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Estimating Indirect Tensile Strength of Mixtures Containing Anti-Stripping Agents Using an Artificial Neural Network Approach

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Abstract: The objective of this study was to develop a series of artificial neural network (ANN) models to predict the indirect tensile strength (*ITS*) and tensile strength ratio (*TSR*) of various mixtures considering five input variables such as asphalt binder source, aggregate source, anti-striping agents (ASA), conditioning duration, and asphalt binder content. The results indicate that ANN-based models are effective in predicting the *ITS* and *TSR* values of mixtures regardless of the test conditions and can easily be implemented in a spreadsheet, thus making it easy to apply. In addition, the developed ANN models can be used to predict (or estimate) the *ITS* values of the mixtures used in other research projects. Furthermore, the results also show that the asphalt binder source, aggregate source, and asphalt binder content are the most important factors in the developed ANN models while the conditioning duration is relatively unimportant (i.e., it has less effect on the *ITS* values in comparison with other variables). In addition, the sensitivity analysis of input variables indicated that the changes of *ITS* values are significant as the changes of the most important independent variables.

Key words*: Artificial neural network; Conditioning duration; Important index; Indirect tensile strength; Sensitivity analysis.*

Introduction

The best efforts of highway engineers in designing and constructing asphalt pavements are often undermined by environmental factors such as water, temperature variations, sunlight, etc. Each of these factors alone is not individually harmful, but when coupled with large volumes of traffic, they frequently lead to significant problems with the durability of the pavements. The phenomenon of breaking the bond between the aggregate and the binder is known as stripping. Stripping usually begins at the bottom of the pavement layer, and travels gradually upwards [1]. A typical situation is the gradual loss of strength over the years, which causes many surface manifestations such as rutting, corrugations, shoving, raveling, cracking, etc [2-7]. To prevent moisture susceptibility, proper mix design is essential. However, even with a proper mix design, among many other factors if the mix is not compacted properly, it may still be susceptible to moisture. Thus, hot mix asphalt (HMA) should be tested in a situation similar to real-world where it is typically compacted to 7 percent air voids. For this reason, the tests for moisture susceptibility are usually conducted on mixes containing 7 ± 1 percent air voids [5-8]. There are many ways to prevent stripping in a pavement, however, the use of anti-stripping agents (ASAs) is the most common [9, 10]. One of the most commonly used ASAs in the United States is hydrated lime [10-12]. Others include liquid ASAs like amines, di-amines, liquid polymers, and solids like Portland cement, fly-ash, flue dust, etc. Pavement contractors usually prefer liquid ASAs as they are relatively easy to use [13]. However, ASAs from an approved list of sources should not be blindly added as some ASAs are aggregate and asphalt specific, and therefore, may not be effective to be used in all mixes; they could even be detrimental at times. Thus, a proper study of the mix should be conducted by systematically testing the mix for moisture susceptibility; using tests like indirect tensile strength (*ITS*), Lottman's and boiling water tests, among many other tests; in the laboratory.

Several studies have been conducted to evaluate the effectiveness of hydrated lime as well as liquid ASAs [13-14]. However, most laboratory studies conducted to assess the moisture susceptibility of mixes evaluated the short term effects of moisture on the mix. The *ITS* test, for instance, tests the moisture susceptibility of mixes after conditioning the samples in water for only 24hrs. This may not always be representative of the actual field conditions, and thus might be, in some cases, a misrepresentation of the actual moisture susceptibility of the pavement itself. In a previous study conducted by Lu and Harvey [15], the long term effects of moisture on the effectiveness of the ASAs were studied. From the study, it was observed that most of the detrimental effects of moisture occurred in the first four months.

The research project reported in this paper evaluated the long term effects of moisture on the moisture susceptibility of several mixes. *ITS* tests were performed on dry and wet conditions. The wet samples were conditioned in water for 1, 7, 28, 90, and 180 day(s) and the results were compared. A total of 600 samples were prepared and tested.

The *ITS* (wet and dry) and tensile strength ratio (*TSR*) values of the mixtures involving a number of interacting factors or engineering parameters such as the binder source, aggregate source, anti-stripping additive, conditioning duration, and asphalt binder content are too complicated to be described mathematically. Increasingly, modern pattern recognition techniques such as neural network and fuzzy systems are being considered to develop models from data to give the ability to learn and recognize trends in the data

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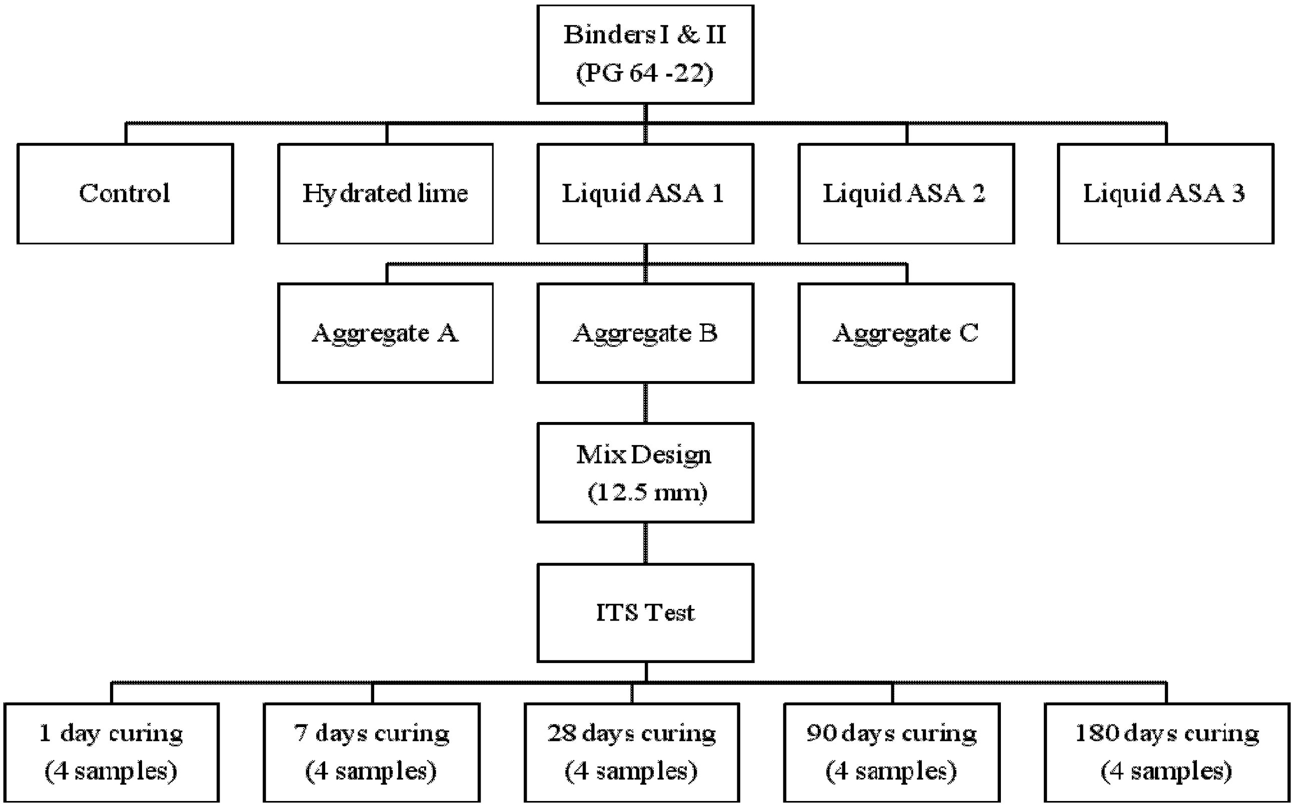


Fig. 1. Experimental Design.

pattern. Artificial neural networks (ANN) are useful in place of conventional physical models for analyzing complex relationships involving multiple variables and have been successfully used in civil engineering applications such as process optimization, slope stability analysis, and deep excavation forecast models [16-23].

The objective of this study was to develop a series of ANN models to predict the *ITS* values of various mixtures at five conditioning durations (i.e. 1, 7, 28, 90, and 180 day(s)). The importance and sensitivity analyses of input variables were performed to evaluate the influences of each independent variable on the dry and wet *ITS* values of the mixtures. The additional *ITS* values from other projects were used to validate the developed ANN models in this study.

Experimental Materials and Procedures

The Superpave method of mix design for a nominal maximum aggregate 12.5*mm* was used for this study. Fig. 1 illustrates the flowchart of the experimental design used in this laboratory investigation. A total of 30 mix designs (2 binder sources × 3 aggregate sources × 5 different ASA treatments) were conducted. The bulk specific gravity, maximum specific gravity, voids in mineral aggregate (VMA), and voids filled with asphalt (VFA) were obtained or calculated to determine the optimum asphalt content of all the 30 mixes.

The aggregates used in this study were obtained from three sources, denoted as A, B, and C. The types of aggregate received from each quarry consisted of #57, #789, Regular Screenings (RS), and Manufactured Sand (MS). Each type of the aggregate (Table 1)

Table 1. Aggregate Properties.

Sieve Size (*mm*)	Gradation Range	Combined Gradation (% Passing)		
		Agg. A	Agg. B	Agg. C
38	100	100	100	100
25	100	100	100	100
19	98 – 100	99	100	100
12.5	90 – 100	94	94	94
9.5	74 – 90	89	84	85
4.75	46 – 62	49	49	51
2.36	25 – 41	30	39	32
0.150	4 – 12	6.6	8.5	8.1
0.075	2 – 8	3.34	5.12	5.01
Stone Type		% Used in the mix		
#57		9	11	30
#789		61	46	32
RS		20	17	20
MS		10	26	18
		Properties		
Aggregate Type		Micaceous Granite	Marble Schist	Granite
Bulk Specific Gravity		2.700	2.830	2.610
% Absorption		0.77	0.49	0.62
Los Angeles Loss, %		52	23	26

was randomly obtained from quarry stockpiles and transported to the laboratory. The aggregates obtained were then tested for gradation as per the ASTM C 136, *Method for Sieve Analysis for Fine and Coarse Aggregate*. Table 1 contains the gradation properties of the aggregates used, and the percentage of each aggregate type used. Two different sources of binder were used in this project, both PG 64-22, denoted as I (a mixture of crude sources that could not be determined) and II (a Venezuelan crude source). The binders were

Table 2. Asphalt Binder Properties.

Property	Binder I	Binder II
Original Binder		
Viscosity, Pa-s (135˚C)	0.405	0.626
G*/sin δ, kPa (64˚C)	1.207	1.801
RTFO Residue		
Mass Change, % (163˚C)	-0.02	-0.24
G*/sin δ, kPa (64˚C)	2.815	4.608
PAV Residue		
G*.sin δ, kPa (25˚C)	2970	2420
Stiffness (60), MPa (-12˚C)	183	129
m-Value (60) (-12˚C)	0.311	0.345
PG Grade	64 -22	64 -22
Mixing Temperature+, ˚C	150 – 155	163 – 170
Compaction Temperature+, ˚C	139 - 144	150 – 155

+*Information provided by the supplier*

transported to the laboratory in sealed containers to prevent oxidation and premature aging. Table 2 gives the properties of the binder sources.

Four different anti-stripping agents were used in this project. They were commercially available hydrated lime, three liquid ASAs denoted as 2, 3, 4, and 5, respectively. The fifth treatment was the control, no ASAs, denoted by '1' in this paper. In the mixes containing hydrated lime as the ASA, 1% hydrated lime by weight of the aggregate, was added in a slurry form. In the mixes containing liquid ASAs, 0.5% liquid ASA, by weight of the binder, was added to the binder. This ASA content rate was based on the 0.25 to 0.75% recommended by the suppliers.

Knowing the optimum binder content for each of the mix designs, *ITS* samples were made for each of the mix types. Four samples for each age (e.g., 1 day, 90 days, etc.) were prepared to test the *ITS*. Two of which were stored as dry samples at 25 ± 1˚C, and two were stored as wet samples. If the samples were to be tested after 1 day, the wet samples were submerged in a water bath (60 ± 1˚C) for 24hrs followed by submersion in another water bath at 25 ± 1˚C for 2hrs before testing. For conditioning durations of more than 1 day, the wet samples were submerged in a water bath at 25 ± 1˚C for one day short of that specific duration (e.g., 6 days, 27 days, etc.) and then they were submerged in a water bath (60 ± 1˚C) for 24hrs followed by submersion in water at 25 ± 1˚C for 2hrs before testing. All the wet samples were vacuum saturated to a saturation level of 70 to 80% before immersing in water.

The wet *ITS* and the *TSR* were used as the measure of stripping for each of the mixes. To study the effects of ASAs and aggregates on the mixes, a Randomized Complete Block Design (RCBD) was developed with the ASAs as the treatment variables and the aggregate sources as the block variables. Similarly, the RCBD was developed with the binder source as the block variable to study the effects of the binder sources. Analysis of variance (ANOVA) was then performed to test the null hypothesis (mean *ITS* (or *TSR*) of each treatment and block variables are not significantly different from each other) at the 5% level of significance.

ANN Model Development

The neural network approach may be used to develop the predictive models of the *ITS* and *TSR* values of the mixtures considering the interaction of complicated variables. In this study, a three-layer feedforward neural network, shown in Fig. 2, was trained with the experimental data. This architecture consists of an input layer (5 variables), a hidden layer (6 neurons), and an output layer (one variable). Each of the neurons in the hidden and output layers consists of two parts, one dealing with aggregation of weights and the other providing a transfer function to process the output.

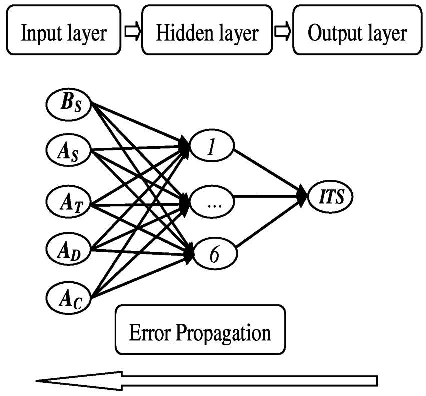


Fig. 2. A Schematic Diagram of Three-Layer Artificial Neural Network.

An artificial neural network can be presented by the following properties in mathematical terms [23-26]:.

1. Each neuron or node consists of a simple processing unit.
2. A state variable is associated with each node.
3. A real-valued weight w_{ij} is associated with each link between nodes *i* and *j*.
4. A real-valued bias b_i is associated with each node *i*.
5. A transfer function, f_i, is defined for each node, *i*, which determines the state of the node as a function of its bias, the weights of its incoming links, and the states of the nodes connected to it by the links.
6. A pattern of connectivity among the nodes is defined.
7. A propagation rule is defined.
8. A learning rule is defined.

For the three-layer network shown in Fig. 2, the outputs of the network, the *ITS* (ITS_D and ITS_W) and *TSR* values, are calculated as follows [18]:

$$ITS/TSR = f_T\left\{B_0 + \sum_{k=1}^{n}\left[W_k \cdot f_T\left(B_{HK} + \sum_{i=1}^{m} W_{ik} P_i\right)\right]\right\} \quad (1)$$

Where,

B_o = bias at the output layer,

W_k = weight of the connection between neuron *k* of the hidden layer and the single output layer neuron,

B_{HK} = bias at neuron *k* of the hidden layer,

W_{ik} = weight of the connection between input variable *i* and neuron *k* of the hidden layer,

P_i = input i^{th} parameter, and

f_T = transfer function, defined as:

$$f(T) = \frac{1}{1+e^{-t}} \quad (2)$$

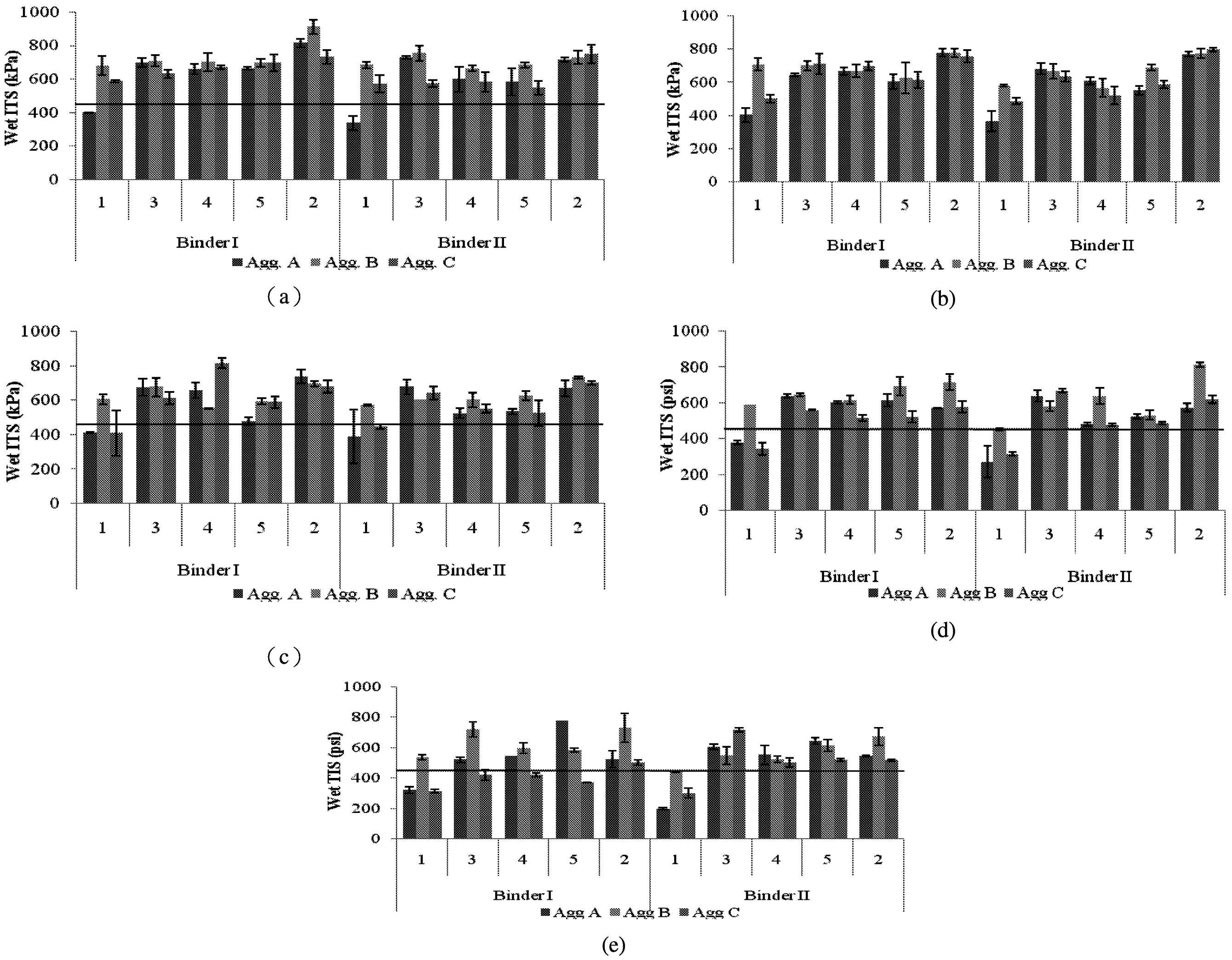


Fig. 3. Wet *ITS* of the Samples at Different Conditioning Durations in (a) 1, (b) 7, (c) 28, (d) 90, and (e) 180 Day(s).

In this study, the independent variables included asphalt binder sources (B_S), aggregate sources (A_S), anti-stripping additives (A_T), conditioning durations (A_D), and asphalt contents (A_C). The dependent variables were selected to be the wet and dry *ITS* values (ITS_W *and* ITS_D) and *TSR* values. In Eq. (1), the number of input variables (m) is 5; the input variables (defined previously) are $P_1=B_S$, $P_2=A_S$, $P_3=A_T$, $P_4=A_D$, and $P_5=A_C$. The number of hidden neuron ($n=6$) is determined through a trial and error procedure; normally, the smallest number of neurons that yields satisfactory results. In this study, the *backpropagation* algorithm was used to train this neural network. The objective of the network training using the backpropagation algorithm was to minimize the network output error through determination and updating of the connection weightsand biases. Backpropagation is a supervised learning algorithm where the network is trained and adjusted by reducing the error between the network and the targeted outputs. The neural network training starts with the initiation of all of the weights and biases with random numbers. The input vector is presented to the network and intermediate results propagate forward to yield the output vector. The difference between the target and the network outputs represents the error. The error is then propagated backward through the network, and the weights and biases are adjusted to minimize the error in the next round of prediction. The iteration continues until the error goal (tolerable error) is reached. It should be noted that a properly trained backpropagation network would produce reasonable predictions when it is presented with input not used in the training. This generalization property makes it possible to train a network on a representative set of input/output pairs, instead of all possible input/output pairs [23-25].

Many implementations of the backpropagation algorithm are possible. In the present study, the Levenberg-Marquart algorithm is adopted for its efficiency in training networks [24-26]. This implementation is readily available in the popular software Matlab and its neural network toolbox [24]. In this study, ANN is treated as an analysis tool.

Experimental Results and Discussions

The Superpave method of mix design was used to determine the optimum binder contents of various mixtures. After conditioning the samples for 1 day and 7 days, mixes with hydrated lime gave the highest wet *ITS*, as shown in Fig. 3. They were followed by mixes with the liquid ASAs. The control treatment was the least effective. After 28 days of conditioning, no general trend was observed. It was

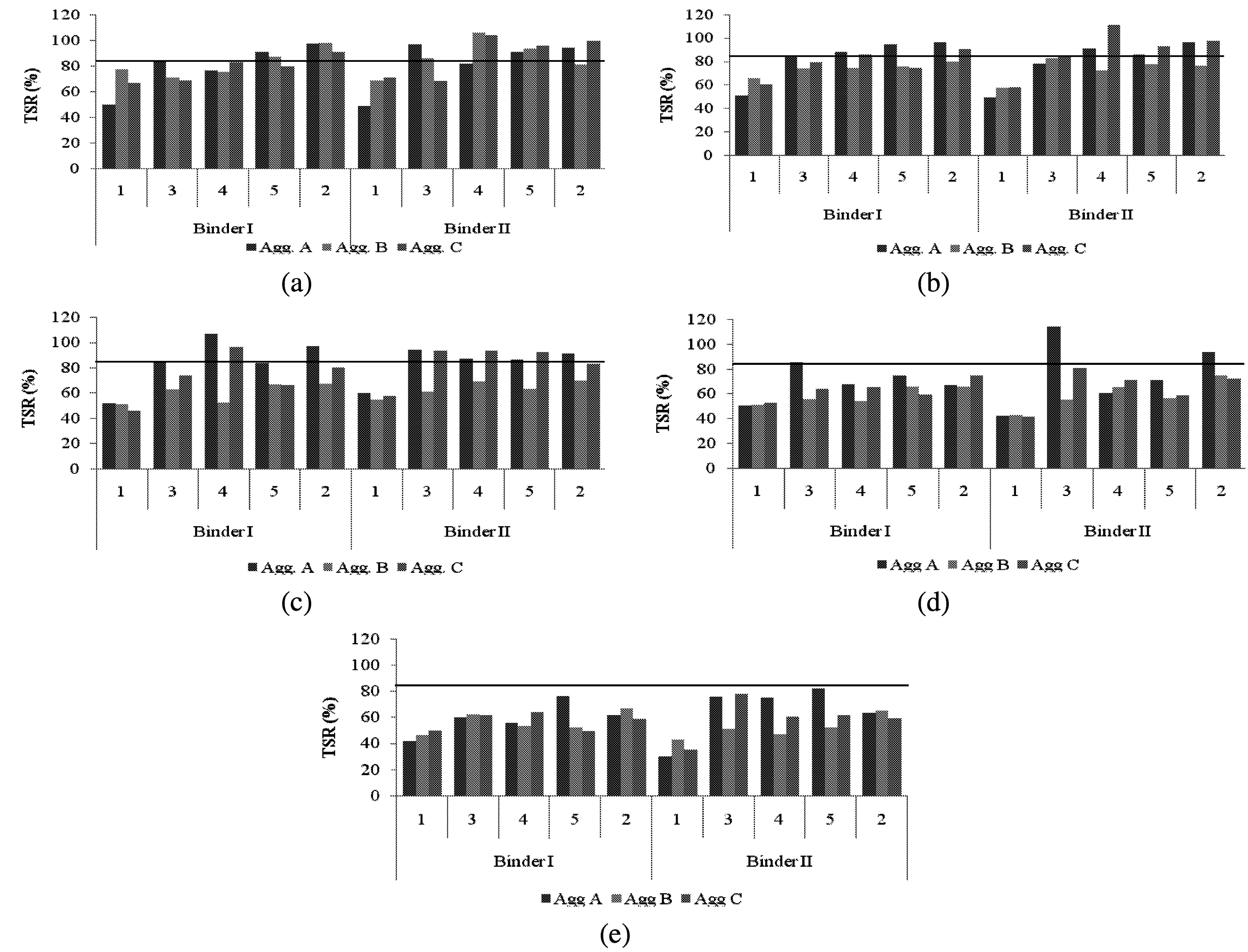


Fig. 4. *TSR* of the Samples at Different Conditioning Durations in (a) 1, (b) 7, (c) 28, (d) 90, and (e) 180 Day(s).

observed that certain aggregate/ASA or binder/ASA or aggregate/binder/ASA combinations work better than others. In general, hydrated lime seemed to be the most effective ASA. For longer durations of conditioning, namely 90 and 180 days, it can be noted that mixes with hydrated lime and the liquid ASAs were equally effective, and performed better than mixes with no ASA treatment. A similar set of ANOVA tests, at the 5% significance level, were performed on the *TSR* values of the samples (Fig. 4). Based on these results, it was observed that mixes with hydrated lime and the liquid ASAs gave similar *TSR* values when conditioned in water for durations beyond 1 day. After conditioning the samples for 1 day, mixes with hydrated lime gave the highest *TSR* values, followed by the liquid ASAs with no significant difference in their effectiveness, then followed by the control treatment. The horizontal line in Figs. 3 and 4 referred to a minimum required *ITS* value of 448*kPa* and *TSR* value of 85%, respectively.

As shown in Fig. 3, in most cases, it was observed that mixes with aggregate source B gave the highest wet *ITS* after all conditioning durations. Mixes with aggregate sources A and C followed with no significant difference in their mean wet *ITS* values after all conditioning durations. As far as the effect of the aggregate source on the *TSR* of mixes was concerned (Fig. 4), there was no significant difference in the values of the mean *TSR* for mixes with different aggregate sources. This was the case at 1 day as well as at 7 days. However, at 28 days, mixes with aggregate source B showed significantly lower *TSR* values compared to the other aggregate sources. This may be explained due to the reason that mixes with aggregate source B showed exceptionally higher dry *ITS* compared to the mixes with other aggregate sources. After longer durations of conditioning (90 and 180 days), there was no significant difference in the *TSR* values of the mixes with different aggregate sources.

Fig. 3 indicates that the mixes with binder I generally gave higher wet *ITS* at 1 day, except in the case of mixes with aggregate source B, where the mean strengths of mixes with both binders were not significantly different. After other conditioning durations, there was no significant difference in the mean wet *ITS* of the mixes with either binder source. In addition, Fig. 4 shows that the binder source did not seem to have any effect on the *TSR* values of the mixes used in this research after all conditioning durations.

ANN Model

Table 3. Sample Training and Testing Data of *ITS* Samples.

No.	B_S type	A_S type	A_T type	A_D days	A_C (%)	ITS_D *kPa*	ITS_W *kPa*	*TSR* (%)
1	1	1	1	1	5.8	754	400	53
2	1	1	1	1	5.8	829	398	48
3	1	1	2	1	5.9	845	717	85
4	1	1	2	1	5.9	810	679	84
5	1	1	3	1	5.9	892	636	71
6	1	1	3	1	5.9	821	681	83
7	1	1	4	1	5.7	718	656	91
8	1	1	4	1	5.7	731	669	92
9	1	1	5	1	5.7	917	834	91
10	1	1	5	1	5.7	749	799	107
11	2	1	1	1	4.6	686	366	53
12	2	1	1	1	4.6	690	307	45
…	…	…	…	…	…	…	…	…
61	1	1	1	7	5.8	792	436	55
62	1	1	1	7	5.8	794	375	47
63	1	1	2	7	5.9	767	638	83
64	1	1	2	7	5.9	763	651	85
65	1	1	3	7	5.9	766	653	85
…	…	…	…	…	…	…	…	…
121	1	1	1	28	5.8	868	406	47
122	1	1	1	28	5.8	722	413	57
123	1	1	2	28	5.9	859	641	75
124	1	1	2	28	5.9	743	710	96
125	1	1	3	28	5.9	639	690	108
…	…	…	…	…	…	…	…	…
238	2	3	4	90	5.7	820	492	60
239	2	3	5	90	5.3	886	634	72
240	2	3	5	90	5.3	831	606	73
…	…	…	…	…	…	…	…	…
298	2	3	4	180	5.7	883	513	58
299	2	3	5	180	5.3	917	523	57
300	2	3	5	180	5.3	843	514	61

Note: B_S= binder source; A_S= aggregate source; A_T= ASA type; A_D =conditioning duration; A_C =asphalt content; and ITS_D, ITS_W= dry and wet indirect tensile strengths, respectively.

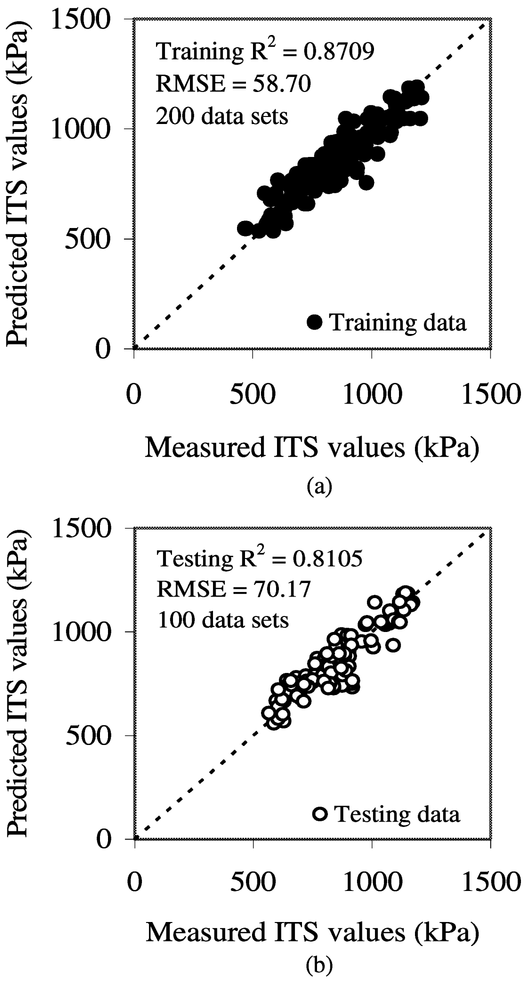


Fig. 5. Predicted and Measured *ITS* Values of ANN for Dry Samples, (a) Training and (b) Testing Data Set.

Statistical analysis results indicated that the developed multi linear and non-linear regression models only provided a poor prediction of *ITS* and *TSR* values, thus these models were not used for prediction. The measured *ITS* values of the testing specimens were used to develop the ANN models. The original dependent and independent data of the *ITS* values were categorized in accordance with the specimen conditions (wet or dry). In this ANN model study, binder sources I and II were referred to as 1 and 2, respectively. Aggregate sources A, B, and C were denoted as 1, 2 and 3, respectively. For anti-stripping agents, the control, lime, and three liquid agents were referred to as 1, 2, 3, 4, and 5, respectively. The independent variables of ANN models included only five basic input variables (i.e., asphalt binder source, aggregate source, anti-stripping additive, conditioning duration, and asphalt content). The dependent variables were selected to be the *ITS* and *TSR* values. Each of 300 dry *ITS* values and 300 wet *ITS* values were employed to develop the *ITS* and *TSR* ANN models. Among 300 data sets, 200 were selected asthe training data set, and the other 100 were used as the testing data set. The sample training and testing data sets are shown in Table 3. The overall ANN models used a goal error of 0.00001 and an epoch of 1000 in this study. The sampling process is largely random, since no effort was made to keep track of the characteristics of input and output variables. While randomness in the data selection was largely maintained, the training data set is believed to be representative [27].

The developed ANN model, expressed in terms of the connection weights and biases in the three-layer topology, can then be used to predict *ITS* and *TSR* values for any given set of data (B_S, A_S, A_T, A_D, and A_C) using Eq. (1). Note that Eq. (1) can easily be implemented in a spreadsheet for routine applications. The spreadsheets for dry *ITS* and wet values are shown in Tables 4 and 5, respectively. While time consuming to develop the ANN models, use of the ANN-based spreadsheet model to calculate *ITS* value is simple and rapid in execution. Figs. 5 and 6 show the results obtained from the ANN models (in the form of Eq. (1)) for the dry and wet *ITS* values, respectively. As shown in Fig. 5, the R^2 values of ANN dry *ITS* model are 0.8709 and 0.8105 for training and testing data sets, respectively. The RMSE values of this model are 58.70 and 70.17*kPa* for two data sets. Fig. 6 indicates that, for wet *ITS* model, the R^2 values of training and testing data are 0.8709 and 0.7931, and their RMSE values are 46.07 and 63.56*kPa*. Based on a minimum wet *ITS* value of 448*kPa* (South Carolina Department of Transportation specification), it can be noted that some of wet *ITS* values are less than this value. As described previously, the control samples exhibit the *ITS* values less than 448*kPa* after a long term

Table 4. Spreadsheet of ANN Model for Dry *ITS* Samples.

1	A	B	C	D	E	F	G	H	I
2		COMMANDS OF EXECUTING EQ.1	Hidden Layer						
3		ARGUMENT("B_S", "A_S", "A_T", "A_D", "A_C")	Weight matrix	Hidden 1	Hidden 2	Hidden 3	Hidden 4	Hidden 5	Hidden 6
4			Bias	16.780	322.217	2.450	-3.183	20.886	-2.222
5		$B_S=(B_S-0.875)/1.25$; $A_S=(A_S-0.75)/2.5$	Input 1	55.889	-226.025	6.360	10.812	2.778	-6.480
6		$A_T=(A_T-0.5)/5$; $A_D=(A_D-21.375)/223.75$	Input 2	-64.432	-142.517	-8.262	4.357	-41.706	8.600
7		$A_C=(A_C-4.1)/2$	Input 3	-122.166	-40.763	1.547	-8.359	-0.955	-1.929
8			Input 4	-130.961	-58.980	1.840	4.928	-20.872	-1.799
9		$pi1=1/(1+EXP(-(\eta*D\$5+S_b*D\$6+B*D\$7+ITS*D\$8+$	Input 5	69.351	-235.729	-0.793	-4.193	9.935	0.207
10		$M_R*D\$9+D\$4)))$							
11		$pi2=1/(1+EXP(-(\eta*E\$5+S_b*E\$6+B*E\$7+ITS*E\$8+$							
12		$M_R*E\$9+E\$4)))$							
13		$pi3=1/(1+EXP(-(\eta*F\$5+S_b*F\$6+B*F\$7+ITS*F\$8+$							
14		$M_R*F\$9+F\$4)))$							
15		$pi4=1/(1+EXP(-(\eta*G\$5+S_b*G\$6+B*G\$7+ITS*G\$8+$							
16		$M_R*G\$9+G\$4)))$	Output Layer						
17		$pi5=1/(1+EXP(-(\eta*H\$5+S_b*H\$6+B*H\$7+ITS*H\$8+$	Bias	-46.325					
18		$M_R*H\$9+H\$4)))$	Hidden 1	0.948					
19		$pi6=1/(1+EXP(-(\eta*I\$5+S_b*I\$6+B*I\$7+ITS*I\$8+$	Hidden 2	-0.848					
20		$M_R*I\$9+I\$4)))$	Hidden 3	49.023					
21		Z=pi1*D18+pi2*D19+pi3*D20+pi4*D21+pi5*D22+	Hidden 4	-1.735					
22		pi6*D23+D17	Hidden 5	-1.456					
23		Z=1/(1+EXP(-Z))	Hidden 6	46.577					
24		Ln(F)=54.18*Z+134.89							
25		RETURN (F)							

Weight matrix:
Cells D4: I4 are B_{HK}
Cells D5: I9 are W_{ik}

Weight matrix:
Cell D17 is B_o
Cells D18: D23 are W_{ik}

Cells B3:B25 are macro commands to execute Eq.1

Table 5. Spreadsheet of ANN Model for Wet *ITS* Samples.

1	A	B	C	D	E	F	G	H	I
2		COMMANDS OF EXECUTING EQ.1	Hidden Layer						
3		ARGUMENT("B_S", "A_S", "A_T", "A_D", "A_C")	Weight matrix	Hidden 1	Hidden 2	Hidden 3	Hidden 4	Hidden 5	Hidden 6
4			Bias	-43.658	11.526	1.433	-81.701	4.664	-4.207
5		$B_S=(B_S-0.875)/1.25$; $A_S=(A_S-0.75)/2.5$	Input 1	36.377	-19.431	0.525	-38.175	-17.342	0.579
6		$A_T=(A_T-0.5)/5$; $A_D=(A_D-21.375)/223.75$	Input 2	7.376	-0.666	-5.083	-59.097	7.392	2.608
7		$A_C=(A_C-4.1)/2$	Input 3	4.280	-1.720	-21.924	151.677	4.291	3.252
8			Input 4	0.007	-0.041	1.114	55.273	0.003	-3.927
9		$pi1=1/(1+EXP(-(\eta*D\$5+S_b*D\$6+B*D\$7+ITS*D\$8+$	Input 5	2.669	-0.661	4.103	-46.789	2.680	0.630
10		$M_R*D\$9+D\$4)))$							
11		$pi2=1/(1+EXP(-(\eta*E\$5+S_b*E\$6+B*E\$7+ITS*E\$8+$							
12		$M_R*E\$9+E\$4)))$							
13		$pi3=1/(1+EXP(-(\eta*F\$5+S_b*F\$6+B*F\$7+ITS*F\$8+$							
14		$M_R*F\$9+F\$4)))$							
15		$pi4=1/(1+EXP(-(\eta*G\$5+S_b*G\$6+B*G\$7+ITS*G\$8+$							
16		$M_R*G\$9+G\$4)))$	Output Layer						
17		$pi5=1/(1+EXP(-(\eta*H\$5+S_b*H\$6+B*H\$7+ITS*H\$8+$	Bias	-1.890					
18		$M_R*H\$9+H\$4)))$	Hidden 1	1908.108					
19		$pi6=1/(1+EXP(-(\eta*I\$5+S_b*I\$6+B*I\$7+ITS*I\$8+$	Hidden 2	1907.656					
20		$M_R*I\$9+I\$4)))$	Hidden 3	-4.397					
21		Z=pi1*D18+pi2*D19+pi3*D20+pi4*D21+pi5*D22+	Hidden 4	0.833					
22		pi6*D23+D17	Hidden 5	-1905.484					
23		Z=1/(1+EXP(-Z))	Hidden 6	2.844					
24		Ln(F)=14.62*Z+135.13							
25		RETURN (F)							

Weight matrix:
Cells D4: I4 are B_{HK}
Cells D5: I9 are W_{ik}

Weight matrix:
Cell D17 is B_o
Cells D18: D23 are W_{ik}

Cells B3:B25 are macro commands to execute Eq.1

conditioning (e.g 90 and 180 days). In comparison with the two developed ANN models (dry and wet), a similarly accurate prediction can be made.

Similarly, the ANN *TSR* models of the specimens were implemented in accordance with Eq. (1). The comparisons of the measured and predicted *ITS* and *TSR* values are shown in Fig. 7. It

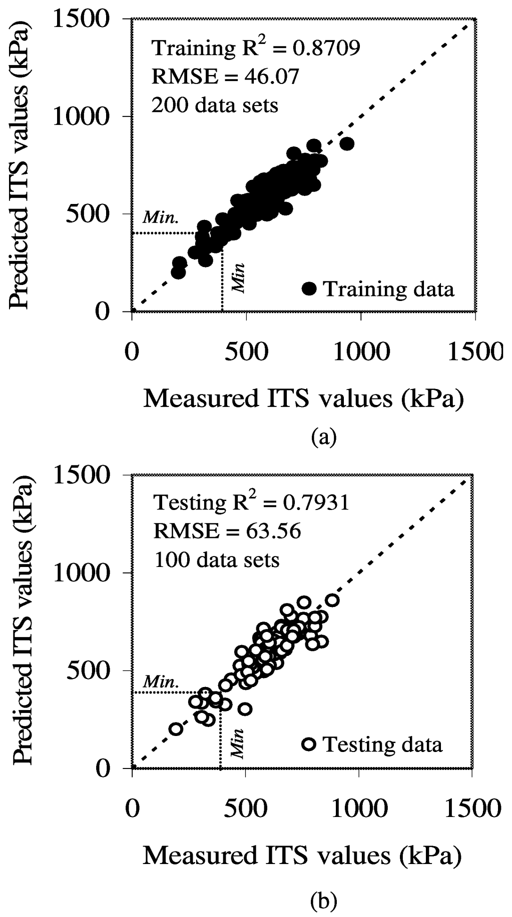


Fig. 6. Predicted and Measured *ITS* Values of ANN for Wet Samples, (a) Training and (b) Testing Data Set.

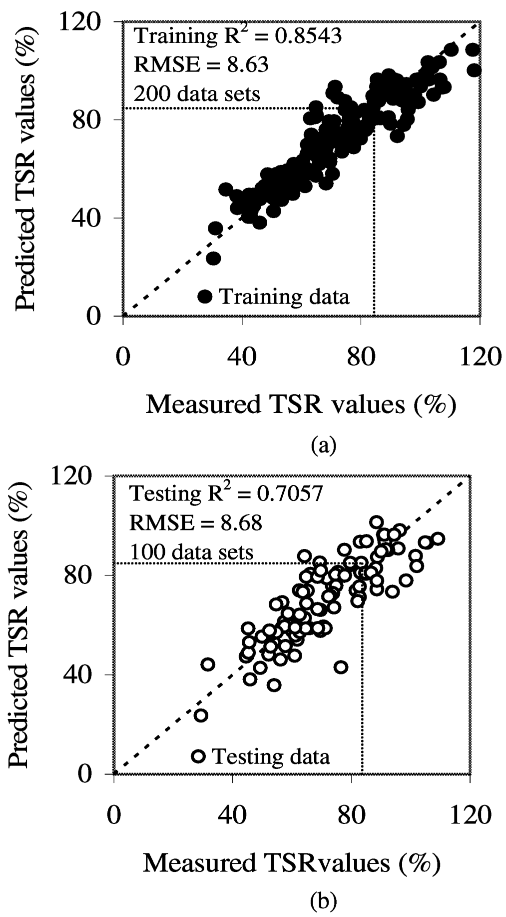


Fig. 7. Predicted and Measured *TSR* Values of ANN, (a) Training and (b) Testing Data Set.

can be noted that this ANN model has the R^2 values of 0.8543 and 0.7057 for training and testing data sets while their RMSE values are 8.63 and 8.68*kPa*, respectively. Although different materials and testing conditions were used in the project, the predicting performance of the trained neural network, as shown in Figs. 5 and 6, is considered satisfactory.

Sensitivity analysis of ANN model

Due to highly complex and non-linear form of analysis of ANN, additional sensitivity analysis was conducted to estimate the impact of input variables on the output. During sensitivity analysis process, one input parameter was changed slightly (approximately ± 5 to 10%) from the initial condition, while the remaining parameters were kept constant. The predicted performance *ITS* values were then determined. Further modification of the parameter consequently yielded increases/decreases in the predicted performance *ITS* values. This process was repeated for all input variables or modifications. Otherwise, the descriptive input variables (e.g., binder source, aggregate source, and ASA type) used 100% as a gap for switching these material types in this study. The five input variables (B_S, A_S, A_T, A_D, and A_c) were considered in the sensitivity analysis of the performance model for the mixtures at dry and wet conditions. Figs. 8 and 9 are plotted on axes depicting relative changes in both input and output parameters. The output variable data set was segregated into several groups regarding predicted and measured results during plotting the trend curves. This segregation of expected ranges of performance temperatures illustrates the non-linearity of the proposed models and the performance of the output at various *ITS* and *TSR* values. For example, the dry *ITS* values were categorized as $ITS_D < 628kPa$, $ITS_D = 628\text{-}1034kPa$, and $ITS_D > 1034kPa$ based on the scope of the measured values. The changes of the input variable values were dependent on their categories. This method facilitates visualization of the relationship between input and corresponding output (i.e., a relative change in an input parameter yields a relative change in the performance *ITS* value) [28].

As shown in Figs. 8 and 9, the input variables show that the changes of input variables result in the changes of output values for the specimens tested in dry and wet conditions. The linear trends were also studied for sensitivity analysis of each input variable. In this study, the asphalt binder source, aggregate sources, and anti-stripping agents, the describing input variables, were designated as the whole number, thus the interval changes of them were 100%. Fig. 8(a) indicates that the change of binder source yields a noticeable percent change of the *ITS* value. For the conditioned specimens, their *ITS* values also change slightly as the asphalt binder source changes (Fig. 9(a)). As described previously (Fig. 3), the same conclusion that the binder source slightly affects the *ITS* value is obtained as using ANN model sensitivity analysis. These relationships are considered likely due to the variation in physical

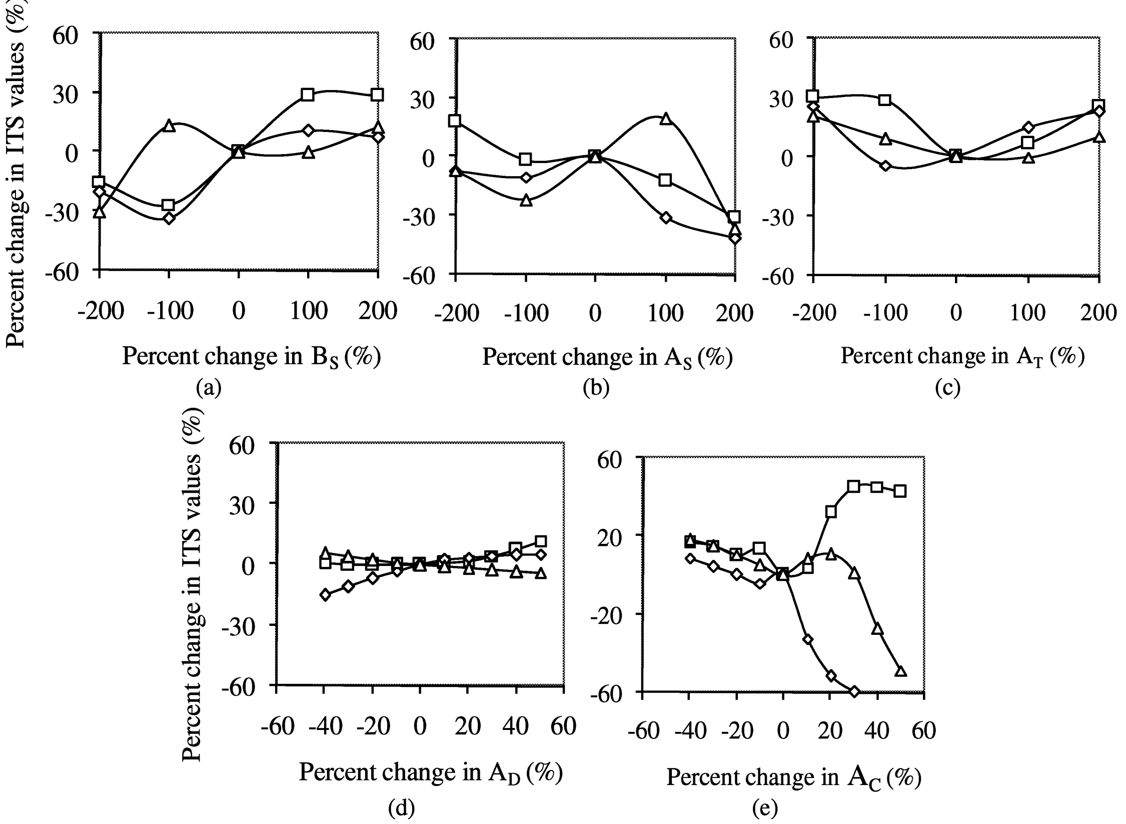
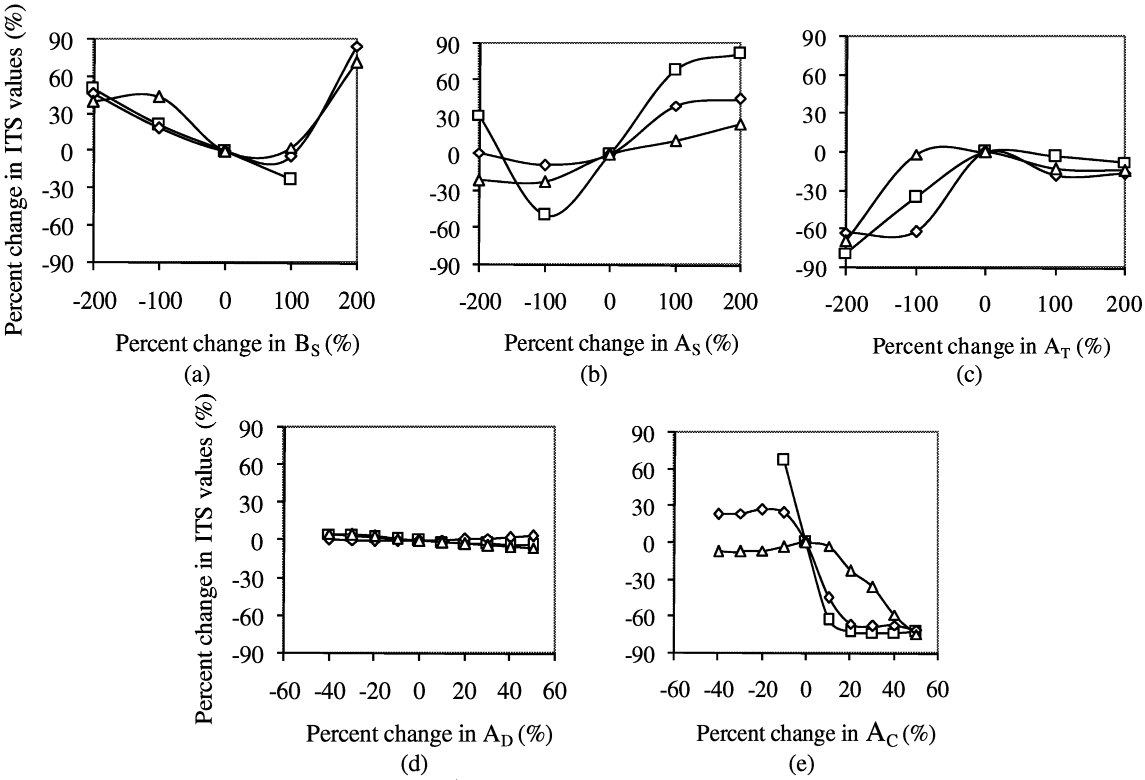


Fig. 8. Sensitivity Analysis of ANN for Dry *ITS* Samples, (a) Asphalt Binder Source; (b) Aggregate Source; (c) ASA Types; (d) Conditioning Duration; (e) Asphalt Content.



0-628*kPa*(100*psi*); 628-1034*kPa* (150*psi*); >1034*kPa* (150*psi*)

Fig. 9. Sensitivity Analysis of ANN for Wet *ITS* Samples, (a) Asphalt Binder Source; (b) Aggregate Source; (c) ASA Types; (d) Conditioning Duration; (e) Asphalt Content.

and chemical properties of binder sources at the various mixing conditions.

Similar to asphalt binder sources sensitivity analysis, aggregate sources obviously affect the *ITS* values of mixtures regardless of the conditions of the specimens. As shown in Figs. 8(b) and 9(b), the increase or decrease of percent change in the aggregate sources (i.e., various aggregate sources) resulted in an increase or decrease in percent change of the *ITS* values only means the change of *ITS* values due to the various aggregate sources. It seems that these various aggregate sources are able to affect the *ITS* values of the mixtures influenced by their different physical and mechanical engineering properties.

Figs. 8(c) and 9(c) present results of the sensitivity analysis on the anti-stripping agents of the mixtures performed in this study for dry and wet specimens, respectively. The results indicate that the change of the anti-stripping agents is related to a remarkable change in the magnitude of the mixture *ITS* value for three categories regardless of their testing conditions. Similarly, the increase or decrease in *ITS* percent is only as a result of the use of different ASA.

As shown in Figs. 8(d) and 9(d), the sensitivity analysis of conditioning duration shows that the percent change of *ITS* values is slight as the percent change of conditioning duration increases from -60% to 60% for three categories regardless of the dry or wet specimens. It can be noted that the short-term conditioning duration does not noticeably affect the *ITS* values.

The percent change of asphalt binder content in the mixture significantly affects the percent change of *ITS* values regardless of the testing conditions. In most cases, Figs. 8(e) and 9(e) indicate that the increase of asphalt binder content results in a decrease of *ITS* values.

Important index analysis of ANN model

Yang and Zhang [29] suggest that the relative strength of the effect of an input variable on the output can be derived based on the weights stored in the network. They define the relative strength of effect (RSE) for each input variable on each output variable. The equation is expressed as follows.

$$RSE = c\sum_{in}\sum_{in-1}\ldots\sum_{i1} W_{ik}G(\lambda_k)W_{i_n-1^{i}{}_nG(\lambda_{in})\ldots W_{i_1i_2}G(\lambda_{i1})} \tag{3}$$

Where

c = a normalized constant;

$G(\lambda_k) = \exp(-\lambda_k)/(1+\exp(-\lambda_k))^2$;

W_{ik} = weight of the connection between input variable i and neuron k of the hidden layer;

$\lambda_k = \sum_i f_T W_{ik} + B_k$;

B_K = bias at neuron k of the hidden layer; and

f_T = transfer function.

The important indices for the five input variables, B_S, A_S, A_T, A_D, and A_c, were obtained from Eq. (3) and are shown in Fig. 10. However, these weights should be viewed only as a rough estimate, as they are determined based on the same assumption that only one input variable at a time is allowed to vary although the developed ANN is highly nonlinear [30].

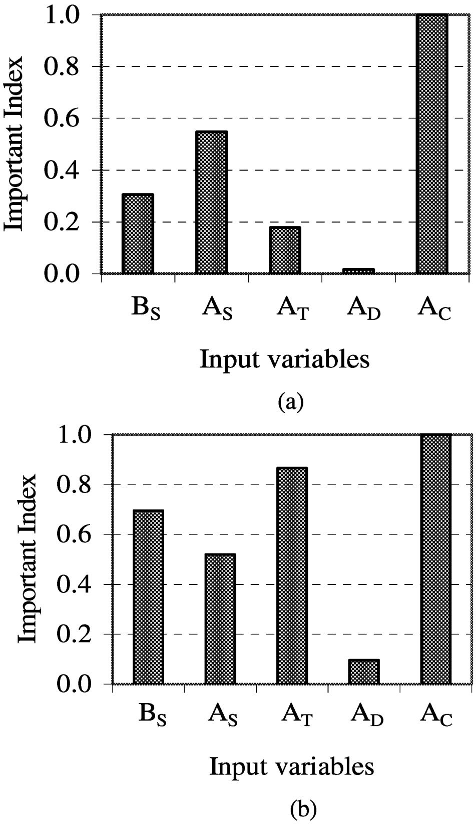


Fig. 10. Important Indices of Input Variables in ANN Model, (a) Dry *ITS*; (b) Wet *ITS*.

Although two types of *ITS* specimens have the same most important index, asphalt binder content *(S_b)*, other independent variables exhibit different important indices due to moisture sensitivity. For dry *ITS* specimen, it can be noted that asphalt binder source (B_S) and aggregate source (A_S) are *relatively* more important, as shown in Fig. 10(a). Other independent variables like anti-stripping agent (A_T) and conditioning duration (A_D) are *relatively* unimportant as reflected in the behavior of the developed ANN. For the wet *ITS* specimens, as shown in Fig. 10(b), it can be found that several input variables such as asphalt binder source (B_S), aggregate source (A_S), and anti-stripping agent (A_T) are relatively more important while only the conditioning duration (A_D) is relatively unimportant (i.e., it has less effect on the *ITS* values in comparison with other variables). In comparison with the dry *ITS* specimens, as expected, anti-striping agents exhibit a relatively unimportant index in the wet *ITS* specimens. Thus, the anti-stripping agents are beneficial in improving the moisture resistance of the mixtures. The important index analysis indicates that the *ITS* value is strongly correlated with those relatively important indices and their test results can be used to predict the *ITS* values of the asphalt mixtures.

Validation of ANN model

The *ITS* values from other projects were employed to validate the developed ANN models. The five given input variable values were used with the developed ANN models to calculate the predicted *ITS* values and compared with the measured data. Fig. 11 shows the

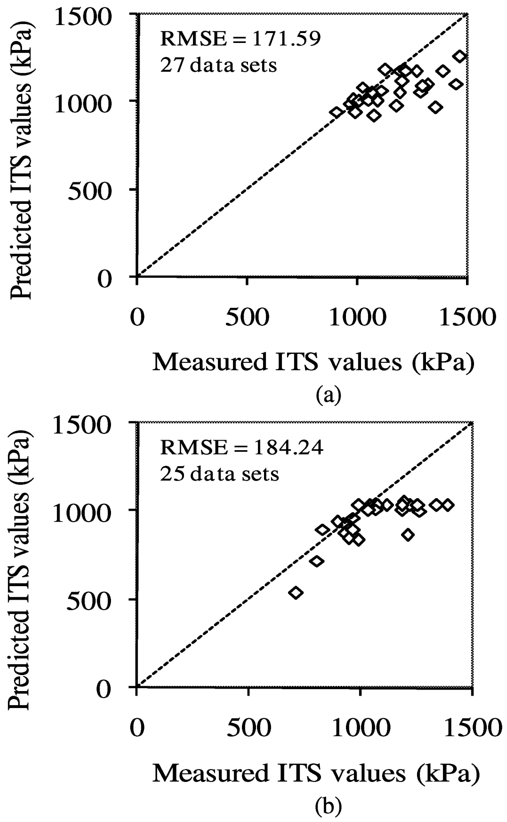


Fig. 11. Validation of ANN Model for (a) Dry *ITS* (b) Wet *ITS*.

measured values and those predicted values by the developed ANN models. The results generally show small differences between the predicted and measured *ITS* values of the mixtures for two types of testing conditions. For instance, the RMSE value of the ANN model for the dry *ITS* specimens is 171.59*kPa* and the data sets used for model validation is 27. The ANN model of wet *ITS* specimen has a RMSE value of 184.24*kPa* and used 25 data sets, which can be considered satisfactorily for the developed ANN.

Conclusions

The artificial neural network (ANN) is becoming a prevalent engineering tool for deriving data-driven predictive models, as the developed ANN can easily be implemented in a spreadsheet module for practical applications. Based on the analysis of the experimental data of the *ITS* values at two testing conditions, this study determined that:

1. The ANN approach, as a new modeling method used in this study, can effectively create a feasible predictive model using five variables from the binders and mixtures. The established ANN-based models could effectively and accurately predict the *ITS* and *TSR* values, as it is proven by higher R^2 and lower RMSE values regardless of the test conditions. These ANN models can easily be implemented in a spreadsheet, thus making it easy to apply.
2. The sensitivity analyses of five input variables indicated that, in most cases, the percent changes in input variables significantly affect the percent changes of the *ITS* values. The sensitivity of input variables is strongly related to the category of *ITS* values and the test conditions due to the moisture sensitivity properties of the asphalt mixtures at the various test conditions.
3. The important indices of five input variables could be calculated using the method developed by Yang and Zhang. The results show that the asphalt binder source, aggregate source, and asphalt binder content are the most important factors in the developed ANN models to predict *ITS* values regardless of test conditions, while anti-stripping agents is relatively unimportant in dry *ITS* model but is relatively important in wet *ITS* model. Moreover, it was found for the materials tested for this research that the conditioning duration is relatively unimportant for two types of *ITS* specimens as compared to the other four independent variables.
4. The developed ANN models could satisfactorily predict the *ITS* values as shown by validation results using the *ITS* values from other research projects

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