

Artificial neural network approach to predict asphalt mixtures' stiffness modulus based on testing frequency and temperature

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Abstract. To successfully guarantee the proper durability and serviceability of asphalt pavements, it is crucial to investigate asphalt mixtures' performance and to design an accurate model to predict their mechanical behaviour. In Machine Learning, Artificial Neural Networks (ANNs) consist of a set of layered and interconnected artificial neurons capable of learning a complex function that maps the input to the target output. This study is specifically aimed at their implementation within the field of pavement engineering. The paper thoroughly discusses the development of an ANN-based methodology capable of predicting the stiffness modulus of an asphalt mixture (AM). The AM under investigation was prepared with spilite aggregate, a 50/70 penetration grade bitumen, and limestone filler. The volumetric properties of each specimen were first determined, and then the sequence of a 4-Point Bending Test was carried out under different conditions. Four testing temperatures (0, 10, 20, 30 °C) and eleven loading frequencies (0.1, 1, 2, 3, 5, 10, 15, 20, 30 and 50 Hz) were selected to investigate the asphalt mixture's mechanical behaviour. The resulting stiffness moduli represented the output of the designed neural model. Prediction accuracy was evaluated utilizing several goodness-of-fit metrics, and the results of this feasibility study proved to be very encouraging. They are certainly limited to the asphalt mixture under investigation. However, the high level of accuracy suggests that trained on a larger dataset, the developed methodology could allow the AMs' mechanical behaviour to be predicted without the need to carry out the conventional tests that are usually expensive and time-consuming.

1 Introduction

Mechanical performance of asphalt mixtures is typically evaluated by performing several laboratory tests. They usually involve expensive and time-consuming experimental campaigns that need to be carried out. To reduce measurement errors and to increase

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measurement reliability, trained and skilled technicians must be recruited. However, whenever any feature related to either the test mixture or a test condition changes, new experiments must be performed in order to evaluate the variation in the resulting performance. On the other hand, a mathematical model could allow the variable in question to be directly changed and its influence on mixture mechanical behaviour to be evaluated, reducing the need for the entire experiment to be repeated. Several mathematical models have followed over the years to achieve similar results, namely complex constitutive equations [1] that have been later implemented in different finite element software [2].

Along with the numerical modelling, some innovative approaches based on data-driven strategies are becoming increasingly popular in recent years. The latter allow asphalt mixtures' mechanical behaviour to be predicted based solely on some compositional parameters and/or testing conditions, relying on a wide variety of soft-computing techniques like artificial neural networks (ANNs). However, these modelling strategies have some drawbacks, namely the challenging definition of the best model hyperparameters.

The aim of this study is to investigate the feasibility of an ANN-based methodology capable of reliably predicting the stiffness modulus of a specific asphalt mixture (AM). The investigated AM is composed of spilite aggregate, limestone filler, and a 50/70 penetration grade bitumen, and it was tested under different temperature and frequency conditions with a 4-Point Bending Test machine. The implemented data-driven methodology identified the correlation between the stiffness modulus and testing parameters, showing remarkable accuracy in the predictions. Finally, to solve the drawbacks related to the definition of the best hyperparameter set, modern k-fold cross-validation and Bayesian optimization procedures were developed and implemented.

2 Materials and methods

The asphalt mixture AC16 considered in the current research was prepared with spilite aggregate, a 50/70 penetration grade bitumen, and limestone filler. The volumetric properties of each specimen have been analyzed. Binder content, bulk density, and air voids content resulted equal to 4.5%, 2.417 g/cm³, and 5.2%, respectively. Subsequently, the sequence of a 4-Point Bending Test has been carried out under different conditions. Four testing temperatures (0, 10, 20, 30° C) and eleven loading frequencies (0.1, 1, 2, 3, 5, 10, 15, 20, 30 and 50 Hz) were selected to investigate the asphalt mixture's mechanical behaviour, Table 1.

Table 1. 4-Point Bending Test results.

Loading frequency [Hz]	Stiffness modulus [MPa] at			
	0 °C	10 °C	20 °C	30°C
50	23751	17844	11618	6387
30	23862	17733	11238	5777
20	24104	17108	10317	4891
15	23785	16639	9722	4496
10	23067	15855	9009	4005
8	22763	15453	8574	3754
5	21874	14510	7769	3285
3	20984	13497	6912	2831
2	20203	12659	6276	2506
1	18939	11335	5325	2140
0.1	14606	7346	3001	1265

3 Machine learning modelling

3.1 Pearson Correlation

To qualitatively determine the strength of the correlations between input and output variables, a Pearson correlation matrix was constructed (Fig. 1) [3]. The absolute value of the correlation between a pair of variables ranges between 0 and 1, representing no correlation and a perfect correlation, respectively. A plus sign stands for a direct correlation whereas a minus sign stands for an inverse correlation. A medium positive correlation ($r = + 0.25$) between loading frequency and stiffness modulus, and a strong negative correlation ($r = - 0.93$) between testing temperature and stiffness modulus can be observed. It can also be noticed that no correlation was identified between loading frequency and testing temperature, highlighting the suitability of these independent variables as input parameters for the developed model.

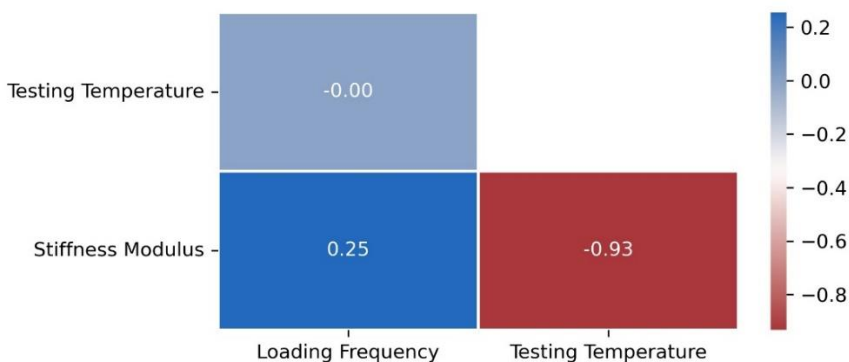


Fig. 1. Pearson correlation matrix.

3.2 Artificial neural network

An artificial neural network (ANN) is a mathematical model, and its structure is closely related to the biological nervous system. By means of its information storage and processing mechanism, it can perform multiple tasks, including function approximation. An ANN has high adaptive learning capabilities, and mainly consists of artificial neurons interconnected and organized into layers. Each input and output variables will correspond to a different neuron in the input and output layers, respectively. Generally, one or more hidden layers are in-between the input and output layers, and it is where computational processing takes place. According to the number of hidden layers, a neural network with a single hidden layer is called shallow (SNN), otherwise it is called deep (DNN). In this paper, a shallow neural network was developed (Fig. 2) since most of the input-output fitting problems can be solved by a SNN with the required number of neurons [4].

The architecture of the proposed neural model consisted of two neurons in the input layer (representing the loading frequency and the testing temperature), a variable number of neurons in the hidden layer (set between 1 and 30), and a single output neuron equipped with linear activation function (representing the resulting stiffness modulus). Four of the most commonly used activation functions for solving regression problems were investigated to identify the one that, employed in the hidden layer, best suited the problem under investigation. Their equations were listed in Table 2.

Table 2. Investigated activation functions.

Activation Function	Equation
Positive Linear (poslin)	$f(x) = \begin{cases} 0 & \text{if } x \leq 0 \\ x & \text{if } x > 0 \end{cases}$
Exponential Linear (ELU)	$f(x) = \begin{cases} e^x - 1 & \text{if } x < 0 \\ x & \text{if } x \geq 0 \end{cases}$
Log-Sigmoid (LogS)	$f(x) = \frac{1}{1 + e^{-x}}$
Hyperbolic Tangent (TanH)	$f(x) = \frac{2}{1 + e^{-2x}} - 1$

Before starting with the training, input and output data were standardized to optimize the network functioning. Furthermore, another pre-processing procedure was implemented, namely the k-fold cross validation (CV). It is a resampling technique used to elaborate an actual model on a limited data sample. k-fold CV consists in dividing the dataset in k-partitions. Each sub-sample is used once as validation set and k-1 times as training set [5]. This procedure is iteratively repeated k times. Finally, the average of the k validation scores is given as general performance of the model. It was decided to assume a k-value equal to 5, consistently with the relevant literature.

The supervised learning process was divided into two distinct phases: a forward pass and a backward pass. After the initialization of the connection’s weights, the forward pass began. It consisted of processing the incoming information through the neurons to compute network outputs. Then, the backward pass carried out a comparison between the experimental targets and predicted outputs so that the Bayesian Regularization backpropagation algorithm could evaluate weights correction until minimum error was reached and weights were confirmed.

For a generic iteration $e \in \{1, \dots, E\}$, the weight correction is determined according to the Equations 1 and 2 [6]:

$$F(\hat{\mathbf{y}}(\mathbf{W}^e), \mathbf{y}, \mathbf{W}^e) = \beta \|\hat{\mathbf{y}}(\mathbf{W}^e) - \mathbf{y}\|_2^2 + \alpha \|\mathbf{W}^e\|_2^2 \quad (1)$$

$$\mathbf{W}^{e+1} = \mathbf{W}^e - [\mathbf{J}^T(\mathbf{W}^e)](\mathbf{W}^e) + \mu_e \mathbf{I}]^{-1} \mathbf{J}^T(\mathbf{W}^e) \mathbf{v}(\mathbf{W}^e) \quad (2)$$

where \mathbf{y} is the experimental target vector, $\hat{\mathbf{y}}$ is the predicted output vector, α and β are regularization parameters set according to David MacKay’s approach [7], \mathbf{W} is the matrix of weights and biases, \mathbf{J} is the Jacobian matrix of the training loss function $F(\cdot)$ with respect to \mathbf{W}^e , μ is the learning step size, \mathbf{I} is the identity matrix and $\mathbf{v} = \hat{\mathbf{y}} - \mathbf{y}$ is the vector of network errors.

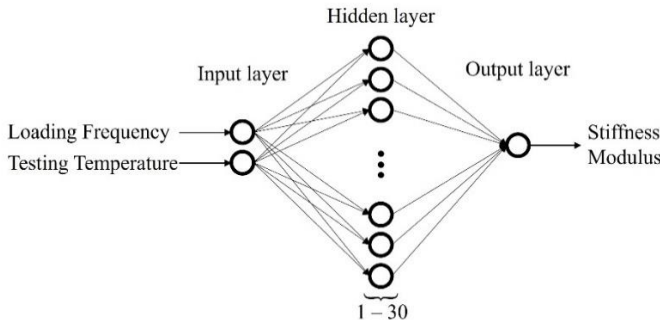


Fig. 2. Architecture of the developed SNN model.

The definition of hyperparameters represented a crucial modeling phase. Hyperparameters that needed to be optimized are listed in Table 3. They were related to both network topology (with the neurons in the hidden layer and the activation function) and training algorithm (with the learning step size, its increasing and decreasing factors, its maximum value, and the number of learning algorithm iterations). To find the best hyperparameters, the standard methodologies involve a random search or, starting from pre-established and well-known intervals of variation, a grid search. Rather than standard methodologies, in this study modern algorithms known as Bayesian Optimization (BO) processes were implemented to optimize the choice of the hyperparameters set. Since the training loss function F is unknown, it can be treated as a random function and a Gaussian Process prior can be used to capture its behaviour. During the optimization process, the prior is updated based on machine learning results produced by different hyperparameters combinations to form the posterior distribution of the function F . To determine the next hyperparameters evaluation point, the hyperparameters space is exploited by means of an acquisition function called Expected Improvement Plus (EIP) [8] until the stopping condition is reached and the best hyperparameters are selected. The BO algorithm was run for 100 iterations.

Table 3. Hyperparameters definition.

Hyperparameter	Symbol	Variation interval ^a
Hidden neurons	N	{1, ..., 30}
Activation function	act	{poslin, ELU, LogS, TanH}
Learning rate	μ	$[10^{-4}, 10^{-2}]$
Increasing factor	μ_{inc}	$[10^1, 10^3]$
Decreasing factor	μ_{dec}	$[10^{-3}, 10^{-1}]$
Maximum learning rate	μ_{max}	$[10^8, 10^{10}]$
Iterations	E	{500, ..., 3000}

^a Integer or categorical ranges are represented with braces whereas logarithmic ranges are represented with square brackets.

4 Results and discussion

To keep the Bayesian Optimization process replicable, the hyperparameters combination of the first iteration must be fixed in advance. In this research it was defined as follows: $N = 15$, $act = ELU$, $\mu = 10^{-3}$, $\mu_{inc} = 10^1$, $\mu_{dec} = 10^{-1}$, $\mu_{max} = 10^{10}$, $E = 1000$. The average over the 5 test folds of the loss function value [9] was reported in the dispersion diagram of Fig. 3. It can be observed that the iteration that produced the best result in terms of average loss value (0.00925) was the 85th, close to the end of the optimization process. The optimal hyperparameter set is given in Table 4: it is characterized by 20 hidden neurons, ELU as activation function, 2208 training iterations, a learning rate equal to 1.00×10^{-2} , an increasing factor of 3.31×10^2 , a decreasing factor of 1.00×10^{-2} , and a maximum learning rate equal to 1.41×10^8 .

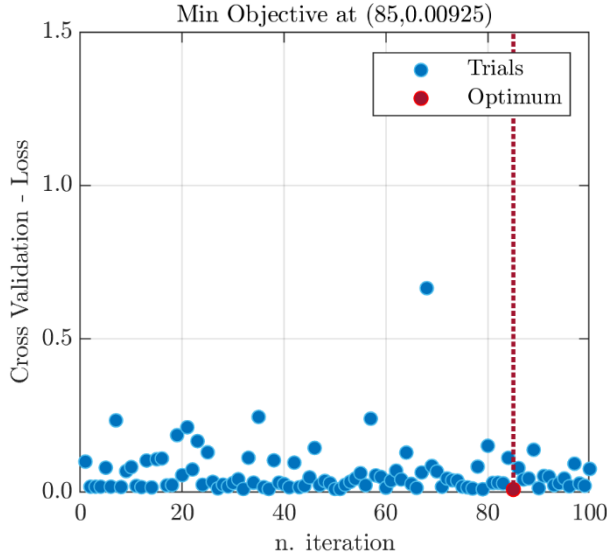


Fig. 3. Average MSE on the 5 test folds vs iteration number.

Table 4. Bayesian Optimization Results.

Hyperparameter	Symbol	Selected Value
Hidden neurons	N	20
Activation function	act	ELU
Learning rate	μ	1.00×10^{-2}
Increasing factor	μ_{inc}	3.31×10^2
Decreasing factor	μ_{dec}	1.00×10^{-2}
Maximum learning rate	μ_{max}	1.41×10^8
Iterations	E	2208

Although the stiffness varies significantly as a function of testing temperature and frequency, the results produced by the model can be considered satisfactory. Regression plots for each of the 5 folds are shown in Fig. 4. In each subplot, the x-axis refers to the target observation values whereas the y-axis refers to the values predicted by the model. The correlation strength between target and predicted values was expressed by means of Pearson's correlation coefficient (equation 3):

$$R = \frac{1}{n-1} \sum_{i=1}^n \left(\frac{t_i - \mu_{t_i}}{\sigma_{t_i}} \right) \left(\frac{p_i - \mu_{p_i}}{\sigma_{p_i}} \right) \quad (3)$$

where t_i is the i-th target observation, p_i is the i-th predicted value, μ_{t_i} and μ_{p_i} are the mean values of t_i and p_i , respectively, whereas σ_{t_i} and σ_{p_i} are the standard deviation values of t_i and p_i , respectively. Other goodness-of-fit metrics were evaluated to fairly determine the accuracy of predictions. In particular:

$$MSE = \frac{1}{n} \sum_{i=1}^n (t_i - p_i)^2 \quad (4)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (t_i - p_i)^2} \quad (5)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (t_i - p_i)^2}{\sum_{i=1}^n (t_i - \mu_{t_i})^2} \tag{6}$$

R-values range between 0 (no correlation) and 1 (total correlation). Values higher than 0.8 typically represent a satisfactory correlation [10]. The best model returns an R-score between 0.9550 (Fold 5 – the worst) and 0.9988 (Fold 3 – the best). The actual predictive performance can be fairly evaluated by averaging the results obtained over the 5 folds (Equation 7):

$$R = \frac{0.9794+0.9892+0.9988+0.9944+0.9550}{5} = 0.9834 \tag{7}$$

Other performance metrics respectively resulted equal to:

$$MSE = \frac{0.0123+0.0083+0.0023+0.0075+0.0159}{5} = 0.00925 \tag{8}$$

$$RMSE = \frac{0.1109+0.0911+0.0477+0.0866+0.1260}{5} = 0.09246 \tag{9}$$

$$R^2 = \frac{0.9568+0.9773+0.9945+0.9836+0.8960}{5} = 0.96164 \tag{10}$$

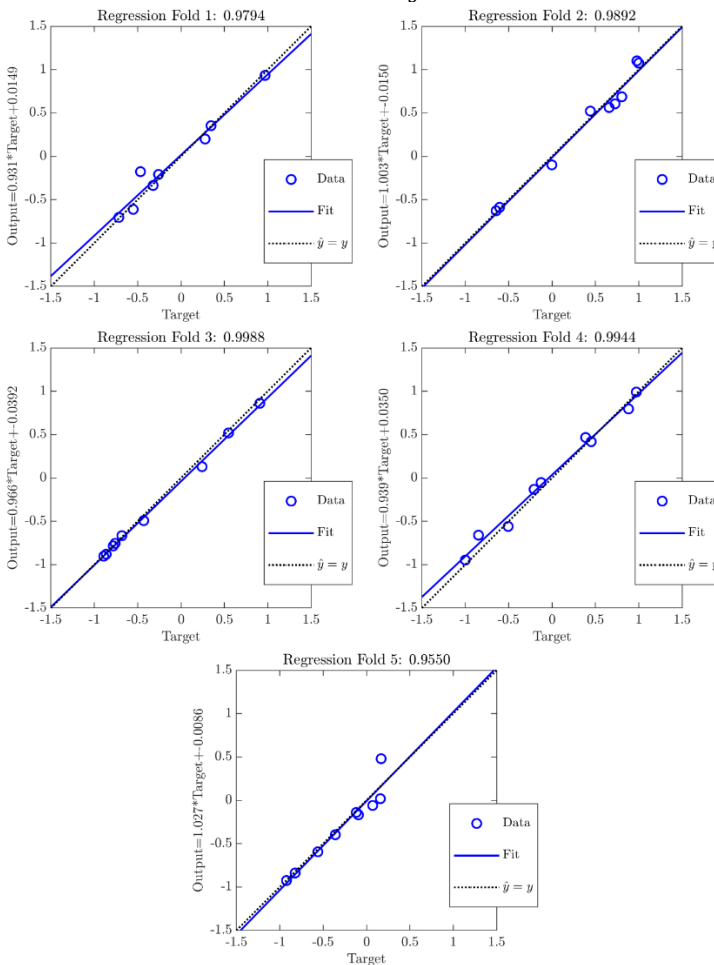


Fig. 4. Summary of the ANN predictive performance.

5 Conclusion

In pavement engineering, innovative procedures based on machine learning could help mix design experts in analyzing experimental data. Furthermore, if properly developed, they could provide reliable predictions in terms of asphalt concrete mechanical behaviour, reducing the need of expensive and time-consuming experimental campaigns.

This paper discussed an artificial neural network approach to model the stiffness modulus of an asphalt mixture prepared with spilite aggregate, limestone filler, and a 50/70 penetration grade bitumen. The observations come from an experimental campaign carried out by means of 4PBT machine under several testing conditions. Thus, stiffness modulus values were evaluated at 11 different loading frequencies and 4 different testing temperatures. The results were used to train the neural model that, knowing in advance the compositional features of the mixture, is able to predict the stiffness modulus based solely on the testing conditions. The entire neural methodology was developed by implementing the MATLAB[®] Toolbox.

By means of the hidden layer equipped with poslin activation function, the neural model was able to approximate the functional relationship between the testing conditions and the resulting stiffness modulus with a remarkable level of accuracy represented by $R=0.9834$.

This research clearly represents only a feasibility study and a starting point. In fact, being aware of the results of this paper, it would be interesting to expand the starting dataset, by adding additional test conditions and data from several other mixtures, thus making such a tool more powerful and high performing. Such a tool would be very useful during mix design operations, allowing the mechanical performance of multiple mixtures to be predicted on the basis of compositional features and testing conditions.

It should be kept well in mind that, any application outside the one proposed in this paper, requires new calibration operations and search for the new best hyperparameters.

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