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Predicting the Mechanical Behavior of Cold Asphalt Mixtures Using Optimized Artificial Neural Networks

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ABSTRACT

In this study, Artificial Neural Network (ANN) models were developed to predict the indirect tensile strength (ITS) of cold asphalt mixes (CAMs) incorporated with different industrial waste materials. Input variables were determined as variables including emulsion content, curing time, sludge ash content, additive type, and aggregate grading, which were investigated the influence on ITS of CAMs from 163 experimental mix designs. The ANN model structure was formulated, and the multilayer feedforward perceptron was trained, while the number of neurons in hidden layer was set to adjust the structure of the network. The neuron number analyze process shown that 5:3:1 structure selected as the final pattern. The efficient of the trained model is reasonably high with a prediction correlation coefficient (R) of 0.963, and it gives a low Mean Absolute Percentage Error (MAPE) equal to 11.9%. The sensitivity analysis also showed that the curing time and water content were the two highest parameters impacting the ITS, and the emulsion content and initial moisture content were the two lowest parameters influencing the ITS. The test error is increased as the neuron of hidden layer was selected as 4, 6, and 7, however the minimum error is seated as the neuron number was 3. We recommend that ANN-based methodologies show great potential in being reliable and efficient tools that can be used to emulate the mechanical responses of the CAMs tested in this study, as well as aid in designing more sustainable pavement materials.

1. INTRODUCTION

The growing global trend toward sustainable infrastructure has cranked up the interest in alternative techniques to Hot Mix Asphalt (HMA) production. One alternative in particular are the new cold asphalt mixes (CAMs). They're a carbon lightweight alternative to HMA because they're produced and used at room temperature, leading to significantly reduced energy consumption and Greenhouse Gas Emissions (GHGs) because production energy moves from the tier 5 stovetop to near zero with CAMs, because of lowered emissions carbon dioxide emissions and the lack of required active ingredient persistence it's a great, new, trending approach to infrastructure [1]. Accessibility for CAMs use perseveres in terms of use in inaccessible or underdeveloped areas globally and is suitable for temporary, low traffic pavements, like caravan sites and patching of highways [2, 3].

In comparison to conventional HMA, cold-applied mixtures (CAMs) report inferior mechanical performances, especially during the early stages after their application. This includes a range of material properties such as indirect tensile strength (ITS), flow, rutting resistance, and moisture susceptibility. These limitations are mainly due to its low initial cohesion made worse by prolonged curing periods, which are the primary reasons for its poor properties. To overcome this drawback, the utilization of additives within CAM compositions has emerged as a popular method respondents have tested to enhance the mechanical behavior of these mixtures.

Various types of polymers, cement, natural and synthetic fibers, waxes, and even recycled materials such as polyethylene terephthalate (PET) bottles, rubber, and fly ash, have been used as modifying agents to improve the mechanical properties and durability of cold mixes. In general, the addition of these modifiers influences and changes the internal structure of the asphalt matrix and the interaction between the binder and the aggregate, thereby enhancing the mechanical properties such as strength, stiffness, adhesion, and durability of the mixtures, towards environmental factors [4]. Despite the significant potential of these additives' effects on the mechanical properties of cold mixtures, predicting the mechanical behavior of modified cold mixes remains complex. This is due to the largely nonlinear and interdependent relationships between a range of mixture parameters, including the type and amount of the additive, the characteristics of the binder used, the curing period, and environmental factors (namely the environmental temperature which significantly affects the curing process of cold mixes).

To respond to the intricacy, current studies have inclined towards data based models, which Artificial Neural Networks (ANNs) are newly found to have great capacities [5, 6]. ANNs imitate the behaviour of the organic neural system and are notable for its ability to depict the most complicated patterns and associations through large multidimensional databases without needing specific mathematical formulas [7, 8]. ANNs mainly consist of neurons and synaptic weights, and these qualities provide the flexibility and resilience necessary to model civil engineering materials, which are difficult to analyse with traditional linear mathematical models.

ANN applications in the field of construction and pavement engineering have grown at staggeringly rates in last few years. A few examples include the forecast of compressive strength of concrete, modeling of asphalt binder viscosity with changing temperature, and long-term behavior of pavement under traffic loading constraints. According to the researches done by Uwanuakwa et al. [9]. ANN has ability to predict the mix proportion of self-compacting concrete by the help of slump flow and compressive strength which was helped by the_help_word multi-output ANN. Similarly, Mugume [10] utilized ANN integrated with multi scale modelling to predict the strength of fly ash enhanced mortar, and the prediction answer was found to be highly correlated with the experimental result.

Aiming at proposing an ANN forecast model for ITS of CAMs which were modified with different common industry additives and exposed to many premature aging conditions, this paper applied the ANNs method to establish the theoretical model under a selection of comprehensively designed and statistically perfect model serial production test data. The accuracy of the model was evaluated based on statistical performance measures and sensitivity analysis, while also use the performance of the model to identify the most prominent factors in the model. Finally, this research focus on providing practical applications for engineers, as a flexible and reliable estimating tool, to optimize the mix design of the cold asphalt and better achieve the requirements of road engineering design, considering economical and spatial distribution issues to apply more sustainable and performance based flexible pavement systems.

2. NEURAL NETWORK MODELING

The method behind this entire study was to use ANN to predict the mechanical test results of cold mix asphalt (CMA) modified with various additives and production parameters. Specifically, the goal was to estimate the residual ITS across different aggregate types used in the asphalt mixture. In essence, the ANN model aimed to capture the complex nonlinear relationships between the input variables and the target outputs.

For this study, a feedforward multilayer perceptron (MLP) model, commonly referred to as ANN, was implemented with backpropagation learning, an approach extensively applied in civil engineering materials modeling [11-15]. The MLP architecture included three layers: an input layer (e.g., emulsion content, additive percentage, curing time, moisture condition), hidden layers for nonlinear transformations, and an output layer representing the predicted residual ITS.

The input variables consisted of both categorical and continuous data across seven scenarios, including types of emulsion, presence of stabilizers (cement, lime, ash), and curing duration (in days). The output variable was the residual ITS obtained under controlled laboratory conditions.

The dataset for model training and validation was compiled from prior verified experiments, including those involving sludge ash-modified CMA. For model development, IBM SPSS Modeler was chosen due to its intuitive interface and powerful learning engine, facilitating flexible architecture adjustments and accurate model performance validation.

3. STATISTICAL TRAINING AND EVALUATION OF ANN PERFORMANCE

The ANN was developed using a structured dataset where the dependent variable was the post-curing ITS, and the independent variables are shown in Table 1. These inputs encompass design parameters of the CMA, such as emulsion content, sludge ash content, curing period, and additive types.

To ensure robust evaluation, the dataset was partitioned into three subsets:

Training set (86%) – used for weight optimization;

Testing set (9%) – monitored during training to avoid overfitting;

Validation set (5%) – used for final model performance assessment.

The training process was halted once the error on the testing set began to increase, a standard practice to mitigate overfitting and ensure generalizability.

Table 1. Definition of variables used in the ANN model for CMA

Variable Type	Symbol	Description
Output	ITS%	Residual Indirect Tensile Strength (%)
Input	EC	Emulsion content (%)
Input	SA	Sludge ash content (%)
Input	CT	Curing time (days)
Input	AT	Additive type (cement = 1, lime = 2, silica = 3, none = 0)
Input	WC	Water content (%)
Input	GR	Gradation type (coarse = 1, medium = 2, fine = 3)
Input	MC	Initial moisture condition (dry = 1, wet = 2)

The development of the linear model structure did facilitate the ability to identify which variables were most influential to the mechanical performance of CMA. Based off the initial results, it was discovered that ITB and SSA had the most significant influence on the ITS, and ATB and MS did in the MBV. The critical level of interaction that was found in the CMA formulation was between ATB and MC.

4. DATA COLLECTION AND MODEL INPUT STRUCTURING

To train the ANN, numerous experiments on CMA were used 163 mix designs from these studies [16-35]. This database aimed at investigating the residual mechanical properties of CMA, represented by the ITS, by considering several mix design and processing parameters.

Temperature and humidity control in lab - with the exception of a few mix designs described in the paper, the majority of experiments were conducted in the lab under conditions of ambient air temperature ranging from 20-25°C and relative humidity of 50-65%. For studies that looked at curing at elevated or reduced temperatures, the higher and lower ranges (e.g., 5-40°C) were also recorded to reflect environmental variation. Curing and moisture control: Curing times ranged from 3 to 28 days, and moisture contents were adjusted to represent typical field compaction conditions (i.e., any free moisture is lost before ITS testing). Of the final materials, the ANN study included replicate measurements for several mix designs tested under different curing or environmental conditions to allow the ANN to capture the influence of environmental variation on ITS without overfitting to a specific situation. Duplicate samples and variability: Outliers were rejected if the ITS of any replicate sample was >25% different from the mean ITS of the replicates, or if the material composition data were incomplete. Support vector regressions were performed to investigate the relationships between the effective diffusivity and other SOC properties.

The ANN model development followed a structured trial-and-error process to identify the optimal data split among the training, testing, and validation sets. This process aimed to maximize the correlation coefficient (r) between the predicted and actual tensile strength values, ensuring high predictive reliability. Data splitting ratios were systematically varied to evaluate their impact on prediction accuracy.

5. MODEL OPTIMIZATION AND VARIABLE REDUCTION

The performance of the ANN was analyzed for different data division ratios, with results summarized in Table 2. The optimal split was determined as 86% training, 9% testing, and 5% validation, which yielded the highest correlation coefficient of 96.3% and the lowest testing error of 2.9%. This configuration was found to provide the best generalization capability of the model. The dataset, consisting of 163 mix designs, was partitioned using integrated random and striped sampling techniques, with the striped division yielding superior performance.

Table 2. Effect of data division ratios on ANN performance for CMA

Training (%)	Testing (%)	Validation (%)	Training Error (%)	Testing Error (%)	Correlation (r%)
60	20	20	8.6	10.7	91.7
76	12	12	6.5	9.6	91.9
80	12	8	6.4	3.8	92.0
88	8	4	8.3	9.9	94.9
68	20	12	6.4	14.6	95.1
80	15	5	6.1	8.6	94.1
86	9	5	5.2	2.9	96.3
67	20	13	8.0	6.7	92.1

Table 3. Effect of data division ratios on ANN performance for CMA

Input Variable	Symbol	Relative Importance	Normalized (%)
Curing time (days)	CT	0.340	100.0%
Additive type (cement, lime)	AT	0.144	42.3%
Emulsion content (%)	EC	0.003	1.0%
Sludge ash content (%)	SA	0.069	20.4%
Water content (%)	WC	0.230	67.8%
Gradation type	GR	0.208	61.2%
Moisture condition	MC	0.006	1.7%

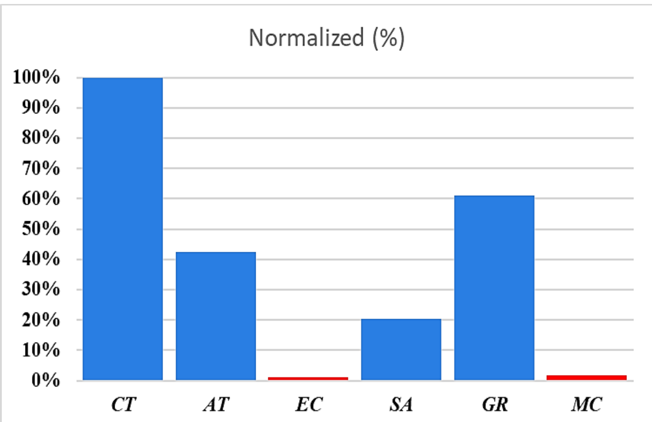

Figure 1. Effect of data division ratios on ANN performance

In order to get optimal performance, particular in computation, and to avoid overfitting a sensitivity analysis was carried out to discover the effect ratio of each input variable. Finally, there were five inputs found in the ANN model out of the seven at first. Pretesting experiments such as curing time, water content, gradation type and additive type percentage indicated the most influence on the output predictions while emulsion content, and moisture condition showed the very low effect and they were deleted.

The process of modeling is able to show the promising of machine learning tools in attempting to predict key mechanical outcomes of sustainable CMA. The research shows that use inclusive of machine learning techniques in predications important mechanical characteristics of interest his globally appears its capacity to reduce the volumes of physical testing required as well to as accelerate material design cycle what been sought for. The significance of the physical of the primary variables: curing time, moisture content, gradation type, type of additive, percentage of additive etc. reflects the main physical mechanisms for the performance of CMAs. The curing time means moisture evaporation and binder setting, in this sense, it has directly dominance on stiffness and cohesion. The moisture content means the method to provide workability; excess of water gives down to a down of strength because pore pressure or incomplete bonding etc. The gradation type gives us internal structure, which means how much percentage of aggregate could take load and how the load would be distributed etc. The additive type and its dosage changes binder-aggregate adhesion and viscoelasticity, etc. On the contrary, emulsion content and initial moisture condition are less significant because of low weightage which means little differentiation, or other significant variables would be less affect under lower variation of laboratory test conditions in Table 3 and Figure 1.

6. ANN ARCHITECTURE AND OPTIMIZATION OF HIDDEN NEURONS

To auto design the optimal number of neurons in the hidden layer, Eq. (1) has been adopted, which expresses the maximum number of nodes in the hidden layer. The ANN model was modelled with six number of input neurons which represent the six number of critical variables of CMA composition and processing, namely emulsion content, additive type, curing duration, Sludge ash percentage, gradation type and moisture condition and single neuron was designed in the output layer to predict the ITS of the CMA mix.

$$\text{Max.No.of Node} = 1 + 2 \times I \tag{1}$$

where, I is the number of input variables (in this study (6)).

Maximally, 13 hidden nodes were considered in the equation. In order to enhance the ANN model structure, a series of trials was done by increasing the count of hidden neurons is 1 to 13. In this regard, the model was trained and validated by finding out the training and testing error percentages as well as correlation coefficient (r) between predicted VS experimental ITS.

7. HIDDEN LAYER PERFORMANCE EVALUATION

Table 4 presents the productive units of the ANN model with diverse hidden nodes. The best prediction accuracy is achieved at having 3 hidden neurons (testing error of 2.9% and correlation coefficient of 96.3%), the test set with the highest correlation coefficient and lowest error rate was chosen because it is the highest set and provides greater reliability of the results because it was trained on more elements., which represents better generalization and stability than that of the others. And also, ANN model with the architecture of 7:3:1, as shown in Figure 2, provides the mapping of non-linear relationships of the cold asphalt mix parameters and mechanical performance. The hyperbolic tangent (tanh) activation function with 0.4 learning rate and 0.9 momentum coefficient is applied in Hidden Layer nodes which leads to faster convergence and improved error backpropagation.

The seventh model architecture, as seen in Figure 2, simple and shorten dependent on the result of relative importance became contains six input nodes, three hidden nodes and a single output node which is capable of accurately predicting the mechanical behaviour of cold-laid asphalt mixtures modified with eco-friendly industrial by-products such as sludge ash.

Table 4. Effect of hidden neurons on ANN prediction accuracy for ITS in CMA

Hidden Neurons	Training Error (%)	Testing Error (%)	Correlation (r%)	Hidden Neurons	Training Error (%)	Testing Error (%)	Correlation (r%)
1	6.8	10.1	91.6	8	7.1	4.9	94.1
2	5.3	10.8	93.0	9	5.5	9.8	93.8
3	5.2	2.9	96.3	10	6.7	12.1	94.2
4	8.1	3.2	92.6	11	9.8	15.3	92.1
5	6.3	18.4	92.4	12	8.4	20.9	91.3
6	7.5	6.6	92.7	13	7.0	13.4	91.2
7	6.6	8.8	95.7	—	—	—	—

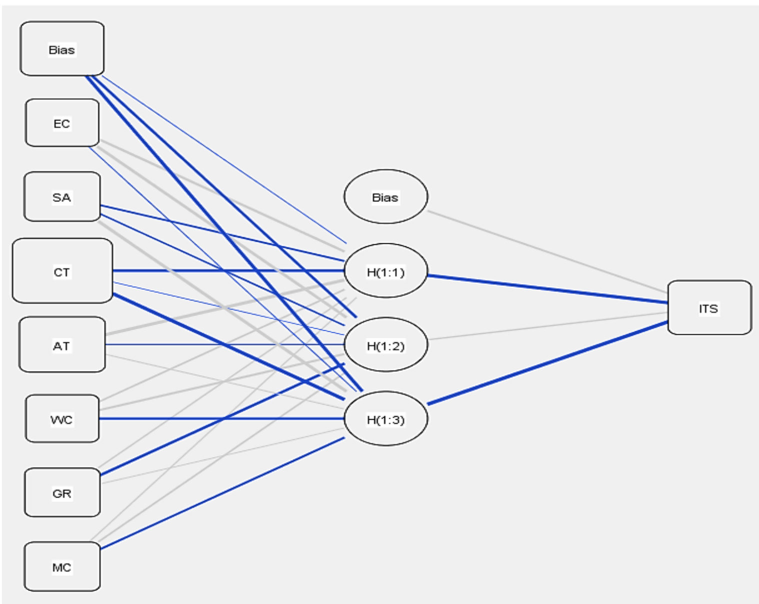

Figure 2. Neural network for CMA

8. DEVELOPMENT OF PREDICTIVE ANN MODEL FOR INDIRECT TENSILE STRENGTH

Synapse weight is found in ANNs that process connection between each neuron, and it is amount of the effect of the output of one neuron affects another one. In general, neurons receive a number of input signals where each of them is multiplied by its corresponding synapse weight, the result of which is then summed and passes through an activation function [36-38]. This mechanism provides learning and generalizing characteristic of ANNs. A three-layer feed forward ANN model used learning was designed to predict ITS of cold asphalt mixtures with the confidence of different types of additives, such as wastewater sludge ash (WSA). The final model which is designed from learning/analytics using SPSS software, has 6 neurons in the input layer, 3 neurons in the hidden layer, and 1 neuron in the output layer. Connection weights of each inter layer connection were determined by the training process provided by the SPSS, and specific inter layer connection weights are given in Table 5.

Table 5. Connection weights and threshold limits in the ANN model predicting ITS of cold asphalt mixes

Parameter Estimates Predictor	Samble	Predicted Hidden Layer 1		
		H(1:1)	H(1:2)	H(1:3)
Input Layer	(Bias)	-0.030	-0.410	-0.538
	EC	0.391	0.490	-0.036
	SA	-0.281	-0.170	0.530
	CT	-0.491	-0.018	-0.791
	AT	0.539	-0.133	0.083
	WC	0.277	0.349	-0.388
	GR	0.153	-0.438	0.080
	MC	0.089	0.217	-0.339

For consistent weight scaling or to improve the convergence behaviour of the model, all input variables have been normalized to give a range [-1, 1] as pre-processing protocol for SPSS. Where so final model can give predictive ITs expression given will be the resultant of weighted summation and activation operations going across the layers of network. The network takes some bias terms inside input and hidden layer(s) functioning as adjustable and trainable thresholds that the response of an activation function to move it (these bias terms play an important role of fine tuning the model during training phase) [39, 40]. The modelling of ANN offers a powerful and capable machine learning means to predict main mechanical performance property of cold asphalt mixtures across varying levels of material compositions, temperatures and mix designs as compared with the classical regression-based prediction method which is always a linear approach.

9. ANN-BASED PREDICTION OF MECHANICAL PERFORMANCE IN COLD ASPHALT MIXTURES

The objective of this study was to develop a feed-forward ANN model for predicting key mechanical properties of cold asphalt mixtures incorporated with industrial additives such as WSA. The developed ANN architecture adopted a hyperbolic tangent (tansig) as activation function at the hidden layer and a linear activation function (purelin) at the output node, given the prior modeling techniques reported by Cui-hong [40] and Al Nageim et al. [17] for asphalt materials.

The mathematical form of the ANN model is given by:

$$y = \sum_{j=1}^{n}(w_j * (\tanh\,(\sum_{i=1}^{3}(w_{ji}.x_i) + \beta_j))) + \beta \qquad (2)$$

where,

y: is the predicted output,

x_i: are the normalized input variables (such as aggregate gradation, binder content, curing time),

Wji: denotes the weight between input neuron i and hidden node j,

βj: is the bias associated with the hidden neuron j,

Wj: is the weight between the hidden node jjj and the output node,

β: represents the bias at the output layer,

n: is the number of hidden neurons.

To assess the accuracy of prediction of the developed ANN model for CAMs with WSA, different structures of network were checked. Out of the various structures tested, it was found that the perfect architecture having 8 input neurons, three neurons in hidden layer and single output neuron gave better performance in term of high correlation coefficient (r = 0.963) and low testing error (2.9%). The prediction capability of the configuration of such network was found quite good for the indirect tensile stiffness modulus in terms of the high consistency between the ANN estimations and laboratory evaluation of CMA specimens. This confirms the high performance ability of the ANN model in capturing the nonlinear interaction of the input parameters with the asphalt mixture behavior, which can be an effective decision support tool for optimal CMA design.

10. MODEL VALIDATION AND STATISTICAL ASSESSMENT

In order to assess the performance of the developed ANN-based model in predicting the mechanical behaviour of cold asphalt mixtures (response variables), some statistical indices have been employed. The ones used in this study were Mean Absolute Percentage Error (MAPE), Average Accuracy Percentage (AA%), Coefficient of Determination (R^2) and Correlation Coefficient (R).

The values resulting from the implementation of each of these indices were evaluated in order to ensure the consistency of the predicted ANN's outcomes in similar laboratory conditions when compared to the corresponding experimental results. The MAPE was calculated using Eq. (3), where it gives the average or mean percentage deviation of the predicted outputs from the experimental results for the selected mechanical property, which is indirect tensile stiffness modulus (A) as shown in Eq. (3). Then, the AA% value was given in Eq. (4), F-Statistic at Eq. (5), and the p-value is not computed from a formula directly but derived from the F (or t) distribution. Once you compute the F-statistic, the p-value p = P(F ≥ F calculated) which determines the accuracy of the ANN and its precision in predicting the input values.

$$MAPE = \frac{\left(\sum\left|\frac{A-E}{A}\right|\right)*100}{n} \qquad (3)$$

$$AA\,\% = 100\,\% - MAPE \qquad (4)$$

$$F = \frac{\mathrm{SSR/k}}{\mathrm{SSE/(n-k-1)}} \qquad (5)$$

where,

A: Actual value of the mechanical property (Residual Indirect Tensile Strength)(%P)

E: Estimated value using the ANN model

n: Number of data samples

SSR = Sum of Squares for Regression

SSE = Sum of Squares for Error

k = number of predictors

Table 6. Statistical evaluation of the ANN model for CMA

Statistical Indicator	Value
Average Accuracy Percentage (AA%)	88.1%
Mean Absolute Percentage Error (MAPE)	11.9%
Coefficient of Determination (R^2)	92.4%
Correlation Coefficient (R)	96.3%
F-Statistic	109.3
P-value	< 0.0001

Validation subset was used to check the generalization ability of the model, where 5% of the total dataset was taken. The statistical results presented in Table 6 exhibited that the ANN model exhibited good predictive ability since the value of the coefficient correlation (R) of 96.3% implying a strong correlation between the actual and network prediction data, the MAPE value of 11.9% to provide a good predictive accuracy of the ANN network, the value of the MAPE (A) of 88.1% also indicates the good average of the prediction accuracy with the corresponding experimental results as shown in Figure 3.

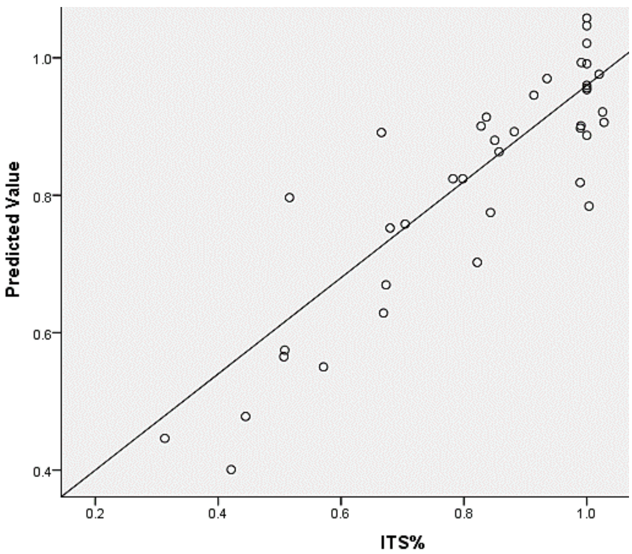

Figure 3. The agreement between predicted and practical values

By using the ANN model, sensitivity of all input parameters on predicting fresh mechanical properties of CMA designed using low carbon emitting materials had been observed. Relative significance of each input parameter on predicting the output response is obtained through this investigation. Based on the analysis conducted in this investigation, the most significant parameter that affecting the output response is the asphalt to emulsion ratio, particularly stiffness modulus, followed by the percentage of WSA and the additive content. Furthermore, the significance of each input parameters was varying with the output response parameters, either rutting resistance, moisture and fuel resistance or fatigue performance.

11. CONCLUSIONS

The optimized ANN model of 5:3:1 structure has exhibited a strong predictive accuracy with the R-Square value of 96.3% and the low testing error of 2.9% for estimating the indirect tensile strength of the cold asphalt mixes.

Curing time and water content were identified as the most influential factors on mechanical performance, while emulsion content and moisture condition had minimal impact.

A dataset of 163 mix designs ensured robust training, validation, and testing, enabling generalizable predictions across various cold mix asphalt formulations.

The sensitivity analysis confirmed sludge ash content and additive type as key modifiers influencing the mechanical behavior of CAMs.

This ANN model provides a reliable, data-driven tool for optimizing sustainable cold asphalt mixtures, reducing reliance on extensive laboratory testing.

The ANN model can be integrated with on-site construction data, enabling parameter adjustments such as curing duration or emulsion rate to suit varying temperature and moisture conditions in field applications.

The model supports stepwise mix optimization by predicting ITS under adjusted aggregate gradations and moisture contents, providing a practical decision-making tool for engineers.

DATA AVAILABILITY STATEMENT

The dataset supporting the findings of this study, comprising 163 mix design records of cold asphalt mixtures, is openly available at Mendeley Data: Ali, Anwer (2025), Predicting the Mechanical Behavior of Cold Asphalt Mixtures Using Optimized Artificial Neural Networks, Mendeley Data, V1. https://doi.org/10.17632/z2mx9vsr49.1

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