimating the loads that are applied to a pavement and the frequency with which those given loads are applied throughout the pavement's design life.

Environmental effects: the key parameter that was selected to reflect the environmental effects is the layer elastic modulus. The elastic modulus of a flexible layer changes with surrounding environment. While an asphalt layer may be more sensitive to temperature, a clayey soil layer will be less sensitive to temperature variation but more affected by the change in moisture. Thus, the environmental parameters that are considered to affect the variation of the pavement properties are moisture for unbound materials and temperature for asphalt bound materials [5, 2].

2.2.2. Modeling Pavement Response

Modeling pavement response is typically utilized to estimate the level of the two most common distress types found in AC pavements: fatigue cracking and rutting distress. Fatigue cracking is caused by horizontal tensile strain at the bottom of asphalt layers, while rutting distress is caused by vertical compressive strain on the top of the subgrade layer [5, 2, 8].

2.2.3. Damage Analysis

The design procedure calculates the damage due to fatigue and rutting using the Minor's law of linear cumulative damage concept [12]. Pavement is considered to have failed when the total damage has reached 100%, whether it is due to fatigue or rutting or other distress combinations.

2.3. Developed M-E Computer Applications

Mechanistic-based pavement design methods are being therefore developed in different countries such as Europe and North America with the main purpose to adequately predict pavement response and performance. For example in the USA, the Washington State Department of Transportation (WSDOT) uses M-E design system developed at the University of Washington and implemented in the computer program EVERPAVE 5.0, March 1999. The Minnesota Department Of Transportation (Mn/DOT) uses M-E flexible pavement thickness design that is implemented in the computer program ROADENT 4.0, January 1999. The Idaho Department of Transportation (ITD) uses M-E overlay design system for flexible pavements developed at the University of Idaho and implemented in the computer program WINFLEX, May 2001 [4]. Recently, the American Association of State Highway and Transportation Officials have also moved in that direction for the new AASHTO 2002 design guide, which is developed through the NCHRP project 1-37A [7].

In Europe, the need of a more comprehensive mechanistic pavement design method for Europe has been recognized by the directorate for transport of the European commission as a research topic deserving a high priority. The two co-ordinated research actions were created and financially supported with the purpose to make definite improvements in this direction. The two projects; COST333 which is: "development of new bituminous pavement design method", and AMADEUS which is: "advance methods for analytical design of European pavement structures", are complementary actions involving the participation of up to 20 countries in Europe in an effort to set up the plans for a future integrated pavement design method. In both these projects, the recommendations are that future pavement design methods should be able to predict functional and structural conditions of a road over time [1].

This paper uses the WINFLEX program as a tool in creating the design cases. Detailed description of the WINFLEX program can be found in [5].

3. Artificial Neural Networks

3.1. Neural Network Theory

It is not necessary to know the details of neural networks in order to use them, but this basic introduction can be helpful. A complete coverage of neural network theory can be found in the references such as a book by Principe, *et al.* [14].

3.1.1. Neural Network Definition

A neural network is an adaptable system that can learn relationships through repeated presentation of data and is capable of generalizing to new, previously unseen data. Some networks are supervised, in that a human determines what the network should learn from the data. In this case, users give the network a set of inputs and corresponding desired outputs, and the network tries to learn the input-output relationship by adapting its free parameters. Other networks are unsupervised, in that the way they organize information is hard-coded into their architecture [11]. Neural network architectures, arranged in layers, involve synaptic connections amid neurons that receive signals and transmit them to the others via activation functions. Each connection has its own weight and learning is the process of adjusting the weight between neurons to minimize error between the calculated and predicted values. In Figure 3, a typical structure of ANN that consists of a number of neurons that are usually arranged in layers, which are the input layer, hidden layers, and output layers [7]

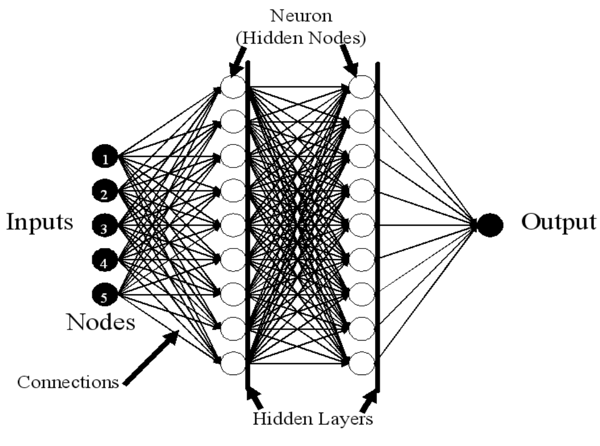

Figure 3. Typical structure of ANN.

3.1.2. Neural Network Use

Neural networks are used for both regression and classification. In regression, the outputs represent some desired, continuously valued transformation of the input patterns. In classification, the objective is to assign the input patterns to one of several categories or classes, usually represented by outputs restricted to lie in the range from 0 to 1, so that they represent the probability of class membership. For regression, a single hidden layer or Multilayer Perceptron can learn any desired continuous input-output mapping if there are sufficient numbers of axons in the hidden layer(s) [11].

3.2. Neural Network Software Packages

There are many available neural network software packages. In this study, neurosolutions software, version 5.06, has been used as a tool in designing and training a neural network. In the neurosolutions software, there is a wizard tool taking the user through the process of designing and training a neural network. Neural networks can be very powerful learning systems. However, it is very important to match the neural architecture to the problem. The Neural-Builder of the neurosolutions software constructs the most popular neural architectures. However, Multi Layer Perceptron (MLP) model is considered the most widely used neural network. MLPs are layered feed forward networks typically trained with static back propagation. These networks have found their way into countless applications requiring static pattern classification. Their main advantage is that they are easy to use, and that they can approximate any input/output map. The key disadvantages are that they train slowly, and require lots of training data. Detailed description of this software can be found in the references [11]. Generally, the seven basic steps of neural network construction are: step 1 input/desired data file selection, step 2 network analysis, step 3 neural topology, step 4 layer configuration, step 5 simulation control, step 6 data display, step 7 simulation.

4. ANN-Based Overlay Design Thickness for Flexible Pavements

4.1. Analysis Methodology

In order to develop an ANN-based overlay design thickness procedure, it is necessary first of all to have a database of design cases. For this reason, a comprehensive analysis was carried out on suggested three typical flexible pavement cross sections: 3-layer, 4-layer, and 5-layer, taking into consideration that new overlay layer and the subgrade layer are counted. For each cross section, seven failure cases to control the design have been selected creating 21 design cases. A range of input data has been suggested for each design case. For this purpose, the WINFLEX computer program, M-E overlay design system, was used to calculate the overlay thickness for each design case. Consequently, design cases database can be created. Training data sets were then being selected to be used in training process for ANN approach. Neurosolutions 5.0 software, version 5.06, was used in designing and training the neural network. Sensitivity analysis on the trained ANN has been conducted. Finally, testing or validating process was performed on the trained ANN. Figure 4 presents in details the analysis methodology adopted in this study, where it can be divided into the following four main steps:

- Development of design cases database.
- Training process.
- Sensitivity analysis on the trained ANN.
- Testing process.

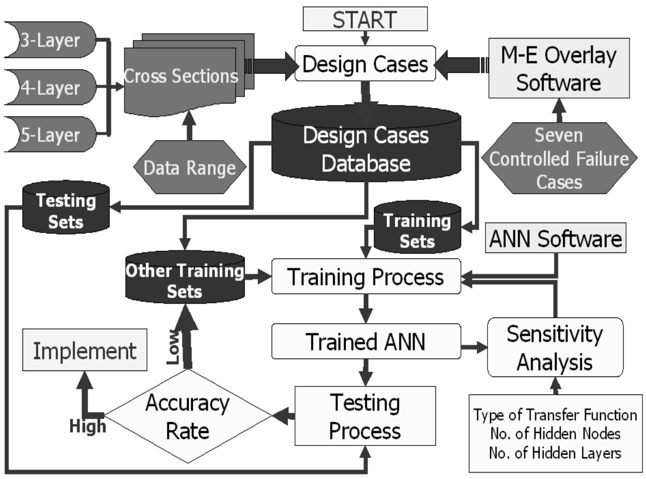

Figure 4. Analysis methodology adopted in this study.

4.2. Development of Design Cases

To build a design cases database, three different pavement cross sections have been suggested: 3-layer, 4-layer, and 5-layer, as shown in Figure 5. It shows also the material data inputs for each layer: elastic modulus (E), layer thickness (H), and Poisson rations (ν).

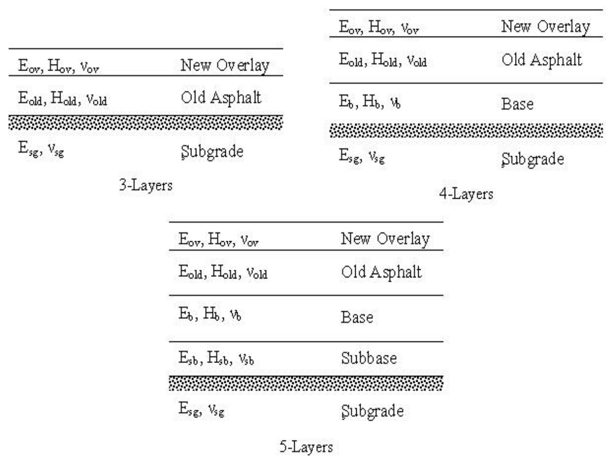

Figure 5. Three different pavement cross sections.

It is noteworthy that the overlay thickness, H_{ov}, is the desired output to be calculated. For simplicity, Poisson rations, performance prediction model for fatigue and rutting failure, and modulus-temperature adjustment for AC layers are assumed to be constant. Whereas the range of elastic moduli, layers thickness, and traffic loading is assumed to be as illustrated in Figure 6.

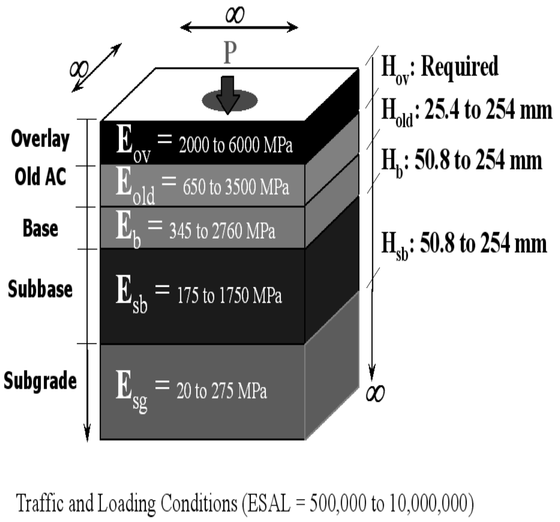

Figure 6. Data range of input values.

For each run, the overlay design software, WINFLEX, was used to determine an overlay thickness for the three cross sections based on controlling both fatigue failure at the bottom of the AC layers and/or rutting failure on the top of the subgrade layer. The fatigue failure mode is selected according to three conditions as follow:

- The first condition of fatigue failure is selected so that the design is controlled by considering fatigue failure in the old AC layer and the new overlay layer.
- The second fatigue failure mode is selected so that considering the fatigue failure in the new overlay layer only controls the design.
- The last condition is chosen with the intention of considering the fatigue failure in the old AC layer.
-

As a result and account for rutting failure with/without, there are seven failure modes for each cross section, i.e., total of 21 design cases, as follow:

- Considering fatigue failure in old pavement.
- Considering fatigue failure in new overlay.
- Considering fatigue failure in new overlay and old pavement.
- Considering both rutting and fatigue failure in old pavement.
- Considering both rutting and fatigue failure in new overlay.
- Considering both rutting and fatigue failure in new overlay and old pavement.
- Considering rutting on the sub grade layer.

Using the data range mentioned in Figure 6, design cases database can be created through more than 1000 runs. Table 1 presents a sample of some selected design cases from the created database. It is noteworthy that pavement is considered to have failed when the total damage has reached 100%, whether it is due to fatigue at the bottom of the AC layers or rutting on the top of the subgrade layer. It is noteworthy that if the calculated overlay thickness is equal to 2.54mm, which was specified as increment value in WINFLEX, this means that there is no need for overlay.

4.3. Training Process

In order to develop ANN-based overlay design approach, it must be well trained using training sets extracted from the developed database. Therefore, 863 design cases have been selected from the created database to represent training sets. Neurosolutions software has been used in the training process.

The Neural-builder of the neurosolutions software only accepts column-formatted ASCII files. First step is to choose the neural model. MLP networks have been selected. After loading the training data sets, the Neural-Builder will scan this file and present a list of the columns that it finds. Initially all columns will be tagged as inputs. User can tag a column as either “Input”, “Desired”, “Symbol”, “Annotate” or “Skip”. To change a columns tag, simply select the column with the mouse and press the corresponding button. In this analysis, the first column “Cross Section” and the second column “Failure Mode” were tagged as “Symbol”. While the last column “H_{ov}” was tagged as “Desired”. The number of hidden layers and transfer function should be specified. In this study, two hidden layers and TanhAxon transfer function were selected.

The problem is to find the best mapping from the input patterns to the desired response (H_{ov}). The neural network will produce from each set of inputs a set of outputs. Given a random set of initial weights, the outputs of the network will be very different from the desired classifications. As the network is trained, the weights of the system are continually adjusted to incrementally reduce the difference between the output of the system and the desired response. This difference is referred to as the error and can be measured in different ways. The most common measurement is the Mean Squared Error (MSE). The MSE is the average of the squares of the difference between each output and the desired output. Figure 7 shows the designed ANN structure using neurosolutions software with some captured screens after finishing the training process. It can be noticed that the MSE is equal to 0.0212.

Table 1. Example of some selected design cases from the database.

Cross Section	Failure Mode	E_{ov}, MPa	E_{old}, MPa	E_b, MPa	E_{sb}, MPa	E_{sg}, MPa	H_{old}, mm	H_b, mm	H_{sb}, mm	ESAL	H_{ov}, mm
3-Layer	1	2000	650	0	0	20	25.4	0	0	5.0E+05	205.74
3-Layer	1	2400	670	0	0	40	40	0	0	7.0E+05	182.88
3-Layer	1	2500	700	0	0	60	60	0	0	1.0E+06	167.64
3-Layer	1	4400	1000	0	0	130	240	0	0	7.3E+06	55.88
3-Layer	1	4500	3500	0	0	140	250	0	0	1.0E+06	2.54
3-Layer	1	4600	3400	0	0	160	25.4	0	0	3.2E+06	152.4
3-Layer	3	3200	1000	0	0	220	100	0	0	4.7E+06	134.62
3-Layer	3	2900	2000	0	0	240	25.4	0	0	4.9E+06	180.34
3-Layer	4	5000	800	0	0	270	80	0	0	5.0E+05	68.58
3-Layer	4	5000	1000	0	0	270	110	0	0	2.0E+06	83.82
3-Layer	4	4000	1500	0	0	100	140	0	0	8.0E+05	35.56
3-Layer	5	3000	2000	0	0	80	150	0	0	8.0E+06	38.1
3-Layer	5	3000	2000	0	0	200	150	0	0	8.0E+06	2.54
3-Layer	7	3000	1000	0	0	100	100	0	0	4.0E+06	86.36
3-Layer	7	5000	1200	0	0	120	120	0	0	5.0E+06	50.8
4-Layer	1	3900	1500	400	0	80	70	90	0	5.8E+06	175.26
4-Layer	1	4000	3000	2700	0	100	80	70	0	6.2E+06	68.58
4-Layer	1	4300	2000	750	0	110	120	55	0	6.5E+06	104.14
4-Layer	1	4400	1000	950	0	130	240	95	0	7.3E+06	5.08
4-Layer	4	3400	670	600	0	180	50	100	0	1.8E+06	124.46
4-Layer	4	3500	700	1400	0	190	60	60	0	1.0E+06	68.58
4-Layer	5	2500	700	900	0	60	60	100	0	1.0E+06	96.52
4-Layer	5	2600	800	1000	0	70	70	110	0	2.0E+06	91.44
4-Layer	5	2700	900	1200	0	90	90	120	0	3.0E+06	58.42
4-Layer	6	2500	700	900	0	60	60	100	0	1.0E+06	93.98
4-Layer	6	2600	800	1000	0	70	70	110	0	2.0E+06	99.06
4-Layer	6	2700	900	1200	0	90	90	120	0	3.0E+06	71.12
5-Layer	1	3700	1000	650	350	40	60	240	220	1.0E+07	162.56
5-Layer	1	3800	1300	1000	360	50	25.4	250	230	1.0E+07	144.78
5-Layer	1	3900	1500	400	500	80	70	90	240	5.8E+06	134.62
5-Layer	3	3900	1500	400	500	80	70	90	240	5.8E+06	134.62
5-Layer	3	4000	3000	2700	1100	100	80	70	80	6.2E+06	5.08
5-Layer	3	4300	2000	750	1200	110	120	55	200	6.5E+06	33.02
5-Layer	4	2000	800	500	200	50	80	70	100	1.0E+07	226.06
5-Layer	5	2000	650	345	175	20	25.4	50.8	50.8	5.0E+05	193.04
5-Layer	5	2300	660	400	200	30	30	60	60	6.0E+05	167.64
5-Layer	7	2400	670	500	210	40	40	80	70	7.0E+05	139.7
5-Layer	7	2450	680	700	220	50	50	90	80	8.0E+05	111.76
5-Layer	7	2500	700	900	240	60	60	100	200	1.0E+06	58.42

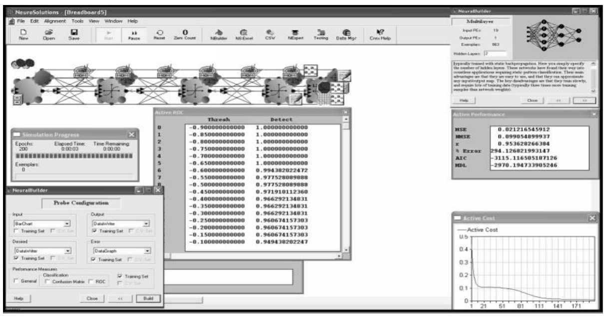

Figure 7. Designed ANN structure neurosolutions software.

4.4. Sensitivity Analysis

The objective of the sensitivity analysis is to express the fitness of neural networks as an effective way in calculating overlay thickness based on M-E design approach with the most achievable accuracy that can be obtained for the most economical cost. The neural networks were influenced to several parameters that can guarantee the greatest achievable accuracy such as type of transfer function, number of hidden nodes, and hidden layers. Figure 8 shows the results of the sensitivity analysis with different parameters.

The analysis indicates that changing the transfer function has a noticeable effect on the accuracy, where using the Tanh function is much better than using the sigmoid function. Furthermore, the Tanh function is mush interacting with number of nodes than sigmoid function. For example, using the Tanh function achieves average 1.48% more in accuracy than the sigmoid function.

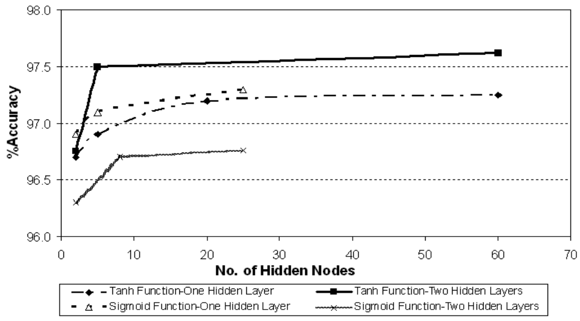

Figure 8. Results of the sensitivity analysis with different parameters.

Furthermore, the number of hidden nodes has an effect on the accuracy, where using more number of hidden nodes gives high accuracy. To achieve high accuracy, the number of hidden nodes is preferable to be more than 25 nodes. On the other hand, neurosolutions predicts much better with the two hidden layers.

Another sensitivity analysis has been performed to investigate between neural models: MLP networks versus Radial Basis Function (RBF) networks. Results indicated that MLP networks are more accurate than RBF networks (MSE=0.042) in predicting the overlay thickness of flexible pavements. The reason for that is RBF networks give an equal importance to all input variables, which is not the case with MLP networks. Weighting process of input variables is very important in overlay design of flexible pavements.

4.5. Testing Process

Once the network has trained, testing process should start using testing data sets selected from the created database. The trained network should not be exposed to these data sets before. Therefore, 105 different design cases have been selected to represent training data sets distributed on the three cross sections. The predicted overlay thickness using the trained network of neurosolutions software should be compared with the actual calculated ones using WINFLEX to come up with the accuracy rate or reliability. If the accuracy rate is low, then the network is not properly trained and other training sets should be generated to retrain the network, otherwise, the network is considered to be reliable and ready for implementation.

Table 2 shows example of some selected results for the calculated and predicted overlay thickness and the corresponding accuracy rate. The average accuracy rate for the 105 testing sets is 82.89%, which is considered acceptable, however 50% of the testing sets have accuracy rate over 90%. Figure 9 presents the relationship between the calculated and the predicted overlay thickness using a trend or a correlation line. It shows that the ANN predicts the overlay thickness around the equality line and slightly under the equality line for high values of designed thickness. In addition, the 105 testing data sets have been plotted against the calculated and predicted overlay thickness to show the fluctuation of the predicted overlay thickness in respect to the calculated ones, as shown in Figure 10.

A correlation analysis was also made between the calculated and the predicted overlay thickness with test of significant 2-tailed. A two-tailed significance is the probability of obtaining results as extreme as the one calculated/observed and in either direction when the null hypothesis is true. It tests a null hypothesis in which the direction of an effect is not specified in advance. This correlation analysis is to show how strong the relationship between the calculated and the predicted overlay thickness is. The correlation coefficient is 0.959 with Standard Error of Estimate (SEE) 11.90mm. Results indicate that the relationship between the calculated and the predicted overlay thickness is strong with acceptable SEE.

Finally, results indicate that the trained network of overlay thickness gave a quite close approximation to the calculated values for the three pavement cross sections. Accordingly, ANN can be effectively used to determine the overlay thickness based on M-E design procedure.

5. Conclusions

ANN have recently received lots of attention and contributed in a wide variety of applications in civil engineering as well as in other fields. In this study, ANN-based pavement overlay design tool has been developed using neurosolutions software, version 5.06. Several network architectures were trained using training data sets developed by M-E overlay design program named as WINFLEX. Trained network has been tested using different testing data sets to determine the predicted overlay thickness, while the calculated ones have been determined by the WINFLEX program. The calculated and the predicted overlay thicknesses have been compared together to come up with the accuracy rate. The results indicate that the ANN technology can be used to determine the pavement overlay thickness with high accuracy based on M-E procedure. This study is considered an important attempt to simulate the M-E overlay design procedure using ANN technology.

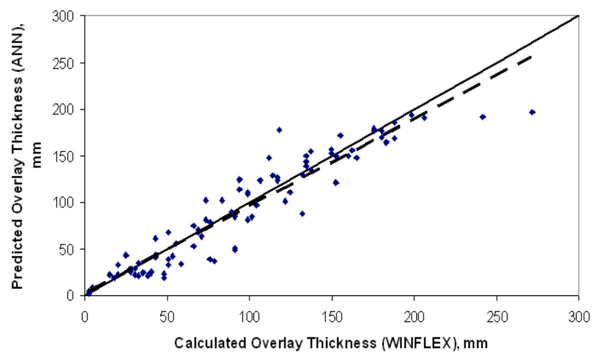

Figure 9. Relationship between the calculated and the predicted overlay thickness.

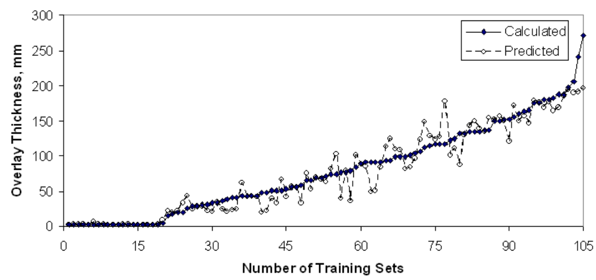

Figure 10. Fluctuation between the calculated and the predicted overlay thickness.

Table 2. Examples of some selected results for testing sets with percentage of accuracy.

	Cross Section	H_{ov} (mm), Calculated (WINFLEX)	H_{ov} (mm), Predicted (NeuroSolutions)	Accuracy, %
Control the Design by Considering Fatigue Failure in Old Pavement	3-Layer	198.12	194.11	97.98
	3-Layer	175.26	179.2	97.80
	4-Layer	99.06	108.23	91.53
	4-Layer	71.12	63.5	89.29
	5-Layer	33.02	35.16	93.91
Control the Design by Considering Fatigue Failure in New Overlay	3-Layer	165.1	147.25	89.19
	4-Layer	93.98	124.14	75.70
	4-Layer	2.54	4.54	55.95
	5-Layer	66.04	74.8	88.29
	5-Layer	2.54	3.21	79.13
Control the Design by Considering Fatigue Failure in New Overlay & Old Pavement	3-Layer	124.46	110.58	88.85
	3-Layer	152.4	149.9	98.36
	5-Layer	76.2	79.03	96.42
	5-Layer	2.54	2.33	91.73
	5-Layer	162.56	156.3	96.15
Control the Design by Considering both Rutting & Fatigue Failure in Old Pavement	3-Layer	20.32	21.93	92.66
	3-Layer	106.68	123.19	86.60
	4-Layer	43.18	42.8	99.12
	4-Layer	83.82	101.68	82.44
	5-Layer	114.3	128.32	89.07
Control the Design by Considering both Rutting & Fatigue Failure in New Overlay	3-Layer	187.96	168.76	89.79
	3-Layer	149.86	152.12	98.51
	3-Layer	88.9	89.31	99.54
	3-Layer	93.98	113.92	82.50
	3-Layer	91.44	85.8	93.83
Control the Design by Considering both Rutting & Fatigue Failure in New Overlay & Old Pavement	4-Layer	43.18	41.42	95.92
	4-Layer	2.54	2.68	94.78
	4-Layer	68.58	67.26	98.08
	4-Layer	175.26	176.34	99.39
	4-Layer	132.08	129.38	97.96
Control the Design by Considering Rutting on the Subgrade Layer	5-Layer	27.94	27.9	99.86
	5-Layer	2.54	3.11	81.67
	5-Layer	73.66	102.23	72.05
	5-Layer	20.32	33.06	61.46
	5-Layer	121.92	100.96	82.81

Comparing with other papers related to the application of ANN in pavement design, the ANN models have proved to be a powerful tool in providing pavement engineers and designers with sophisticated solutions, without the need for a high degree of expertise in the input and output of the problem, to rapidly analyze and design flexible pavements [19, 7, 12].

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