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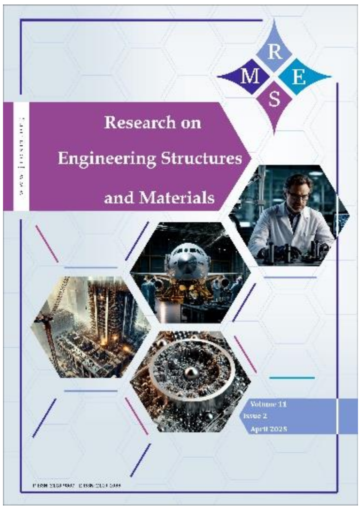

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Research Article

Machine learning-based evaluation of indirect tensile stiffness modulus of fiber-modified cold asphalt mixtures

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Abstract

This study aims to evaluate the Indirect Tensile Stiffness Modulus (ITSM) of fiber-modified cold asphalt mixtures using advanced machine learning models. Several asphalt mix designs (123 mixes) from many previous studies incorporating various fiber types, contents, and curing conditions were experimentally tested. Artificial Neural Networks (ANNs) and Deep Neural Networks (DNNs) were developed to predict ITSM based on seven input features, including fibre characteristics and mix design parameters. The ANN model (ANN-I) demonstrated superior performance, with a correlation coefficient (R) of 0.951 and an RMSE of 174.85 MPa, outperforming the DNN model (DNN-II), which showed lower predictive accuracy (R = 0.884, RMSE = 252.56 MPa). Curing time emerged as the most influential variable across both models. These conclusions verify that ANN provides a stronger and more generalizable means of modelling the stiffness behaviour of cold asphalt reinforced with fibres and provide evidence of its effectiveness when optimising sustainable pavement designs.

1. Introduction

Pavement technology has advanced in recent decades due to environmental pressures, resource limitations, and the rising costs of conventional asphalt, a sustainable pavement type. In this context, cold asphalt mixtures [1] can be produced and compacted at ambient temperature, serving as a replacement for hot-mix asphalt (HMA). There are several advantages to the production and road use of Cold Mix Pavement Mixtures over traditional HMA, including higher production temperatures that can save energy and significantly reduce greenhouse gas emissions [2]. Additionally, cold asphalt is much safer than hot asphalt, as it can be produced and compacted at ambient temperature, which is always hot around 160^0C. It can also be placed by hand in the field, unlike the more common hot-mix (HMA) pavement mixtures.

Several performance factors can be improved by adding reinforcement fibres to cold asphalt. Different fibres used to modify the mechanical properties of cold asphalt are cellulosic, glass, polyester, and natural fibres, with jute and coconut fibres prevailing. Previous studies show that these fibres increase tensile strength, moisture stability, and stiffness of cold asphalt mixtures [3,4]. When added to the matrix of a bitumen-aggregate material, these fibres form a continuous, denser structure that retards cracking and deformation in the mix. Among all performance properties of fibre-reinforced cold asphalt, the Indirect Tensile Stiffness Modulus (ITSM) is of great importance, as it measures the material's resistance to deformation and tensile loading and provides an important platform for performance-based design as per [5].

Traditional empirical or mechanistic models often struggle to capture the complex, nonlinear relationships among ITSM variables such as fibre type, content, blend ratios, curing conditions, and air voids. Generally, traditional regression-based approaches demand a predetermined

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mathematical (statistical) association between inputs and outputs, which restricts the ability to represent the interdependent and nonlinear relationships among multiple component parameters in mixtures. Because ITSMs are modified due to multiple interacting factors (as opposed to isolated components), the predictive power of traditional models will decrease as the material behaviour becomes more heterogeneous or complicated [6-8]. To overcome modelling challenges, machine learning (ML) techniques have emerged as a viable alternative for evaluating material performance in civil engineering. ML models, particularly Artificial Neural Networks (ANNs) and Deep Neural Networks (DNNs), are well-suited to tackle high-dimensional, nonlinear, and noisy datasets [8-10].

Artificial neural networks (ANNs) are models of the structure and functional aspects of biological neurons. They can approximate highly complex functions using learning algorithms that iteratively adjust node weights to minimise mean squared error (MSE) [11]. DNNs have been gaining tremendous attention for being powerful models to describe mechanical behaviours of materials due to their ability to learn intricate underlying features found within high dimensions. DNNs have been used extensively for many types of cementitious materials, such as concrete [12], soils [8], asphalt [13], and other issues related to materials engineering and geotechnical engineering. More recently, DNN models with multiple hidden layers have been shown to generalise better for very large and complex data sets than simpler ANN architectures; however, their computational costs and tendency to overfit the training set are also higher than those of simpler architectures. [14]

ML has been used to predict rutting, fatigue life, resilient modulus, and stiffness modulus in pavement engineering applications, and has consistently outperformed classical regression methods in terms of accuracy and interpretability [15 - 16]. In contrast, there have been relatively few studies that have compared the predictive performance of shallow and deep learning models for predicting ITSM of fibre-modified cold asphalt mixtures; this limitation is noteworthy given the heterogeneity of mix design variables and curing conditions.

This research will create and compare the predictive power of ANN and DNN Models for determining the ITSM of fiber-reinforced Cold Asphalt Mixtures. A dataset containing 123 different mixtures with a variety of fiber types, quantities and curing durations was used as the basis for evaluating the two model architectures with respect to their accuracy, generalizability, and variable importance. The findings from this study will contribute to the broader literature on data-driven asphalt mix design and demonstrate the utility of machine learning tools for optimising high-performance, environmentally sustainable pavement materials.

2. Methodology

2.1. Artificial Neural Networks ANNs

Artificial neural networks (ANNs) have become increasingly valuable for modelling complex, nonlinear relationships where traditional regression techniques fall short, particularly in the field of civil engineering. Unlike linear modelling techniques, which are effective only for single-input variables, ANN models can capture relationships among inputs. ANN lets you see all possible relationships among multiple variables. In the field of material property prediction, ANN has been successfully used to predict the Indirect Tensile Stiffness Modulus (ITSM) of Cold Mix (N), as shown in Figure 1, using Artificial neural networks, Fiber type, and Fiber Length. The ANN model is built using thousands of computational units that mimic neurons in the brain, communicate with one another (interconnected), and can learn (adapt) from a given (trained) database, thereby modelling complex relationships between a set of input variables and an output target variable [8,9].

Using the seven input parameters, fibre type one (FT1), fibre type two (FT2), fibre blend Ratio (FT1/FT2), Fiber Content by weight (%FC), Curing time (CT), Fiber Length (FL), Air Void Content (%AV), the Artificial Neural Networks (ANN) model has been developed. To predict the ITSM of fibred mixes using experimental test data, a model was constructed. The ANN model consists of an input layer, one or more hidden layers, and an output layer. The ANN was trained using the backpropagation algorithm. Backpropagation is the most common method of training multi-layer perceptron (MLP) networks and is also used in supervised learning. Gradient descent was used for model optimisation. This study also revealed that the ANN model has the capability of generalisation (prediction). The model was fine-tuned by optimising key hyperparameters, including the learning rate, number of neurons, and data partitioning, to improve accuracy.

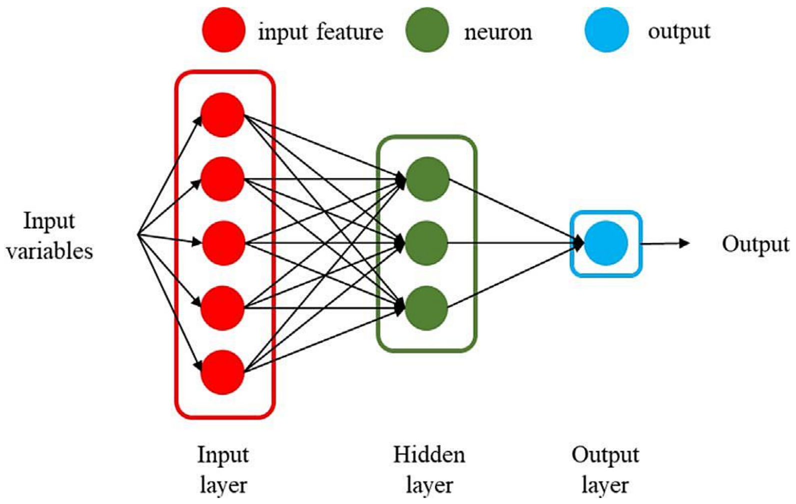

Fig. 1. Simplest artificial neural network ANN

2.2. Deep Neural Networks DNN

Generally speaking, the DNN will have at least an input layer for processing the input data, more hidden layers for computation, and an output layer for the computed results. This AI system can model nonlinear relationships between inputs and outputs, as shown in the graph (Fig. 2). Nonetheless, deeper architectures such as deep neural networks (DNNs) are introduced to capture much more complex patterns, increasing the representational capacity but in the opposite way they also bring some risks such as possibility of overfitting and increased computational demand [9].

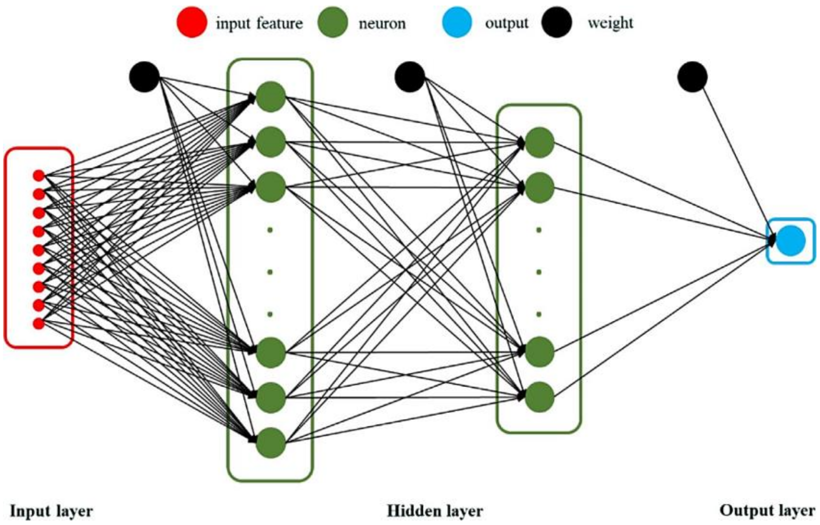

Fig. 2. Deep neural network DNN

Usually, DNNs are feed-forward networks with multiple layers, each containing weights, biases, and an activation function [17]. In the training phase, the forward pass computes the output values, while the backpropagation updates the parameters to minimise the function's predicted error. There are several strategies to improve the generalisation ability of DNNs, including dropout [18], early stopping [19], batch normalisation [20], and advanced optimisers like Adam [21].

The DNN framework is developed for predicting the ITSM of the fiber-modified cold asphalt mixtures, based on various input features like fiber types (FT1, FT2, FT1/FT2), fiber content (% FC), curing time (CT), air voids (% AV), and fiber length (FL). This architecture can capture nonlinear interactions among variables [20], thereby enhancing regression accuracy in asphalt mix performance modelling.

2.3. Data Base

To assess the predictive capability of deep learning models such as DNNs and ANNs, the formation of training datasets is crucial and highly depends on the structure, quality, and representativeness of the data collected, as networks learn complex, nonlinear relationships between inputs and outputs [9]. In this study, datasets were developed and used to train, develop, and validate models for predicting the Indirect Tensile Stiffness Modulus (ITSM) of fibre-reinforced cold-mix asphalt mixtures.

The primary data set consists of 123 cold-mix asphalt designs obtained from prior experimental studies simulating fibre reinforcement under varying conditions, including curing durations and moisture contents [13,23-28]. Both Deep Neural Network (DNN) and Artificial Neural Network (ANN) models employ the fiber type that is applied in the 1st (FT1) and 2nd fibers (FT2), the hyprid fibers in mixture (FT1/FT2), the percentage of the fiber that is added to the mixture (%FC), the curing time (CT), the length of the fiber (FL) and air void content (%AV) as the inputs values. The ITSM in MPa metric in Table 1 is the output variable.

Table 1. Definition of variables used in models for fiber-modified cold mix asphalt

Variable Type	Symbol	Description
Input	FT1	Fiber Type 1 (0 = No fiber, 1 = Cellulose, 2 = Glass, 3 = Nylon, 4 = Polyester, 5 = Basalt, 6 = Hemp, 7 = Jute, 8 = Coir)
Input	FT2	Fiber Type 2 (0 = No fiber, 1 = Cellulose, 2 = Glass, 3 = Nylon, 4 = Polyester, 5 = Basalt, 6 = Hemp, 7 = Jute, 8 = Coir)
Input	FT1/FT2	Fiber Blend Ratio by Mass (FT1:FT2)
Input	%FC	Fiber Content (% by weight of total aggregate)
Input	FL	Fiber Length (mm)
Input	CT	Curing Time (days)
Input	%AV	Air Void Content (%)
Output	ITSM	Indirect Tensile Stiffness Modulus (MPa)

Both models were fashioned as multi-input, single-output regression structures. The Deep Neural Network (DNN) model was applied with a 2-hidden-layer architecture. In contrast, the Artificial Neural Network (ANN) model was trained with a single hidden layer architecture, in view of possible greater training flexibility and better accuracy. Training was done using the Levenberg-Marquardt backpropagation algorithm built into the IBM SPSS Modeller environment, a behaviour it has shown in handling nonlinear regression problems relating to material performance reasonably well.

A 'trial and error' method has been used to determine the optimal number of hidden neurons and the suitable data distributions for training, testing, and validation. The ANN-I model with three hidden nodes was found to be the most effective and the most stable. The DNN-II model with two hidden layers (4 nodes in the first and 3 in the second) performed best. Both models were tested with and without regularisation methods and layer normalisation [29,30] to improve generalisation and avoid overfitting. The activation function used for both models was the hyperbolic tangent (tanh), with a learning rate of 0.4 and a momentum coefficient of 0.9 to ensure faster, stable convergence during training.

Table 2 includes all the parameters used for the model configurations, including the hidden layers and the number of nodes. These configurations correspond to the ANN-I model illustrated in Figure 3 and the DNN-II model shown in Figure 4. Based on performance metrics, the optimal number of hidden nodes for the ANN-I model was determined to be three. In contrast, the DNN-II model achieved its best performance with four nodes in the first hidden layer and three nodes in the second hidden layer.

Table 2. Data division ratios on ANN-I model and DNN-II model performance for fiber-reinforced cold mix asphalt

ANN-I model					
Input layer	7	Hidden layer	3	Output layer	1
Training (%)	Testing (%)	Validation (%)	Training Error (%)	Testing Error (%)	Correlation (r%)
70	20	10	7.4	11.5	91.5
70	25	5	6.2	11.7	90.6
80	10	10	8.8	8.8	93.2
80	15	5	6.1	6.8	94.6
90	5	5	4.8	5.9	95.1
90	8	3	5.2	4.7	92.3
DNN-II model					
Input layer	7	Hidden layer 1 Hidden layer 2	4 3	Output layer	1
Training (%)	Testing (%)	Validation (%)	Training Error (%)	Testing Error (%)	Correlation (r%)
70	20	10	10.6	21.3	85.6
70	25	5	12.4	16.9	85.6
80	10	10	9.6	11.6	87.8
80	15	5	9.9	12.8	83.2
90	5	5	7.9	20.4	80.9
90	8	3	6.7	7.3	88.4

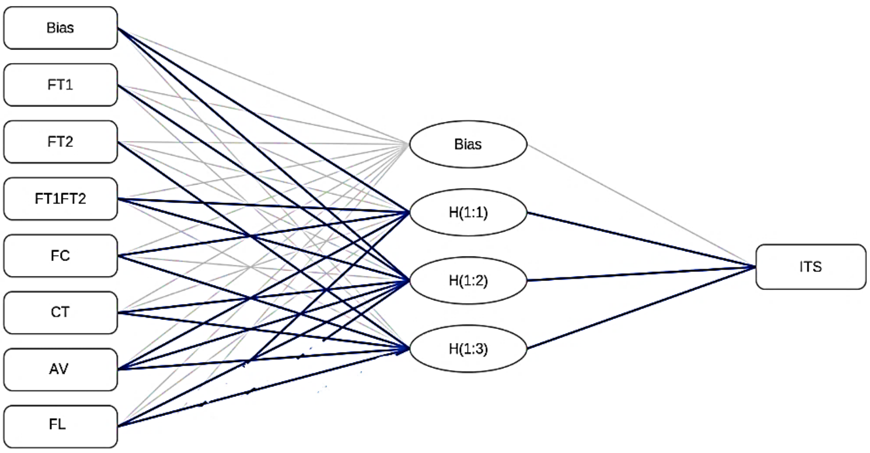

Fig. 3. Architecture of an artificial network model for ANN-I

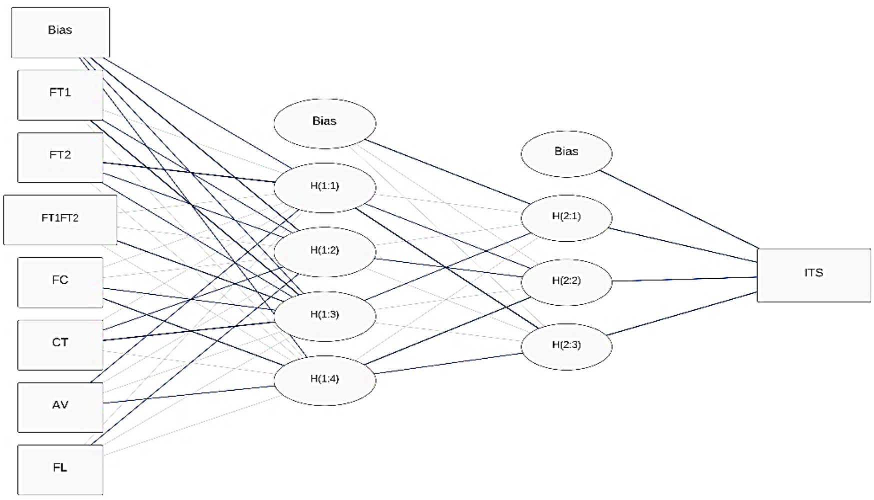

Fig. 4. Architecture of an artificial network model for DNN-II

To assess prediction accuracy, six performance metrics were used: Root Mean Square Error (RMSE), Normalised RMSE (NRMSE), Mean Absolute Percentage Error (MAPE), Average Accuracy Percentage (AA%), Coefficient of Determination (R^2), and Pearson Correlation Coefficient (R). Lower RMSE and MAPE values, alongside higher R and R^2, indicated superior model accuracy and generalisation [31], as calculated using Equations (1-5).

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N} (A_n - P_n)^2} \tag{1}$$

$$NRMSE = \frac{RMSE}{S} \tag{2}$$

$$R^2 = 1 - \frac{\sum(A_n - P_n)^2}{\sum(A_n - S_n)^2} \tag{3}$$

$$MAPE = \frac{\left(\sum\frac{|A_n - P_n|}{A_n}\right) * 100}{N} \tag{4}$$

$$AA\,\% = 100\,\% - MAPE \tag{5}$$

Where (An) actual and predicted (Pn) values are compared, and the estimated (N) number of points within the dataset is normalised by the mean of the actual values (S). To evaluation of both types of architecture in terms of input consistency and noise sensitivity, ultimately justifying the practical application of residual connections in civil material prediction problems [25,32].

3. Analysis and Result

3.1. ANN-I Model

In order to properly study and test the predictability of the low-cost Artificial neural networks (ANNs), it was carried out through the use of indirect tension stiffness modulus (ITSM) as a parameter for performance measurement for the construction of ANN model, with the use of certain fibres, the ratio mix, curing time values, as well as multiple other parameters. Also indicated are the types of fibres along with fiber indicators (FT1: Fiber 1, FT2: Fiber 2, FT1/FT2: Fiber Blend Ratio, FC: Fiber Content, FL: fiber length, CT: curing time, AV: air voids), which trained using the Levenberg- Marquardt algorithm combined at the same time as the input data for prediction models. In addition to ITSM, the representation of asphalt stiffness type is based on indirect tensile loading.

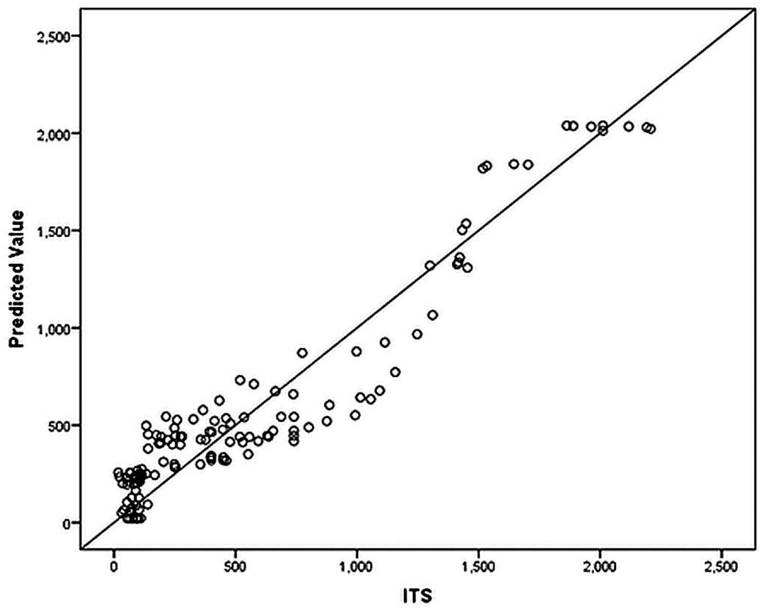

Fig. 5. Plot of actual vs predicted ITSM values by ANN-I

The ANN-I architecture was built to operate independently of predefined physical correlations and instead to extract patterns from empirical observations. The dataset incorporated a wide range of material combinations sourced from many origins, covering 123 distinct mix designs. A standard feed-forward neural network was trained, followed by evaluation using both visual and numerical diagnostics. Figure 5 shows the results of comparing both predicted ITSM values with the test dataset using a scatter plot. Generally, the predicted values fall reasonably close to the ideal 1:1 reference line, particularly in the mid- to high-stiffness range (> 800 MPa). This indicates that the model captures the underlying data well. A greater amount of variability is observed in the lower-stiffness data (< 400 MPa), where predicted values are noticeably lower, suggesting the potential to underestimate softer mixtures.

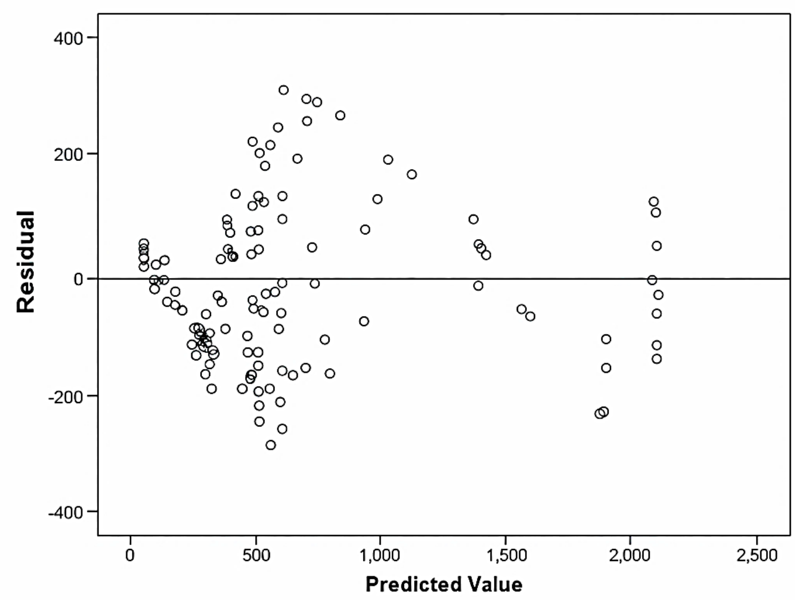

Fig. 6. Residual distribution plot for the ANN-I model predicted ITSM

Residuals were used to show any discrepancies between predicted and observed ITSM values. Most of the residuals in Figure 6 are clustered around the zero line (the x-axis), but there was a consistent underestimation with low-productivity outputs in the low output range. This can occur due to a lack of low-strength mix representation in the training set and/or to the extent to which certain variables, such as short curing periods or low fibre content, influence low productivity output. The RMSE of the model was 174.85 MPa, and the NRMSE (RMSE/mean ITSM) was 32.2%. The MAPE value was calculated to be 84.83%, indicating substantial deviations between some predictions and the actual values in the independent test set, particularly for lower-stiffness values. The AA% obtained with the ANN-I model averaged 15.17%. However, despite this high AA%, the R2 and R values were 0.903 and 0.951, respectively, indicating that the ANN-I model maintained a strong overall correlation with the experimental data, as shown in Table 3.

Table 3. Performance evaluation metrics of the ANN-I model

Indicator	Value
RMSE	174.85 MPa
NRMSE	32.2%
MAPE	84.83%
Average Accuracy Percentage (AA%)	15.17%
Coefficient of Determination (R^2)	0.903
Pearson Correlation Coefficient (R)	0.951

In Figure 7, we can see that curing time (CT) is a dominant factor influencing the prediction model, verifying its critical role in the development of cold asphalt mix stiffness. This was followed closely by fibre length (FL) and air void content (%AV), further supporting the notion that environmental factors associated with compaction also play a significant role in stiffness development. Limited significance within the prediction model exists for fibre content (%FC) and individual fibre types (FT1 & FT2) in the dataset, indicating either a lack of or limited variability in those variables or the presence of nonlinear effects not fully accounted for by the current ANN architecture.

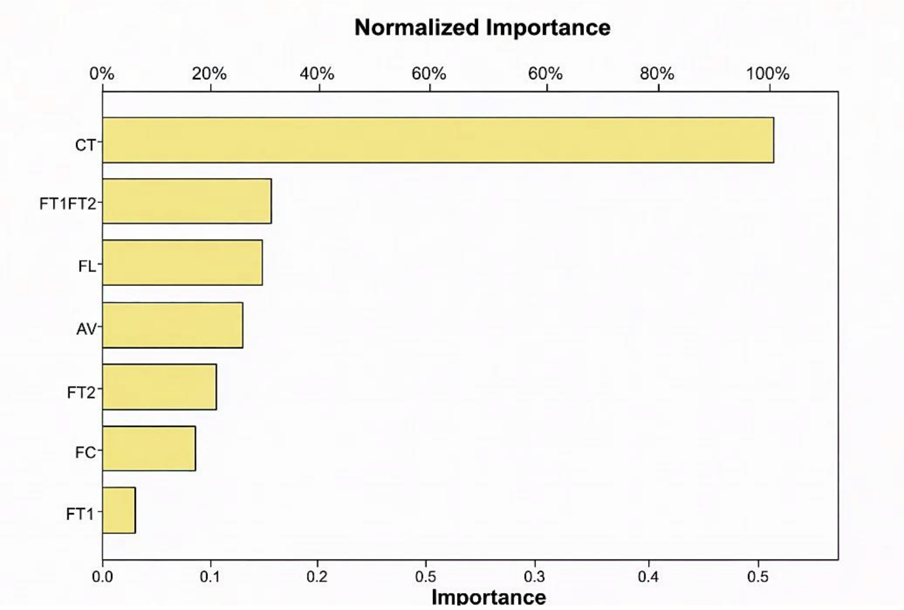

Fig. 7. Normalised importance of input variables in ITSM prediction

The results of this research support previous findings about the primary engineering parameters of curing and hybrid fiber ratios that influence the tensile stiffness of fibre-reinforced cold mixes due to their high sensitivity with respect to time and environmental conditions regarding the binder-fibre interaction. The poor performance in low-stiffness areas suggests that there may be a need for continued dataset enrichment and rebalancing, and that more advanced hyperparameter tuning or hybrid modelling techniques should be used to improve generalisation across all material conditions. Overall, the strengths of the ANN-I model as a basis for modelling ITSM for many different types of fiber modified mixtures support its use; however, its current state would benefit from additional refinement aimed at better modelling of low-strength properties and through developing more experimental data or the use of interaction effects between the input parameters.

3.2. DNN- II Model

Development of the DNN-II Model employed a multi-layer, multi-input/single-output regression structure, similar to that used for the ANN-I Model. The overall objective of both the ANN-I and DNN-II Models was to create an architecture capable of mapping an input set of key parameters to their associated ITSM values, while improving generalisation and predictive performance. In the case of the DNN-II, the input dataset consisted of all fibre-related and mix design parameters, including; Fibre Type 1 (FT1), Fibre Type 2 (FT2), FT1/FT2 ratio, Fibre Content by Aggregate Weight (%FC), Fibre Length (FL), Curing Time (CT) and Air Void Content (%AV). The sole output variable for both the model training/validation phases was the ITSM. The DNN-II architecture consisted of two hidden layers, each with four neurons in the first and three in the second.

The visual representation of the analysis results (Figure 8) indicates that the DNN-II model's predictions are moderately accurate relative to the actual test values. Although there is some evidence of clustering around the 1:1 line, the model displays a fairly large degree of spread in its predicted values, particularly in the lower to mid-range of the ITSM (i.e., below 1000 MPa). This suggests that there may be an overfitting issue or that some fibre mix combinations may not have been adequately represented in the data used to build the DNN model.

Figure 9 depicts the residual plot which supports this assumption. Most residuals have an approximate symmetric distribution about the zero-error line; however, a number are found in the negative range suggesting some high ITSM values were underpredicted by the model (i.e., it has tended to underpredict those high values). Likewise, a number of low ITSM values have been overpredicted. Furthermore, the presence of outliers (and especially those corresponding to very large negative residuals) indicates that the model fit may not be reliable for certain observations or for observations made under specific conditions.

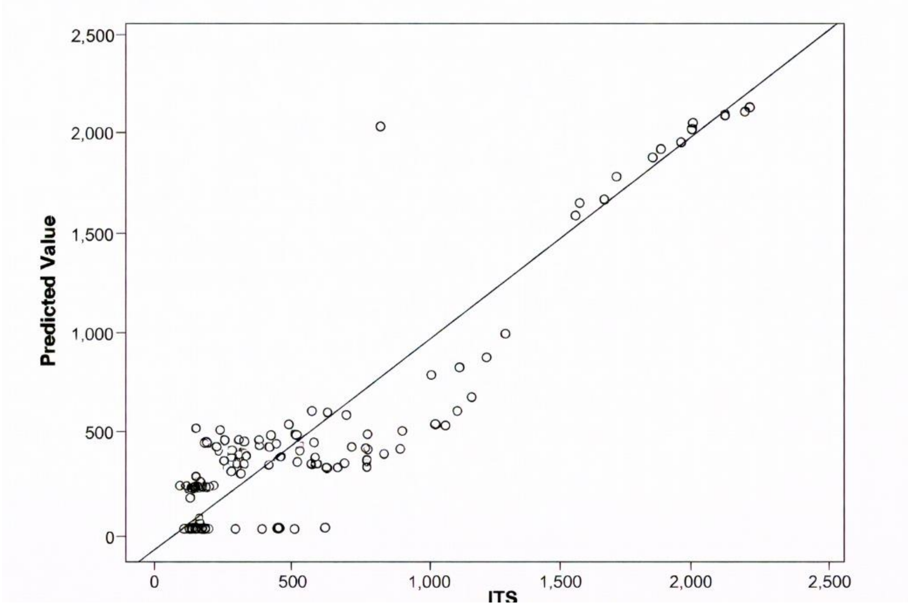

Fig. **8**. Scatter plot of predicted vs actual ITSM values using DNN-II

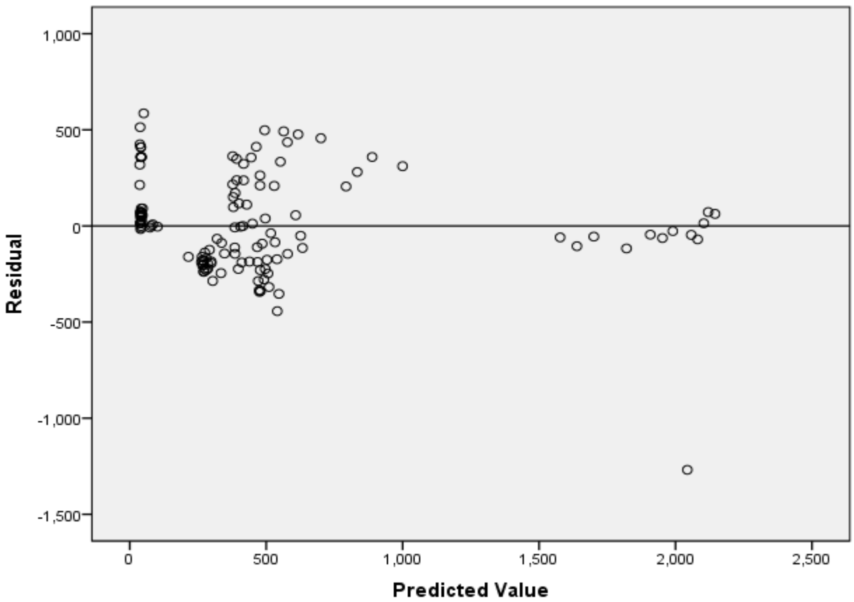

Fig. 9. Residual plot for DNN-II predictions

Performance metrics based on the quantitative data in Table 4 demonstrate that the DNN-II model has several significant limitations in predicting stiffness. The calculated Root Mean Square Error (RMSE) for the DNN-II model was 252.56 MPa, with an NRMSE of 52.68% above acceptable limits compared to other ANN models, and a MAPE of 106.90%, AA% ratios reduce the MAPE of accuracy (AA%)by providing negative values. More importantly, when the MAPE value becomes greater than 100%, the AA% level becomes meaningless and loses its usefulness for determining the accuracy of stiffness prediction because the concept of a negative accuracy percentage cannot exist in the real world. For this reason, we recommend that when assessing model reliability, the typical performance measures (RMSE, MAPE, R^2) be the main source of evaluation. These results indicate a considerable discrepancy between predicted and actual measurements, making the use of DNN-II models for practical purposes highly unreliable. The coefficient of determination (R2) value of 0.773 and the Pearson correlation coefficient (R) value of 0.884 suggest that, while there is an acceptable degree of correlation between the actual results and DNN-II model predictions, the required reliability for a reliable stiffness prediction model is still not met.

Table 4. Performance evaluation indicators of the DNN-II model

Indicator	Value
Root Mean Square Error (RMSE)	252.56 MPa
Normalised RMSE (NRMSE)	52.68%
Mean Absolute Percentage Error (MAPE)	106.90%
Average Accuracy Percentage (AA%)	-6.90%
Coefficient of Determination (R^2)	0.773
Pearson Correlation Coefficient (R)	0.884

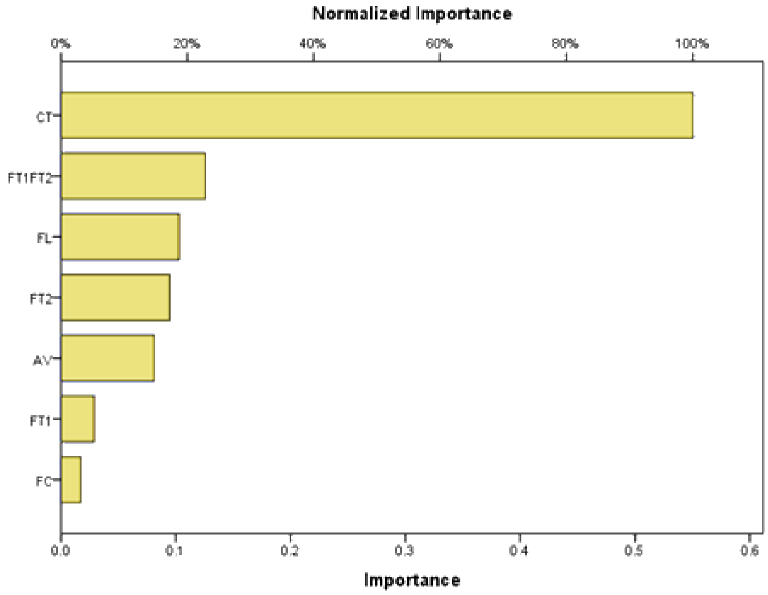

Fig. 10. Normalised importance of input variables in DNN-II

4. Comparative Analysis: ANN-I vs DNN-II

The performance of the ANN-I and DNN-II models for prediction depends on how the models were created based on the training data's structure, variability, and representativeness. The ANN-I model, with one hidden layer and using a very diverse and broad range of mix designs for the 123 mix designs (RMSE = 174.85 MPa) and statistically high correlation R^2 = 0.903, was able to develop models that accurately predicted mid-to-high stiffness (effectively discovering the most dominant relationships created with curing time (CT) and air void content (%AV)). In contrast, the values for lower stiffness were systematically biased towards under-representing this application, indicating a gap in the dataset's range (specifically, a lack of low-strength curing, low-strength curing time, or low-fibre mixtures).

The performance of DNN-II's two-layer model is negatively affected compared to DNN-I, particularly in terms of data balance and cohesion, despite its design intended to enhance generalisation through a deeper layer structure. This resulted in DNN-II achieving the lowest performance metrics (RMSE = 252.56 MPa; MAPE = 106.9%) due to overfitting and residual irregularity. DNN-II had elevated prediction rates for higher values of the Indirect Tensile Stiffness Modulus (ITSM), whereas its predictions did not equalise or stabilise across the entire mix/condition distribution. Figure 11 showsquantitative graph summarizing the performance differences between the two models.

While the ANN-I model has a fairly high R^2 value (0.903), this reflects more its ability to predict the overall trends than its ability to predict point by point accurately. Both the significant amount of error reflected by MAPE (84.83%) and the very low AA% (15.17%) demonstrate that the two models have very little ability to predict individual ITSM values accurately. The DNN-II model has performed even worse than the ANN-1 (MAPE = 106.90% and AA% = −6.90%), suggesting a severe lack of confidence by predict individual ITSM values accurately. So when MAPE exceeds 100% AA% becomes meaningless; a negative AA% cannot be interpreted in a useful manner for stiffness predictions. Therefore, the reliability of models should be determined to a greatest extent possible with standard indicators (e.g., RMSE, MAPE, R^2). Overall, the two models performed better predicting the general trend of the data than they did predicting individual ITSM values and are therefore not yet applicable for direct engineering design or field use.

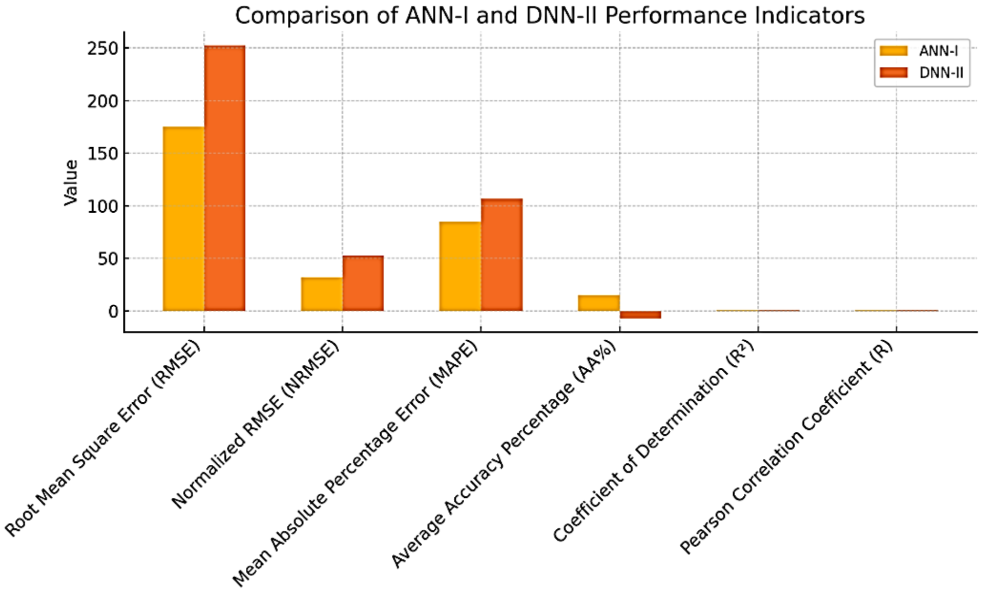

Fig. 11. Comparative Analysis indicating the ANN-I model vs the DNN-II model

The outcome of this study has identified the superior ability of the simplified ANN model to generalise in comparison to the DNN model, based on two models being developed from the same set of 123 samples; it has been suggested that one possible reason for this is due to the amount of data available to effectively train a deep neural network is not adequate with 123 samples. Deep neural networks have a greater number of trainable parameters and multiple hidden layers as opposed to simple ANN models; therefore they require a significantly larger amount of training data to learn generalisable and robust patterns in the data set. If a DNN has been trained using an inadequate sample size, it is highly susceptible to memorising the training data and therefore has poor generalization ability. The results of this study indicate that the differences in model type demonstrate a difference in the available sample size to support the model; therefore model depth alone does not guarantee greater predictive accuracy but is dependent on using an appropriate model type for the given sample or training set.

5. Conclusion

- The ANN-I model produced superior results to the DNN II in ITSM predictions, with a higher correlation (R=0.951) and lower RMSE (174.85 MPa), thereby improving prediction accuracy.
- The most critical factor to the stiffness of these cold asphalt mixtures was curing time; both models demonstrate the importance of this parameter when predicting stiffness development.
- While the ANN-I produced superior generalisation across a 123 different mixtures (single dataset), DNN II showed greater sensitivity to data distribution, though both behaviours pose a risk of overfitting.
- The lower performance of DNN II indicates the need to use higher-quality, balanced datasets with deeper architectures to limit excessive prediction errors.
- The findings suggest that shallow architectures outperformed the tested deep architecture in describing the general character of ITSM; however, the reported level of predictive error demonstrates that the accuracy of predictions are still not adequate for the reliable

prediction of stiffness or direct optimization-based design of pavements, and further model refinement and data enhancement is necessary.

5.1 Future Study

Future studies should evaluate advanced data generation techniques such as GANs for augmenting existing data sets prior to model training, which addresses the limitations of this study. Furthermore, algorithms that can be used with small number of samples (tabular-type data), e.g. XGBoost, RFs, are worthy of consideration as additional sources of more dependable and solid predictions in ITSM.

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