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ORIGINAL ARTICLE

Moisture damage evaluation in SBS and lime modified asphalt using AFM and artificial intelligence

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Abstract Damage due to moisture in polymer modified asphalt pavements has been investigated for several decades; yet, the exact and mathematical causes of moisture are not precisely known. Nanoscale experiment has been conducted in this study with an atomic force microscopy (AFM) to determine these effects in terms of adhesive and cohesive forces. A base asphalt binder and one polymer styrene–butadiene–styrene (SBS) were utilized to modify asphalt binders, which was used to prepare sample for testing on glass substrates under AFM. The asphalt samples were conditioned under wet and dry conditions. Current study formulates an artificial intelligence rule which predicts the moisture damage relation in lime and SBS modified asphalts. Base asphalt binders have shown larger adhesion/cohesion values compared to the polymer modified asphalt samples under dry conditions. However, this trend is opposite under wet conditions. Base binders are more susceptible to moisture damage than the polymer modified asphalt binders. ANFIS model (as compared to MLP and SVM) was found to be very promising in these points. The mean relative error was very low 0.02 and 0.03, respectively, for projected and observed data, which also showed the steady performance of the model. Statistical analysis was also performed for dry sample by executing of the three neural network models and found MLP's performance was very good to other two models.

Keywords Atomic force microscopy · Adhesion forces · Functionalized tips · Moisture · Damage model · Artificial neural network

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1 Introduction

Moisture damage in asphalt concrete which is a universal problem may cause in two different ways. One is from the inside of the asphalt binder, and the other one is at the interface between asphalt and aggregate. In the first type, water action weakens or damages the adhesion bonding within the asphalt binder. In the second type, asphalt binder peels off the surface of aggregate due to moisture action which is known as stripping. Lottman [1] discovered that the stripping of pavements in asphalt concrete is a major drawback which is experienced by over 50 % of the agencies of state highways in the USA. Transportation Research Board seminar reported that the application of an antistripping agent is being utilized in hot mix asphalt concrete by almost 82 % of highway agencies [2]. Currently, almost all the state DOTs use some antistripping agents in asphalt/bitumen binder. A tiny amount of antistripping agents could be mixed with asphalt binder to avoid stripping. At present, moisture damage of pavement is protected by using two different antistripping agents, such as lime (non-liquid) and chemical (liquid) [3]. Binder energy, or surface tension, or force of asphalt binder can usually be reduced by using antistripping agent. Application of antistripping agents is also found to modify the charge of the aggregate surface owing to adhere to or stick

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to the binder. In this study, the moisture-induced damages in asphalt binder and concrete are defined in two prime phenomena: the loss of adhesion and the loss of cohesion. Loss of adhesion, (also called stripping), is caused by the breaking of the adhesive bonds between the aggregate surface and the asphalt binder (aggregate–asphalt) which is primarily due to the water action as well as the water vapor [4, 5]. Loss of cohesion can be defined as the softening/breaking of the same material bonding within the asphalt binder system (asphalt–asphalt) due to water action or water diffusion [6].

Since damage in asphalt binder due to moisture is mainly related to chemistry of asphalt, the adhesion/cohesion characteristics are below the micron scale. This study evaluates the asphalt chemistry and adhesion values at the nanoscale in order to understand the moisture damage in antistripping modified asphalt binders. The nanoscale measurements were taken with an atomic force microscope (AFM), and then, the data were modeled using ANN.

2 Previous Study on Asphalt binder, Antistripping agents, and the Effective percentages

Most of the states department of transport recommend use of 0.5–1.0 % antistripping in all asphalt binders. A group of pavement professionals and researchers consider antistripping agents as caring to decrease moisture damage. However, there is debate among some other researchers whether antistripping agents can minimize moisture damage effects or not. Such inconsistency has been unsuccessful to come into conclusion by traditional macroscale strength test, for example AASHTO T283. Frequently, a mixture that is made by antistripping agents or beyond is being proved to pass laboratory AASHTO T283 test but failed in the real-life application. Macroscale experiment in laboratory has shown counterfeit positive or negative result in terms of moisture damage potential of asphalt concrete. Some researchers consider that some other antistripping agents except lime may evaporate during mixing and compaction, because mixing and compaction require a very high temperature (usually 160 °C). Some believe the amount of antistripping agents used in asphalt is too small to have an effect on the end product, which is asphalt concrete. All of these are speculations; no real process has been introduced so far on binder to examine the performance ability of antistripping agent to protect moisture damage [7]. State DOTs depend on lime type more than other chemical antistripping agents. For instance, 1 % lime has been used within asphalt binder by New Mexico, USA DOT, for almost all of the mixes. In spite of using lime, some contractors, in New Mexico, are very keen to use chemical morlife. Thus, it is the emerging issue to study the property of antistripping agents to reduce adhesion. It is also required to examine the most effective type and percentages of antistripping agent. The objective has been accomplished in this research based on the adhesion/cohesion force quantification with a functionalized AFM system and artificial intelligences.

A study had been conducted by Putman and Amirkhanian [8] to investigate the long time behavior of HMA mixtures those were conditioned. The findings of their study addressed two subjects, such as samples mixtures with fresh binder and binder stored under 163 °C for 3 days. Both samples were experimented for indirect tensile strength (ITS). Before testing, the first category samples were conditioned for 1, 7, 28, 90, and 180 days; on the other hand, second samples were conditioned for 1, 28, and 90 days. According to their study, if the mixtures of fresh binder are conditioned more than a single day, using liquid antistripping agents or hydrated lime has similar effect. However, yet more than 1 day of conditioning the mixes those were made by stored binder had no significant distinct behavior of using liquid antistripping agents or hydrated lime.

Stripping is a physiochemical phenomena in asphalt binder aggregate process [9]. Asphalt mixes (HMA) at fully saturated stage, as a result of scouring action of hydraulic force, will separate the aggregate and bitumen binder. According to Kandhal and Rickards [9], this system of stripping is defined as “mechanical breakdown of the asphalt pavement system where the tradition moisture vulnerability experiments are impractical. This lesson was found from case studies of the regions such as Oklahoma and Pennsylvania in the USA, and New South Wales in Australia. Visual apparent of distressed pavement, samples collection, and then laboratory testing had been done, and some recommendations were found from those case studies. The observable fact of stripping was experimented from a universal viewpoint. The study introduced some properties of the pavement such as relative permeability of its ingredients, the interface among different courses of asphalt, and subsurface drainage system. They presented the suppositions to make clear about the process that is observed in the saturated pavement.

3 Literature review on AFM testing

In AFM test protocol, a sample face is scanned with a spiky and tiny AFM tip, and then, the force (i.e., repulsive or attractive) existing between the sample surface and the small tip is calculated. AFM has various applications in respective fields such as researchers of electrical engineering field are using AFM to determine the surface irregularity of nanodevices which are grown in the laboratory and produced for the microelectronic or related equipment [10]. Besides, AFM can be applied to measure adhesion and cohesion forces, which are mostly used by the chemical engineering research group. Researchers of Harvard University (i.e., Lieber and his group) have introduced functionalized AFM, and its application in chemical process is defined as chemical force microscopy [11]. Drag off action between hexadecanethiol monolayers, which is spontaneously pulled together on gold-covered silicon nitride tip as cantilever, and silicon wafer was examined by Beach with the help of an AFM [12]. To chart the adhesion forces and make image of the samples, Okabe utilized hydrophobic –COOH and –CH3 functional modified [13]. AFM was used by Du to discover the modulus of elasticity and yield strength of thin films made by polymer [14]. AFM has also been applied to measure the rigidity of tar where they confined the research to non-functionalized AFM tips [13]. Pauli accomplished AFM to test asphalt binder and after that computed the surface energy [16]. Masson also carried out period imaging of asphalt using an AFM and correlated them with chemically analyzed ingredients of asphalt binder such as saturates, polar aromatics, asphaltenes, and naphthene aromatics [17]. Tarefder studied the consequence of polymer alteration on moisture damage of asphalt by AFM [18] without using the artificial intelligence for modeling the damage behavior.

4 Objectives

The objectives of this study were

1. To develop artificial intelligence rule for predicting the damage relation in lime and polymer modified asphalts.
2. To determine the damage vulnerability between base asphalt and polymer modified asphalt under dry and wet conditions.
3. To develop the models for observing damage trend of above asphalts in wet or dry weather based on the experimental data by applying multicriteria decision analysis tools and find out the best suited model.

5 Principles and experimental setup of AFM for moisture damage study

In AFM experiment, a tiny (with a length of 125 μm, natural frequency of 90 kHz, and spring constant of 3 N/m) and spiky tip is attached at the unsupported end of a cantilever and keeps it close to an asphalt film. Due to close contact of the tips and the surface of the film, impulsive or attractive force between the atoms of top layer of asphalt and AFM is created which makes the deflection of the cantilever. The extent of the deflection absolutely depends on the developed force involving the molecules of the tips and the film. This deflection can be calculated by optical handle made by laser diode and location responsive photo detector (as shown in Fig. 1). The amount of deflection is the parameter to compute the force denoted as F substitute on the AFM tips by $F = k\ d$, where d and k are representing deflection and stiffness of the cantilever, respectively. The adhesion can be termed as force which is created within the molecules of asphalt film and AFM tips. The frequency of to-and-fro actions of the sample under the AFM query is the scan rate. A messy image appears is found if the frequency ranges 4–5, as a result of getting insufficient time of feedback loop to react to change the surface roughness. However, slow rate of scanning gets enough time for feedback circle to create good resolution of the picture, but quick scan rate is very much effective where time limitation exists. This study found quality images with scan rate of 1 and 3 Hz. Cantilever arm is vibrated by the drive amplitude which is produced by AC current signal of the sine-wave generator. The amplitude range could be 25–45 as was demonstrated as drive amplitude for imaging of asphalt by trail process. It was found that too long drive amplitude impedes the cantilever to make irregular contact with the top layer of the asphalt.

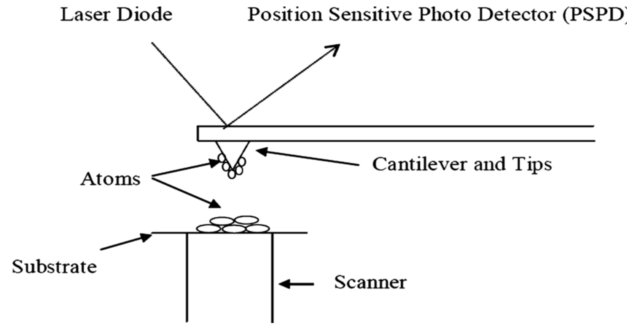

Fig. 1 Schematic of an atomic force microscope (AFM)

6 Description of polymer

Pavement structures are facing increased load of traffic with wide variety of weather effects worldwide. Besides, some failures, for instance, enduring twist and cracking and damage due to moisture effect, are frequently encountered which directly reduce the life span of pavement. For these reasons, studies are continuing to improve quality of bitumen mixtures. This process has guided to a basic change in the design and construction of long durable asphalt pavements [19]. At present, the largely and generally applied polymer for bitumen alteration is the styrene–butadiene–styrene (SBS). Some other polymers which have descending order of use, such as styrene–butadiene rubber (SBR), polyethylene, and ethylene vinyl acetate (EVA), are also applied [20]. For getting better properties of asphalt binder, particular performance risers have been examined in this research. These comprise three steps such as change in additive, polymer, and chemicals reaction [21]. Polymers are potential to observe as dispersed process of the network of polymer [22]. This study used SBS type of polymers, which is described in detail as follows:

6.1 Styrene–Butadiene–Styrene (SBS) polymer

According to Becker, SBS is the frequently used polymer for modification of asphalt binders, followed by reclaimed rubber tire [23]. It is an elastomeric polymer which consists of two styrene ($C_6H_5CH = CH_2$) and one butadiene ($CH_2 = CH–CH = CH_2$). Molecular formula of it is $C_{20}H_{22}$ with molecular weight of 262.39 g/mol. It has tensile strength of 43 MPa with an elongation (strain) of about 95 % as well as average shear modulus 1.5 MPa. According to Danish Road Directorate, SBS modified binder aggregates demonstrated no greater rut opposition compared to other Danish asphalt aggregates [24]. Joint study of The Florida department of transportation (FDOT) and FHWA published seeking the impacts of SBS alteration on cracking resistance and curative characteristics of Superpav mixes. Their study discovered the benefits of using SBS to withstand cracking of asphalt where primary cause was to concentrate on the rate of microdamage grow up. However, adding SBS had not any effect to reduce the aging type of distress of the asphalt concrete [25]. The tensile strength of SBS is around 43 MPa in addition to elongation strain of around 95 % [26]. The shear modulus varies from 1.26 to 1.78 MPa. The polymer is mainly used to increase the strength of the asphalt binder. According to a review by Becker et al. 2001, it is the most appropriate polymer for the asphalt binder modification.

7 Antistripping agent (lime)

Lime is used as the antistripping agent in this study. It has been used in hot mix asphalt pavements for over 25 years in the USA. Currently, over 400,000 tonne lime is used in asphalt every year [27]. Lime has enormous effects to the mechanical and rheological attributes of asphalt mixtures. It is believed that lime helps to increase the resistance of asphalt mixtures subject to moisture environment. It also withstands fracture toughness as well as protects aging of asphalt binder by lowering the rate of oxidation process [28]. Majidzahed and Brovold [29] recommended that surface tension of bituminous layer can also be reduced by using antistripping additives by which pick up wetting. Hunter also found same result like as them by using antistripping agents [30]. Different types of antistripping agents, for example, silicone with silane coupling agent, quick lime, and hydrated lime, have been experimented by Stuart [31]. The result indicated that both limes performed very well. To increase the bonding strength of aggregates and bitumen, hot mix asphalt (HMA) added with lime is very effective [32]. Another advantage of lime is that it can react with extremely polar molecules to restrain the creation of water-soluble soaps that endorse stripping. The ingredients of lime are mainly ferrous oxide (10 %), silicium dioxide (40 %), and water (40 %).

8 Functionalization of AFM tips and effective functional groups in asphalt

According to Little and Jones, asphalt/bitumen binder consists of long carbon (C) chains and rings which are saturated with hydrogen (H) atoms, which may be considered as essentially nonpolar in nature [4]. The static character/nature of these molecules stalks from the fact that they are saturated as well as made up solely from single C–H and C–C bonds, with comparatively balanced electron distributions. Those nonpolar molecules work together mainly through the van der Waals forces. Since van der Waals forces are by nature additive, their involvement in these large molecules formation could play key role. Bitumen binder is comprised of not only nonpolar hydrocarbons but as well as some other but small in number of heteroatoms such as sulfur (S), nitrogen (N), and oxygen (O), which may be responsible for forming different functional groups in the binder system. A functional group can be defined as a collection of atoms of a particular arrangement which gives the entire molecule some special characteristics. Functional groups in chemistry are named following the composition of this particular group. As an example, –OH is a hydroxyl functional group in bitumen. The most common functional groups in bitumen according to their availability can be described as carboxyl (–COOH), methyl ($–CH_3$), ammin ($–NH_3$), and hydroxyl (–OH) [33, 34]. Therefore, we have used these functional groups for the modification of AFM tips in this study. In our research, silicon nitride (Si_3N_4) AFM tips were functionalized using –OH, $–NH_3$, –COOH, and $–CH_3$ chemical functional groups. Exploring a polymer modified bitumen binder film surface with a tip functionalized by similar to bitumen molecule facilitates the quantification of intermolecular forces between two bitumen molecules. The tip possesses a beam bounce cantilever (designed as RFESPA-CP MPP211) having length of 125 μm with 90 kHz frequency as well as spring constant (k) value of about 3 N/m. These tips were functionalized with ammin (–NH_3), methyl (–CH_3), carboxyl (–COOH), and hydroxyl (–OH) functional groups from Novascan Technologies, USA. The tip alteration procedure includes an inhibited deposition of a monolayer very slim film onto the AFM tip followed by captivation of the AFM tip under solution of organic thiol/chlorosilane [35]. One end of the thiol is covalently linked to the AFM tip surface, and the other end contains the suitable functional group. The functionalization of AFM tips by coating them with bitumen binder and molecules is quite novel, not only in bitumen area but as well as in nanotechnology and polymer areas for studying specific interactions at the level of molecule.

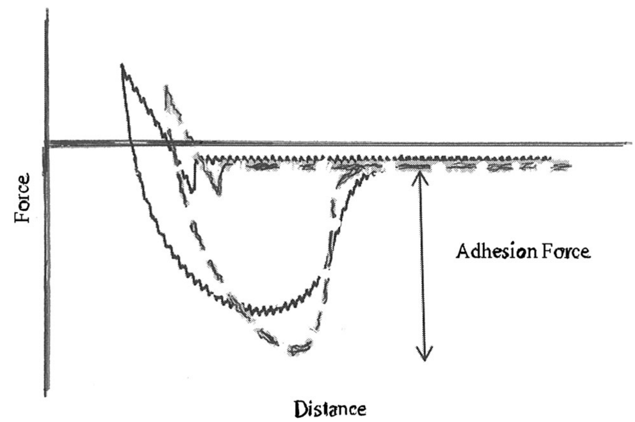

Fig. 2 Force–distance graph of PG 76-28 sample with –COOH tip (*solid line* for dry sample, *dotted line* for wet sample)

9 AFM testing on asphalt samples

Styrene–butadiene–styrene (SBS) polymer was used to modify a base binder at 3, 4, and 5 % by weight. Lime was used as antistripping agent (0.5, 1.0, and 1.5 %). The test template consists of three types of SBS modified binders and 3 % of antistripping agents, two sample conditionings (wet and dry), and five types of chemically functionalized tips (–CH_3, NH_3, –COOH, –OH, and –Si_3N_4). In this study, a total of 45 AFM laboratory tests were performed.

10 Force–distance measurement on asphalts

Force is the function of the distance of the tip and sample surface which can be presented by the graph which is defined as F-D curve. At the time of approaching the AFM tip close to the sample, the sample molecules react with the tip, and the cantilever arm becomes deflected. In F-D curve, force is plotted against the distance/displacement of the AFM cantilever holder with respect to sample surface. A relative presentation of force–distance (F-D) curves of dry and wet samples is shown in Fig. 2. The black and dotted colored curves are representing dry and wet samples, respectively. The rotation in measurement of force begins at a tip surface taking apart. When the distance is large enough, no force exists between them, but as soon as tip subjected to the surface, the attractive force developed to pull the tip in the direction of the sample and make deflection. When the attractive force is greater than repulsive force and spring constant together with, the bending of tip holder takes place. Same amount of cantilever deflection is found by displacing the tip again and shoved the sample. Then, the tip is positioned to its initial point. On the time of renunciation, tip reaches a point of snapping outward. Maximum force is indicated by the lowest point of the force curve (Fig. 2), and the adhesion is broken at that point. At this point, the cantilever becomes separated from the surface. There are two types of adhesion forces such as electrostatic force and van der Waals force. Since top of asphalt is free of charge, van der Waals interaction is responsible for adhesion. Here, adhesion forces of wet samples are found higher than that of dry sample of asphalt (Fig. 2).

11 Modeling moisture damage with artificial intelligence (AI)

The tip types, percentages of SBS and lime, and dry and wet conditions were the input values in AI, whereas the adhesion/cohesion force was the output value. The statistical analysis of the force value data is shown in Table 1. The standard deviation reveals 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. Several of the AI are described below:

Table 1 Statistical analysis results for dry and wet SBS samples

	SBS (dry)	SBS (wet)
Maximum	302.27	470
Minimum	46.2775	73.75
Mean	167.9093	205.5847
SD	69.19105	99.83571
Kurtosis	−0.67737	0.166308
skewness	0.148213	0.803461

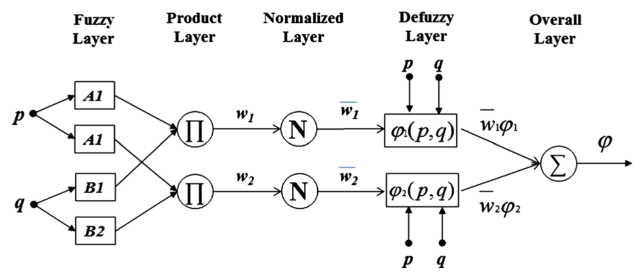

Fig. 3 Schematic of an adaptive network fuzzy inference system (ANFIS)

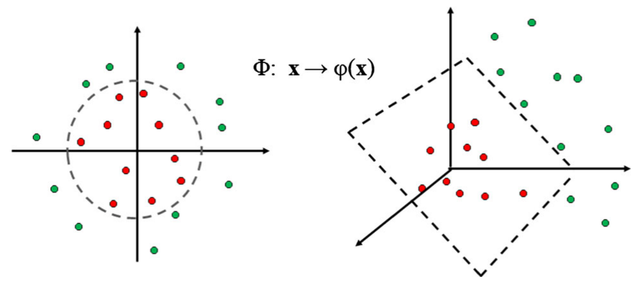

Fig. 4 Schematic of SVM-KM model

11.1 Adaptive network fuzzy inference system (ANFIS)

In 1993, adaptive network fuzzy inference system (ANFIS) has been developed by Jang [36]. The system is serving as a basis to construct if–then rules and fuzzy inference system (FIS). It is the process found in reforming the structure of adaptive networks by implanting the FIS. Tabatabaei [37] presented a model which is based on ANFIS in order to determine the deduct value to calculate the asphalt pavement conditioning index (PCI). ANFIS combines the best attributes of both neural networks (NN) and fuzzy systems (FS). From FS, ANFIS represents the former knowledge into a set of constraints (network topology) to trim down the optimization investigate space. For best performance, it is necessary to minimize the optimization search space, and for this reason, ANFIS model introduces the concepts of using the preceding knowledge to convert into a group of constraints with the help of FS. Alternatively, NN theory is applied in ANFIS to ordered network to make the automatic system of FC parametric tuning by performing adaptation of backpropagation. The ANFIS architecture is used to solve many real-life problems that are very complex such as nonlinear function modeling, identifying nonlinear components in a control system, and foresee disorder time series. [38]. Recent studies show the utilization of ANFIS and related model in civil engineering applications. Mohammadhassani et al. [39] predicted the deflection in concrete deep beam with ANFIS. The ANFIS structure has five-layered feed forward network (Fig. 3), and its nodes in individual layer represent the same functionality [40].

11.2 Support vector machines (SVM)

Corinna and Vladimir [41] proposed a simulation tool on the origin of statistical analysis theory namely support vector machines (SVM). Support vector regression (SVR) model introduced the regression process in SVMs. The basic of SVM/SVR is built a most favorable outcome of geometric hyperplane to separate the data. It is the system where the data are mapped hooked on a high-dimensional characteristic space through a nonlinear mapping ($\emptyset$). After that, the linear regression is done to the transformed feature space [44, 45]. The mathematical expression of this process is $x \in \mathbf{R}^n$, $y \in \mathbf{R}$, and the hyperplane function can be presented as $y = f(x) = w.\emptyset(x) + b$, where $w \in \mathbf{R}^n$ is the symbol for weight vector, $b \in \mathbf{R}$ is the bias. The function $\emptyset(x)$ denotes a nonlinear transformation from $\mathbf{R}^n$ into a higher dimensional space (Fig. 4). The values of w and b determine that values of x can be found by reducing the regression risk.

$$R = \frac{1}{2}\sum_{i=1}^{n}\{f(x_i) - y_i\}^2 + \frac{\lambda}{2}\parallel w \parallel^2 \quad (1)$$

where n indicates the sample inputs ($x1,\ldots\ldots,xn$), λ is regularization constant, ($y1,\ldots\ldots,yn$) are the measurements. The drawback of SVM/SVR is that to analysis hefty amount and complex dataset, the accuracy level does not achieve as like as expected and obviously takes longer time for analysis. Consequently, it is one of the study area to improve the efficiency of SVR. Tran et al. [42] found that the numbers of support vectors in SVR are the determinant of the computational complexity of the whole procedure. The combined process of SVM-KM method proved as a novel and efficient system of minimizing the number of support vectors which is verified computationally efficient [43, 44]. The model uses clustering technique as K, to allocate the data of every class to k number of clusters. Afterward, only the center of cluster techniques is used by the SVM/SVR model to analyze the trend (Fig. 4).

11.3 Artificial neural network

Artificial neural network (ANN) can be defined as computer program-based simulation technique similar to that of the brain performs a particular learning task. It consists of interlocking parts namely "neurons" which operate in parallel. One of the most popular ANNs is multilayer perceptrons (MLP), which has earned vast reputation in many research areas including petroleum, pattern recognition, pattern identification, classification, speech recognition, computer vision, and control systems. Mohammadhassani et al. [45] applied ANN for the prediction of deep beam deflections at the mid span. The study was concluded with a high confidence level predicting the deflection at mid span of the deep beam in comparison with the other available methods. It has one output layer, one input layer, and one/more hidden layers of processing units. By name, it is understand that the hidden layers are invisible from outside environment and situated within the input and output layers (Fig. 5). The process can be trained to carry out a specific function (Eq. 2) by adjusting the standards of the connections or weights between elements. Usually, MLP are trained in such way that an individual input directs to a particular target output. In this model, the values are changed continuously to achieve the target based on the process outcome till to the point of getting matches target by the network output. Typically, many such input or target pairs are needed in order to train a network. The following equations show a neuron with sigmoidal activation function where

$$y = z_j = f\left(\sum\nolimits_i w_{ij}x_i + w_{0j}\right) = f(h) = \frac{1}{1+e^{-h}} \quad (2)$$

12 Analyses of experimental data

The flow diagram for overall process in AI is depicted in Fig. 6. The developed models were tested for both dry and wet samples. After several trails, we found 80 % (training) and 20 % (validation) data sets produce the best results. Moreover, some literature suggests the validation and training data set to be 20 and 80 % [46–49]. In this case, both predicted and observed data were analyzed by different models, for example, SVM, MLP, and ANFIS model. The statistical outcomes of both data for two types of samples such as SBS dry and SBS wet have been then discussed below in details with special focused on errors and the correlation found in the applications of developed models. It was done for both trained and observed data, and it was seeking that whether it shows consistent performance between the predicted results and experimental results or not. It mainly indicates the credibility of the models. The overall performance is shown in Tables 2 and 3, which showed that, for wet sample, the outcomes of ANFIS model were very good, and, for dry sample, the results of MLP model were satisfactory. In both cases, performance of SVM model was not as good to use in this type of study.

13 Statistical performance analyses of AI data

The predicted and experimental data of the models developed by SVM, ANN (i.e., MLP), and ANFIS (i.e., FCM) were again examined based on some important statistical parameters to justify the accuracy of the models used in SBS and lime modified asphalt. Two types of samples were used for this purpose such as dry sample and wet sample. This study used root mean square error (RMSE), correlation coefficient (CC), mean absolute percentage error (MAPE), mean absolute error (MAE), mean relative error (MRE), and standard deviation (SD) to investigate the accuracy of the models. The RMSE is the frequently applied performance parameter to know the differences in numerically predicted data resulted by any model and the data found by laboratory experiment. It is the result of mean square root differences between each predicted value and its corresponding intentional value. CC is the statistical measures to show how much strong co-relation exist between trend and observed data. The value of CC "1" means ideal co-relation exists and "0" means there is no co-relation between predicted and tested result. The MAPE shows the error as percentage to visualize more understandable way. The MAE indicates the closeness of predictions to the observed outcomes which is computed by the average of absolute error. The performance analysis of SBS wet sample (Table 2) showed that the RMSE is very large from experimental data which is 63.29 by SVM

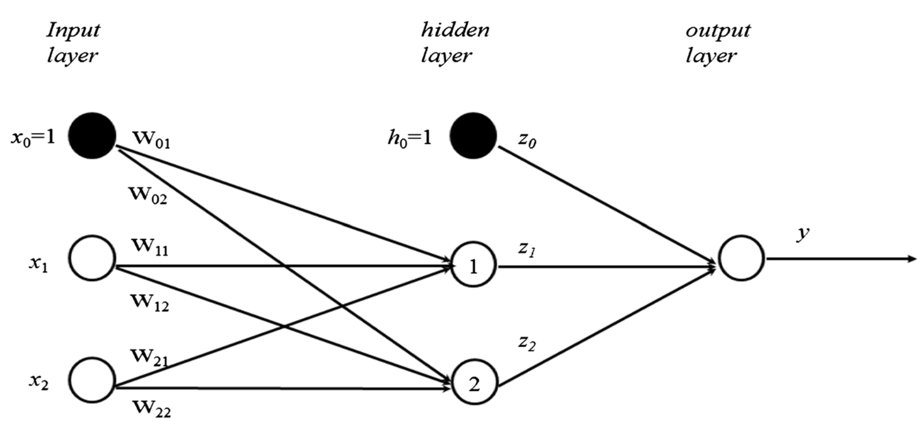

Fig. 5 Schematic of an artificial neural network (ANN)

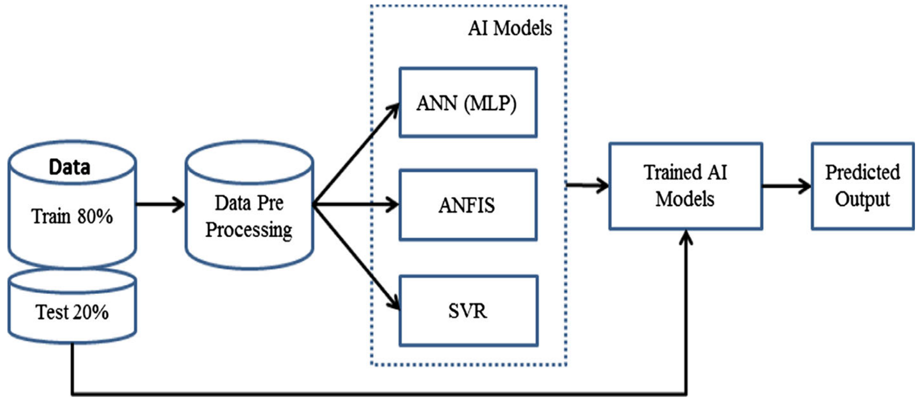

Fig. 6 Flowchart for artificial intelligence (AI) models

Table 2 Performance measures of the ANN and ANFIS models for wet sample

Statistical parameter	SVM-KM		MLP		ANFIS_by_FCM	
	Train (80 %)	Test (20 %)	Train (80 %)	Test (20 %)	Train (80 %)	Test (20 %)
RMSE	40.1193	63.2925	14.7293	57.7385	34.9144	36.4708
CC	0.9426	0.8046	0.9895	0.7858	0.9376	0.9309
MAPE	18.8938	17.6330	7.3598	15.9455	17.1568	15.8106
MAE	32.6608	46.2858	11.6650	43.5721	27.4170	30.8518
MRE	0.1889	0.1763	0.0736	0.1595	0.0233	0.0379
Time	0.3120	0.0000	0.8736	0.0624	0.7098	0.1501
SD	6.0030	9.6309	0.4915	11.5508	0.3425	0.0600

Table 3 Performance measures of the ANN and ANFIS models for dry sample

Statistical parameter	SVM-KM		MLP		ANFIS by FCM	
	Train (80 %)	Test (20 %)	Train (80 %)	Test (20 %)	Train (80 %)	Test (20 %)
RMSE	38.2850	40.3204	28.8451	33.0028	37.3467	36.0526
CC	0.8531	0.9505	0.9211	0.8096	0.8529	0.7223
MAPE	19.8008	21.6526	16.7708	17.5623	23.2327	24.1009
MAE	17.8519	31.6254	21.0612	24.9595	30.0750	30.6259
MRE	0.1980	0.2165	0.1677	0.1756	0.0986	0.3672
Time	0.3276	0.0158	7.4724	0.0312	0.1905	0.4873
SD	2.6754	4.5292	2.8053	5.6481	0.2446	0.3602

followed by MLP, and ANFIS model which are 57.73 and 36.47 respectively. Furthermore, very good co-relation (0.93) exists in both trained and observed data performed by ANFIS model, and its accuracy is far better by MLP and SVM. Besides, CC is considerably varied between trained and test data carried out by succeeding models. The MAPE performance of ANFIS model is very good among three models, i.e., 15.81, which is the most lower value, and it noticed that the observed data showed similar result of trained value which indicates the consistency of the model; on the other hand, rest of the two models clearly depicted different values performed in comparison with trained and test data. However, the trained analysis of MLP provided good result regarding MAPE (7.36), but it has no consistency when performed for observed values (15.94). Similar results have been found in MAE and MRE analysis for both data by the two models (SVM and MLP). Nonetheless, performance of ANFIS model is very good in these points, and mean relative error was very low 0.02–0.03, respectively, for projected and observed data which also showed the steady performance of the model. Unlike other two models, observation of standard deviation, the ANFIS model for experimental data analysis demonstrated excellent application; for instance, SD of SVM, MLP, and ANFIS was 9.63, 11.55, and 0.06, respectively. In conclusion, error analysis for data found the dry sample, showed strong evidence of successful application of ANFIS model compared to that of other different models like SVM, and MLP. Statistical measures were also taken for dry sample by executing three models mentioned above and found MLP's performance was very good than the other two models. MLP model gave more accurate result regarding error analysis and was steady in both data; for example, MAPE was very low compare to that of other models and very close to both trained and test data (16.77 and 17.56, respectively). Similar result also has been found regarding mean relative error analysis of both data and the value was more like 0.17 for both case. This model also found good co-relation between experimental and predicted data, and the CC of both was 0.92 and 0.81. This likeness of performance in trained and observed data showed strong evidence for the application of the model in study. However, SVM model showed that strong correlation exists in both trained and test data, but error analysis performed poor than the MLP model, and there is lack of steady relation between projected and experimented data which kick off the model's reliability. For example, value of RMSE is highest for both trained and test data (38.28 and 40.32, respectively) compared to that of other two models such as MLP (28.84 and 33.0) and ANFIS (37.34 and 36.05). In case of percentage error (MAPE), this model resulted just lower than MLP model, but there is no consistent performance for train to test data in mean average error (MAE) analysis where test data showed almost double error than trained data (31.62 and 17.85) which is the most weak observation of this model. Besides, mean average error (MAE) is found highest 31.62 among all the models for observed data of dry sample. Calculation of mean relative error (MRE) also found more differences between two data (train and test) experimented by SVM unlike MLP and ANFIS models. However, all the models performed very well in predicting value and showed minimum error than observed values. In addition, MAE for both data (i.e. projected and experimented) of ANFIS model found less difference, but the amount of error is higher to that of preceding model.

14 Conclusions

ANN-related modeling (specifically ANFIS, MLP, and SVM) is used for the first time in the AFM applied moisture damage formulation in asphalt area in this study. The technique can be considered as artificial and nanoscale tool that can address directly the roles that different chemical functional groups of asphalt play in influencing the intermolecular adhesion/cohesion force due to moisture-induced damage. Based on the finding of this study, the following conclusions can be drawn:

1. The study formulates an artificial intelligence relation that can be easily fitted for prediction of moisture damage in lime and SBS modified asphalts.
2. ANFIS model (as compared to MLP and SVM) found very promising in these points, and mean relative error was very low such as 0.02 to 0.03, respectively, for projected and observed data which also showed the steady performance of the model.
3. Statistical measures have also taken for dry sample by executing the three models mentioned above and found MLP's performance is the best as compared to other two models.

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