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Advanced ANN Prediction oF Moisture Damage in CNT Modified Asphalt Binder

Md Arifuzzaman[1*]

1. Assistant Professor, Department of Civil Engineering, University of Bahrain

* Corresponding author: *st100132@gmail.com*

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ABSTRACT

Moisture penetration causes many direct and indirect distresses in flexible asphalt pavement. Due to damage in asphalt concrete and binder by moisture are the prime concern of failure for flexible pavement worldwide. The causes and prediction are investigated in this study. The asphalt binder was modified with carbon nanotubes (CNT) with very small percentages. The modified binder was simulated with moisture damage with AASHTO T-283 methods. In this study, polymer and carbon nano-tubes (CNT) have been added to liquid asphalt binder to examine whether the resulting modified binder has improved moisture damage resistance. Using laboratory tested data, an artificial intelligence modeling technique has been utilized to determine the moisture damage behavior of the modified binder. Multi-Layer Perceptron (MLP) provides the best prediction for wet and dry samples AFM readings with R^2 values respectively 0.6407 and 0.8371.

1. Introduction

Asphalt binder has been used in roadway pavements since the early 1900's. The USA has nearly 3.2 million kilometers of pavement made of asphalt binder. Since the pavement is not impervious hence the water from various sources enters the pavement and consequently damage it. Nonetheless, the moisture damage occurs globally with the presence of water. In literature, asphalt pavement distresses are related to the moisture intrusion in asphalt roads. Four attributes, namely: the adhesive bond between the binder, cohesive resistance of binder, the frictional resistance between the aggregate particles and the aggregate interlock are related to pavement strength (Divito and Morris 1982).

Damage due to moisture in pavement causes loss of integrity of a Hot Mix Asphalt (HMA) mix through the weakening of the adhesion bond between the asphalt binder and aggregate via the act of water. This occurrence is well known as the stripping which eventually leads to the breaking of the aggregate-asphalt adhesion bond and finally direct towards the failure of flexible pavement. Moreover, asphalt binder may experience changes in strength, stiffness, and viscosity which refer to the cohesion in asphalt as a result of moisture related sensitivity of asphalt pavements (Epps Martin 2003).

Although the research scientist and practicing engineers are thriving to prolong the life of the nation pavement but till now due to lack of proper understanding of moisture interaction with asphalts, pavements are prone to early failure from the infiltration of moisture. Several distresses may occur individually and simultaneously inside pavement due to this moisture entrance. The water reduces the internal bonding strength which leads to fatigue cracking/rutting in pavements (Sebaaly 2007). Since damage starts from nano to micro level, current research aims to conduct binder testing at nano level using Atomic Force Microscopy (AFM). The AFM produced laboratory output data were finally modeled with three advanced artificial neural intelligence tools.

2. Background of Research

Moisture damage in asphalt pavements is one of the main and primary distresses which is associated with the fracturing of the pavement surface, permanent deformation and excessive cracking (Kutay et al. 2007). Some literature related to pavement distresses, and ANN related works are investigated and described below:

Gandhi et al. (2009) constructed ANN models to predict tensile strength ratio (TSR) and the indirect tensile strength (ITS) of various asphalt pavement mixtures considering 5 no. of input variables such as aggregate source, asphalt binder source, anti-striping agent (ASA), conditioning duration, and asphalt binder content. It is worth mentioning here that, ANN is a widely used computational tool that can identify the complex unknown relationship among the inputs and desired output to the system. The activity of an ANN was introduced following the activities of a biological brain. ANN-based pavement thickness determination in order to back-calculate the layer moduli was accomplished by Tarefder et al. (2015). Xiao et al. (2009) also incorporated ANN for prediction of the stiffness behavior of asphalt concrete in order to reuse reclaimed asphalt pavement materials.

Although, artificial neural network (emphasized on data science and data mining) is not new in civil engineering application (Flood and Kartam 1994). Mohammadhassani et al. applied ANFIS, ANN model to concrete deep beam experiment and analysis (Mohammadhassani et al. 2013). But for moisture damage in asphalt binder and concrete in pavement construction, modelling with artificial network and data science is a relatively new area. Not too many attempts can be found to model and investigate artificial data for modeling the moisture damage and associated effect in the asphalt pavement area.

Arifuzzaman and Hassan (2014) used SVR to predict the moisture damage in asphalt binder without adding CNT. Adham and Arifuzzaman (2014) used CNT to resist moisture damage. They did not accomplish modelling work with ANN. Amirkhanian et al. (2011) evaluated the rheological and engineering properties of different asphalt binder modified with various percentages of carbon nano particles (0.2%, 0.5%, 1.0%, and 1.5% by weight of the binder). They included in the experimental design of their study the utilization of three binder sources containing one type of nano particle (PG 64-22). Hassan (2015) used CNT and ANN to model moisture damage without application of Functional AFM tips (COOH, CH3, NH3 and OH groups) which are needed to predict the asphalt binder adhesion and cohesion forces. To the knowledge, this research is the first time attempt to model the moisture damage behavior with CNT modified asphalt binder with functionalized AFM probes.

3. Aim of the study

To make a good relationship for moisture damage study in carbon nanotubes (CNT) mixed asphalt binder, the research oriented specific objectives are proposed as:

1. Application of artificial neural network (i,e. SVM, ANFIS and MLP) on CNT modified asphalt binder

2. Model the large data set from moisture damage of asphalt binder using ANN, ANFIS and SVM.

3. To compare the performance of all models and to suggest the best one.

4.1. Test Matrix

In this experiment, very used small percentages of carbon nano tubes (CNT) were used in SB and SBS modified base asphalt binder. Both dry and wet samples were tested under AFM with functionalized tips (-CH3, NH3, -COOH, -OH and –Si3N4) to get 269 data point for force distance measurement. Three methods SVM, ANFIS and ANN were used several hundred times to model these 269 data points to achieve the perfect results. The description for CNT, SB and SBS additives are given below:

4.2. Materials and Additives

Base Binder: The base binder was collected from an oil-asphalt refinery commercial factory. Then SB, SBS and CNT were added to it according to the following discussions.

Description of polymer: Styrene-Butadiene (SB) polymer

This is a latex type polymer used to improve the elastic recovery as well as cohesive and adhesive properties of the pavement structures. In this experiment total 2 percentages (4% and 5%) by weight of SB polymer was mixed with the base binder (Arifuzzaman 2010).

Styrene-Butadiene-Styrene (SBS) polymer: Becker et al. (2001) described SBS to be the most preferable and used polymer to modify the base binder. In this experiment, total 2 percentages (4% and 5%) by weight of SBS polymer was mixed with the base binder.

Carbon Nano Tubes (CNT): Carbon nanotubes are structural as rolled-up graphite sheets having one end as capped. These type of tiny tubes may have single walls or multiple walls. The single-wall carbon nanotubes (SWNT), unlike carbon/graphite black, possess highly desirable mechanical, electrical and thermal properties (Ball 2001, Arepalli et al. 2001), with many potential applications in the computer, electronics as well as in aerospace industries. It is reported that the addition of a very small amount of carbon nanotube CNT (around 1%) by weight may increase both the compressive and the flexural strength as well as mechanical properties of civil engineering materials (Mann 2006). Our research found very few attempts to use CNT with asphalt binder for improvement (Al-Adham and Arifuzzaman 2014; Tarefder and Arifuzzaman 2016). In this study, Single Wall (0.5%, 1.0% and 1.5%) CNT were used to resist moisture damage in asphalt binder.

4.3. Sample Preparation

The moisture damage in field was simulated in laboratory sample of the asphalt binder (AASHTO T-283 method). In this method the asphalt samples were conditioned under freezing and thawing environment for several days. Thus the wet samples were ready for AFM testing. Dry samples were usual samples without any interference of water.

5. Modelling Moisture Damage Data with Artificial Intelligence (AI) Approaches

The input values for ANN were Condition (dry and wet), percentages of SB and SBS polymer mixed with the base binder, percentages of CNT, AFM tips type (COOH, CH3, NH3, OH and Si3N4). The output result value was AFM experimental output as adhesion/cohesion force in terms of nano-newton in asphalt binder.

Statistical analysis of the data set are shown in Table 1.

The statistical analysis of the AFM laboratory generated data is shown in Table 1. The standard deviation value tells the necessity of artificial intelligence modeling of the highly deviated values from the standard one. The Kurtosis values of the data indicate that all the AFM produced data are less outlier prone than that of the normal distribution of the data.

Table 1. The statistical analysis of data used for the study

	Dry	Wet
Maximum	382.51	405.01
Minimum	41.95	106.45
Mean	168.4945	225.7373
St Dev	88.48392	80.15665
Kurtosis	0.360758	-0.996740
skewness	1.13887	0.50977

To model the 269-data set from AFM run test a total of three advanced ANN was used in this research. The ANN modelling work was accomplished in this study be splitting data set into two subsets: training set (80%) and validation set (20%). In order to train the NN system for tracing the complex and the nonlinear relationships between output and input values the training data set was utilized. The stopping criterion (trials and error) helps prevent the overfitting in ANN. The forecasting ability of the network was tested with 20% ANN dataset. One of the key concern in the NN architecture selection are the hidden layers as well as the number of nodes in each one of them. It may depend on complex relationship which need to be addressed further (Lefteri and Robert 1997). It also requires several trial-error as well as good selective judgment for appropriate ANN architecture which is the best suited for the concerned data set.

The brief description of the three systems are described below:

5.1. Adaptive Network Fuzzy Inference System (ANFIS)

This special ANN was proposed by Jang (1993). It serves as basic function to construct Fuzzy Interference System (FIS) and if-then formulated rules. More precisely, the ANFIS combines both neural network and fuzzy system from the best attributes and characteristics point of view. It can be successfully applicable to many real-life problems which are complicated for modelling work such as highly nonlinear function, for identifying nonlinear components in control type of systems, foresee-disorder time series etc. ANFIS description can be found more in details in Jang (1993).

5.2. Support Vector Machines (SVM)

SVM was proposed by Cores and Vapnik (1995). This simulation tool is best suitable outcome based geometric hyper-plane function for special separating data points. In this technique, the input data are mapped in highly dimensional characteristics space. The main and critical shortcomings of SVM are the duration for runtime and accuracy issues.

5.3. MLP based Artificial Neural Network (ANN)

This process can be described as the human brain performing computational programming which simulates the data learning and predicting tasks. One of the most popular used in this study is Multi-Layer Perceptron (MLP) which has vast applicability in pattern recognition and identification, speech recognition, control systems, petroleum engineering etc. (Agatonovic-Kustrin and Beresford 2000). Hence the MLP based process can be used for novel and efficient system for computational efficiency.

The overall flow diagram for the above mentioned methods is shown in Figure 1.

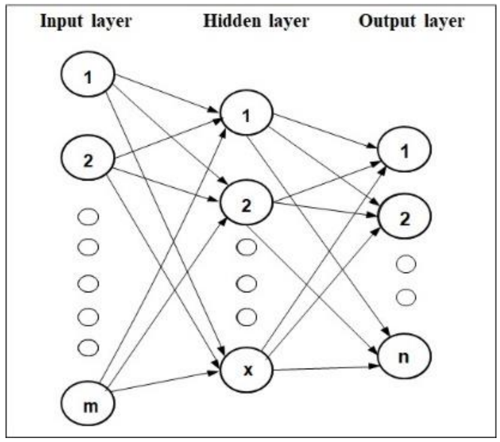

Fig a. ANN

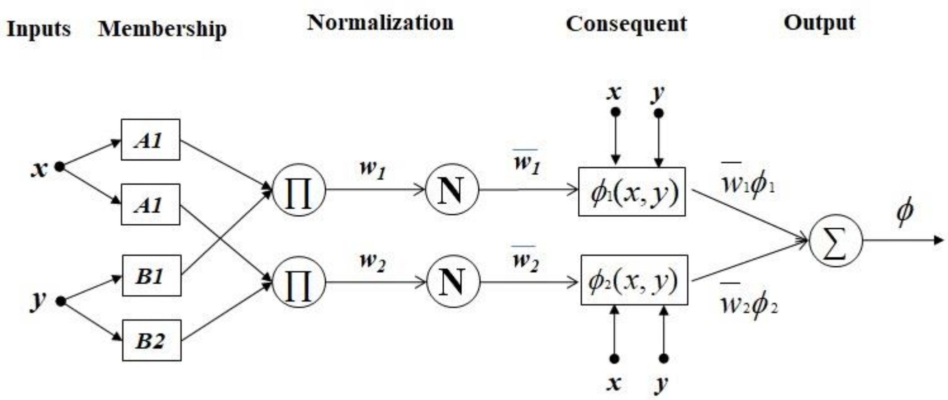

Fig b. ANFIS

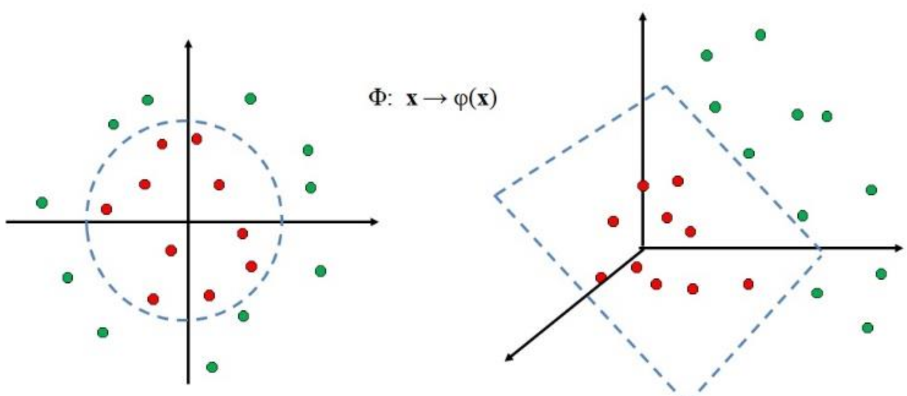

Fig c. SVM

Figure 1 Schematic of an ANN (Figure a), ANFIS) (Figure b) and SVM (Figure c) models

6. Analyses of Experimental Data

The data Table 2 and Table 3 show the analysis summary of the dry and wet samples with the above three mentioned method with respect to the six measured performances as:

Table 2. Dry Samples Results

	SVM		ANFIS		MLP	
	Train (80%)	**Test (20%)**	**Train (80%)**	**Test (20%)**	**Train (80%)**	**Test (20%)**
RMSE	16.2117	42.9149	38.4550	36.8155	29.5374	34.8987
CC	0.9810	0.7567	0.8476	0.8161	0.9149	0.8386
MAPE	7.2659	31.2811	18.6932	24.0868	14.9529	20.8287
NRMSE	0.2227	0.6672	0.5282	0.5724	0.4057	0.5426
MAPE (/100)	0.0727	0.3128	0.1869	0.2409	0.1495	0.2083
MAE	10.3951	30.0103	26.6549	29.8941	22.5585	25.4221
SD Error	0.2714	6.3164	1.8757	3.6325	2.9787	1.1294
AOC	9.99340322	27.314005	25.8901	28.4880	22.1676	23.6528
Time (Sec)	0.780005	0.0156	0.6240	0.0156	5.6472	0.0000
MRE	7.2659	31.2811	18.6932	24.0868	14.9529	20.8287

Table 3. Wet Samples Results

	SVM		ANFIS		MLP	
	Train (80%)	**Test (20%)**	**Train (80%)**	**Test (20%)**	**Train (80%)**	**Test (20%)**
RMSE	36.6028	48.7577	30.5458	54.7252	31.0656	46.2332
CC	0.9078	0.7723	0.9368	0.7563	0.9373	0.8004
MAPE	11.1859	17.4761	12.8757	18.7533	12.5359	19.0857
NRMSE	0.4175	0.6254	0.3484	0.7019	0.3543	0.5930
MAPE (/100)	0.1119	0.1748	0.1288	0.1875	0.1254	0.1909
MAE	22.7841	37.5612	24.0691	39.9564	24.0460	37.6852
SD Error	0.8901	2.2477	0.7049	1.2707	0.2676	2.0414
AOC	22.1674	35.4661	23.5699	37.5300	23.5184	35.7585
Time (Sec)	0.8736056	0.0000	0.6240	0.0156	2.8704	0.0000
MRE	11.1859	17.4761	12.8757	18.7533	12.5359	19.0857

The Correlation Coefficient (CC), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Relative Error (MRE) and Standard Deviation (SD) were calculated to investigate the accuracy of our utilized models. To find how much strong co-relation exists between the trend and the observed data, CC value is used. The value of CC "1" represents very much ideal co-relation exists while "0" means no co-relation can be predicted for the tested results. MAE is the measurement of the size of error while RMSE utilizes squaring mechanism to enlarge bigger error as well as suppressing smaller error. MAPE co-relates the magnitude of error to the magnitude of the observed real data.

For all cases, the performance of models was better for training datasets (80% samples) as compared to test datasets (20%) which are understandable. However, the variation between model performance for train and test datasets is more in case of dry samples as compared to wet samples. This could be because dry samples' data contains more variations/noise. Moreover, the performance measures of all models for error terms (RMSE, MAE, etc.) were higher for wet samples' test dataset while the relative error terms (MAPE) were lower for them. This could be because the magnitude of the dependent variable for wet samples was higher so the error term magnitude was higher corresponding to that. However, the performance of wet samples' models was better, which resulted in better relative error terms.

This experimental test analysis run is made with different values of dry and wet samples with SVM, MLP and ANFIS-FCM method. For dry samples, plot of predicted versus measured is developed in these three methods. Generated R^2 values and equations are shown through linear trend line in the corresponding graph plots for each method in Figures 2 and 3.

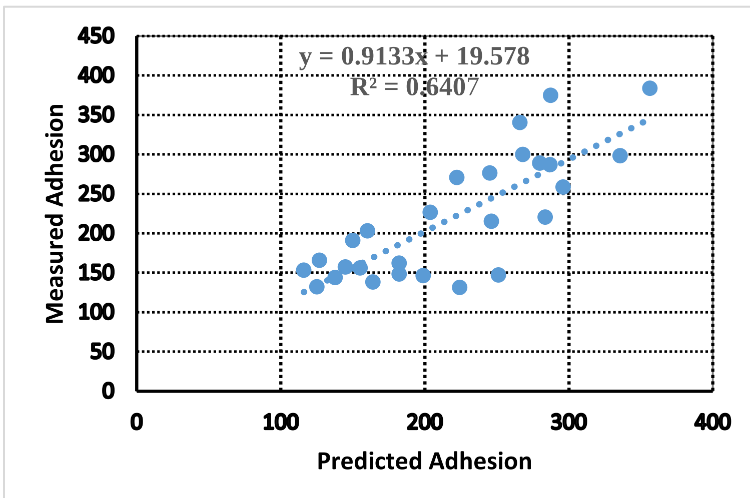

Figure 2 MLP result on Predicted vs Measured Data (Wet Samples)

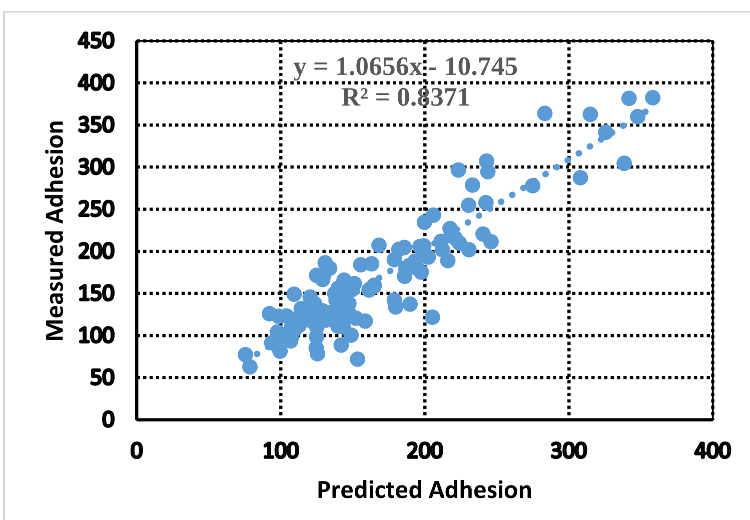

Figure 3 MLP result on Predicted vs Measured Data (Dry Samples)

The best two selected graphs out of sixteen are shown below based on the R^2 values. Plotting of wet material analysis through SVM, MLP & ANFIS has been created. For wet materials, generated R^2 values and equations are also shown through linear trend line in Figure 2 and 3.

The training and prediction time was calculated in terms of seconds in this study. The prediction time was very low for all the models, because it has comparatively small dataset and does not include any optimization algorithm as the model is already developed. Among the three methods for overall computation, MLP took the highest amount of time for training of both the dry and wet samples which was done for 80% of the total dataset. Hence, use of MLP on a large dataset cannot be recommended based upon these observations.

7. Discussion and Conclusion

The investigations provide a detail description of the test methods taking place for dry and wet samples. The measurement techniques & procedures are developed by a generation of linear trend line through the plotted points and comparing the R^2 value to find the efficient technique or procedures for the test of dry and wet samples.

Artificial neural network and related modeling (ANFIS, MLP and SVM) tools are used for the first time on AFM produced moisture damage data of CNT modified asphalt binder.

The conclusions drawn from the experimental and modelling work are listed below:

1. Neural network can address the complex relationship between adhesion and test variables incorporated in AFM testing. The developed NN model shows good prediction ability.

2. All models employed in this study, gave CC value more than 70% for all cases which is evident of their applicability for the prediction problem of this study. Moreover, the standard deviation of error was also relatively small for all models for training as well as prediction datasets which shows robustness of these models.

3. The study shows that MLP test for dry and wet sample produces convincing error terms with RMSE improvement of 2–8 units (approximately 3 – 5%) over SVM and ANFIS method.

4. So, it can be concluded with the promising fact that MLP procedure for dry (R^2 = 0.8371) and wet (R^2 = 0.6407) sample is more effective to predict real life moisture damage data.

5. Despite the above reasoning, it was also observed that MLP took longer training time than SVM and ANFIS. This could be due to optimization algorithm of MLP models; hence their applicability for large datasets should be further investigated.

8. Recommendation

The economic aspect, health consequences and availability of CNT utilization in road and highways are recommended for further investigation.

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