Application of Artificial Neural Networks for Predicting the Structural Number of Flexible Pavements Based on Subgrade Soil Properties

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Abstract:

The structural number (SN) is a critical parameter in the AASHTO design method, representing the overall load-bearing capacity of flexible pavements. Traditional determination of SN requires resilient modulus (MR) and California Bearing Ratio (CBR) tests, which are both costly and time consuming. This study proposes an artificial neural network (ANN) model as an alternative approach for predicting SN using readily available subgrade soil properties and environmental factors. A dataset of 2,810 samples was compiled and preprocessed, with dry unit weight (γd), moisture content (w), weighted plasticity index (wPI), and number of freeze–thaw cycles (NFT) employed as model inputs. The ANN was developed in MATLAB using a feed-forward architecture with a single hidden layer of 10 neurons and trained with the Levenberg–Marquardt algorithm. Model performance was evaluated using mean squared error (MSE) and correlation coefficient (R). The results showed strong predictive capability, with R values of 0.954, 0.948, 0.942, and 0.951 for training, validation, testing, and overall datasets, respectively. Error histograms and regression plots confirmed the model's robustness and generalization capacity. The proposed ANN framework provides a reliable and cost-effective tool for estimating SN, reducing dependence on expensive laboratory testing while supporting efficient and accurate pavement design.

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Keywords: Artificial neural networks (ANNs), flexible pavement design, structural number (SN), subgrade soil properties, machine learning in transportation engineering.

1. Introduction

The design of flexible pavements plays a critical role in ensuring long term performance, safety, and cost efficiency in transportation infrastructure. Among the various methodologies developed, the American Association of State Highway and Transportation Officials (AASHTO) design method for flexible pavements remains one of the most widely adopted systems worldwide. The 1993 AASHTO Guide for the Design of Pavement Structures incorporates multiple factors such as traffic loading, material properties, drainage, environmental conditions, and reliability to determine the required pavement strength (AASHTO, 1993). Central to this design framework is the structural number (SN), which quantifies the overall load carrying capacity of a pavement. The SN is subsequently translated into pavement layer thicknesses through layer coefficients that represent the relative contribution of asphalt, base, and subbase materials (Abaza & Abu-Eisheh, 2003).

Despite its robustness, the AASHTO design method relies heavily on parameters such as the resilient modulus (MR) and the California Bearing Ratio (CBR) of the subgrade soil. However, determining these parameters through laboratory testing is both expensive and time-consuming, often requiring specialized equipment and controlled testing conditions. Consequently, these tests are not always practical or feasible in routine pavement design projects, especially in regions with limited laboratory resources or time constraints.

Nevertheless, many researchers continue to employ traditional pavement design methods that depend on these parameters. In such studies, the resilient modulus of the subgrade is either measured directly through repeated load triaxial testing or estimated indirectly by converting CBR values to equivalent MR values. These parameters are then used as key geotechnical inputs for the characterization of the subgrade, base, and subbase layers (Jain et al., 2013; Kumar et al., 2020; Mendoza-Sanchez et al., 2024; Pranay Kumar et al., 2018; Ziar et al., 2023)

Due to the economic and logistical challenges associated with MR and CBR testing, researchers have increasingly explored alternative methods for predicting pavement strength using readily available soil index properties and environmental factors.

Among these researchers, the first alternative solution to this problem was proposed by Ziar (2025), who utilized four machine learning algorithms to predict the structural number of flexible pavements based on the subgrade soil’s index properties (Ziar, 2025).

On the other hand, several studies have focused on the effective structural number (SNeff), which represents the remaining structural capacity of a pavement during its service life. For instance, Karballaeezadeh et al. (2020) employed various machine learning models—such as Gaussian process regression, model trees, and random forests—to estimate SNeff from pavement deflection and temperature data (Karballaeezadeh et al., 2020). Similarly, Abd El-Raof et al. (2020) enhanced structural number prediction models by incorporating temperature correction factors into Long-Term Pavement Performance (LTPP) datasets (Abd El-Raof et al., 2020).

These studies demonstrate the growing potential of data-driven approaches in pavement engineering. However, most existing research has primarily focused on pavement evaluation and performance monitoring, rather than addressing the initial design stage of pavement systems.

The present study addresses this gap by developing an artificial neural network (ANN) based model for predicting the initial structural number (SN) of flexible pavements at the design phase. Unlike previous work on SNeff, this research emphasizes the estimation of SN prior to degradation, ensuring accurate thickness design from the outset. The ANN model eliminates the reliance on costly MR and CBR tests by utilizing easily measurable subgrade soil properties such as dry unit weight (γd), moisture content (w), and weighted plasticity index (wPI) along with the number of freeze thaw cycles (NFT) as an environmental factor.

By leveraging the learning capacity of artificial neural networks, this study aims to provide a reliable, efficient, and cost-effective prediction framework for flexible pavement design. The proposed approach contributes not only to reducing design costs and testing requirements but also to advancing the integration of artificial intelligence in pavement engineering practice.

2. Research Methodology

The primary objective of this study is to develop and evaluate an artificial neural network (ANN) model for predicting the structural number of flexible pavements at the design stage. This research also aims to demonstrate the applicability of ANN as a robust alternative to traditional laboratory-based methods, thereby supporting future studies in integrating advanced artificial intelligence techniques into the design of both flexible and rigid pavements.

To achieve this, the SN was predicted using fundamental subgrade soil properties, namely dry unit weight (γd), moisture content (w), and the weighted plasticity index (wPI), which is defined as the product of the percentage passing through the No. 200 sieve and the plasticity index

(Kardani et al., 2022). In addition, environmental conditions exert a substantial influence on pavement behavior and longevity. Variations in climate directly affect how quickly pavements deteriorate, thereby impacting maintenance requirements and overall lifecycle expenditures (Mendoza-Sanchez et al., 2024; Qiao et al., 2020; Zapata et al., 2007). The environmental influences governing pavement response can generally be grouped into external and internal factors. External influences include climatic and hydrological elements such as temperature changes, rainfall, groundwater fluctuations, and freeze–thaw activity. Internal factors, by contrast, are related to the in-situ conditions within the pavement system, including moisture migration, drainage capacity, and water infiltration between structural layers (Zapata et al., 2007).

Among these environmental factors, the number of freeze–thaw cycles (NFT) was specifically included as a variable in this study, as it represents a key indicator of cyclic freezing and thawing effects on pavement materials. These cycles induce volumetric changes, often leading to cracking, loss of stiffness, and accelerated structural degradation, particularly in regions with severe seasonal temperature variations (Jafari & Lajevardi, 2022; Su et al., 2017; Zou et al., 2021). Including NFT as a variable allows the model to account for the environmental impact on pavement performance alongside fundamental soil properties. These input features were utilized in the ANN prediction model, as detailed in the dataset description and preprocessing sections.

The dataset employed for this study consists of 2,810 data points. The data were preprocessed and divided randomly into three subsets: 70% (1,966 data points) for training, 15% (422 data points) for validation, and 15% (422 data points) for testing. The ANN was implemented using MATLAB R2024b's neural network fitting toolbox with a feedforward architecture comprising a single hidden layer of 10 neurons. The Levenberg–Marquardt backpropagation algorithm was adopted as the training algorithm, with mean squared error (MSE) selected as the performance function. The creation and development of the model are discussed in detail in the subsequent sections following the data description and preprocessing.

2.1. Data Collection and Preparation

The dataset applied in this research was first assembled and made publicly available by Zou et al., (2021) as supplementary material to their publication (Zou et al., 2021). It contains experimental outcomes of resilient modulus (MR) tests on compacted subgrade soils, which were classified under both the AASHTO system (A-4, A-6, and A-7-6) and the Unified Soil Classification System (USCS) (CL, CH, and CL-ML). The dataset was downloaded directly from the supplementary files provided by the publisher. The compiled database integrates results reported in several prior studies, including those of (Ding et al., 2020; Rahman, 2014; Ren et al., 2019; Solanki et al., 2013).

The principal input parameters considered in relation to MR include the weighted plasticity index (wPI), dry unit weight (γd, kN/m^3), confining stress (σc, kPa), deviator stress (σd, kPa), number of freeze–thaw cycles (NFT), and moisture content (w, %). In their work, Zou et al. (2021) employed this dataset to construct prediction models based on gene expression programming (GEP) and artificial neural networks (ANNs), linking soil properties, stress conditions, and environmental effects to the resilient modulus of pavement subgrade soils (Zou et al., 2021).

In this study, instead of directly applying the dataset for resilient modulus prediction, it was reformulated to suit the specific goal of developing and evaluating an artificial neural network for predicting the total structural number of flexible pavements. The prediction framework was based on subgrade soil properties and environmental influences under a specified traffic level and fixed pavement design conditions. To achieve this, the original MR values were transformed into corresponding SN values using the bisection method, which iteratively solves the AASHTO 1993 pavement design equation. This equation defines the relationship between SN and a set of design parameters, including cumulative traffic loading (W18), reliability factor (ZR), overall standard deviation (So), serviceability loss (ΔPSI), and MR (AASHTO, 1993). For this study, the design inputs were adopted in line with the AASHTO 1993 Guide for Design of Pavement Structures, with W18 set to 5 million equivalent single axle loads (ESALs), a reliability level of 95% (ZR = –1.282), So fixed at 0.45, and ΔPSI taken as 2.5. The selection of these values provides a conservative but realistic representation of traffic, material, and construction variability.

The traffic loading of W18 = 5 million ESALs was chosen to reflect conditions typical of medium- to high-volume facilities such as major arterials and intercity corridors. The reliability level of 95% falls within the commonly applied range of 85–99.9% for critical highway systems (see Table (1)), thereby ensuring robustness against design uncertainties. While the AASHTO design guide recommends an initial serviceability index (Pi) of 4.2 and a terminal serviceability index (Pt) of 2.5 (ΔPSI = 1.7) (AASHTO, 1993), this study adopted a more conservative ΔPSI of 2.5 to reflect higher performance standards and stricter intervention thresholds. These parameter choices strengthen the analytical framework by aligning with accepted design practice while ensuring a resilient pavement structure.

In the AASHTO equation (see Equation (1)), W18, ZR, ΔPSI, So, and MR are treated as known parameters, whereas SN is the unknown to be determined. To calculate SN, an objective function was formulated as the difference between log10(W18) and the right-hand side of the equation. The bisection method, implemented in Python, was employed as a root-finding technique, iteratively refining the SN value until convergence was achieved within a tolerance of 0.001. This procedure was applied to all MR records in the dataset, resulting in a newly constructed database where SN served as the target output variable. The input features included weighted plasticity index (wPI), dry unit weight (γd, kN/m³), moisture content (w, %), and freeze–thaw cycles (NFT), which are recognized as key factors influencing MR and, consequently, SN. The statistical characteristics of these variables are presented in Table 2. This revised dataset was subsequently utilized for the development and training of the artificial neural network prediction model.

Fig. 1 illustrates the Pearson correlation heatmap showing the relationships between the input variables and the structural number (SN) of flexible pavements. Correlation coefficients range from −1 to +1, where positive values indicate direct relationships and negative values indicate inverse relationships. In the heatmap, yellow shades represent strong positive correlations, dark blue indicates strong negative correlations, and gray tones correspond to weak or near-zero correlations. Among the variables, moisture content (w) shows the strongest positive correlation with SN (r = 0.51), followed by NFT (r = 0.36), suggesting that both moisture and freeze–thaw cycles increase pavement thickness requirements. In contrast, dry unit weight (γd) exhibits a moderate negative correlation with SN (r = −0.35) and a strong inverse relationship with moisture content (r = −0.90), highlighting their interdependence. The weakest association is observed between wPI and SN (r = 0.12), indicating that wPI has a relatively limited direct influence on pavement design.

Fig. 2 presents histograms of wPI, γd, w, NFT, and SN, showing the frequency distribution of observations across their respective ranges. These plots provide insights into data spread, central tendency, and variability, while also revealing potential skewness, clustering patterns, or outliers.

$$\log_{10}(W_{18}) = Z_R S_o + 9.36\log_{10}(SN+1) - 0.20 + \frac{\log_{10}\left[\frac{\Delta PSI}{4.2-\Delta PSI}\right]}{0.40 + \frac{1094}{(SN+1)^{5.19}}} + 2.32\log_{10}(MR) - 8.07 \quad (1)$$

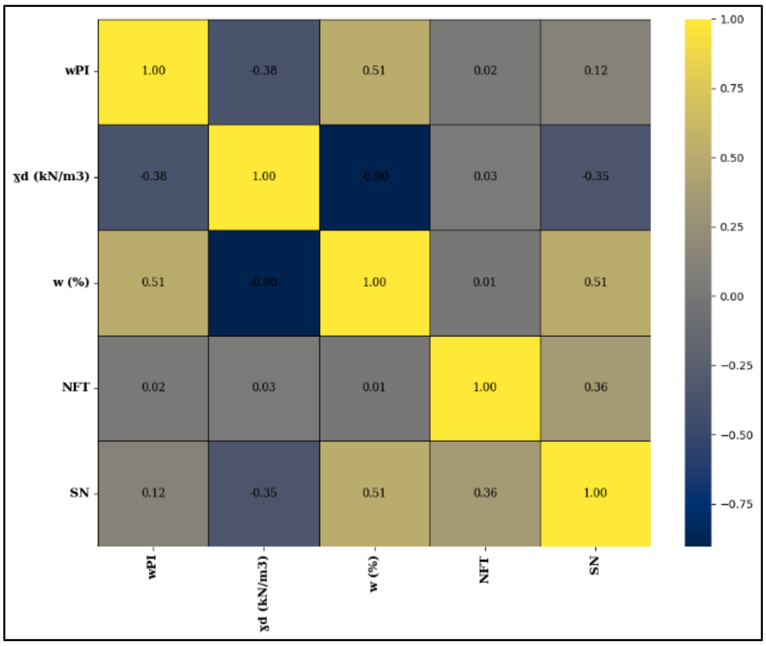
Table 1. Recommended reliability levels for different functional classifications(AASHTO, 1993)

Recommended Level of Reliability (%)		
Functional Classification	**Urban**	**Rural**
Interstate and other Freeways	85-99.9	80-99.9
Principal Arterials	80-99	75-95
Collectors	80-95	75-95
Local	50-80	50-80

Table 2. Summary statistics of input and output variables

Parameters	wPI	γ_d (kN/m^3)	w (%)	NFT	SN
Maximum	31.08	20.40	41.54	20.00	9.37
Minimum	5.82	15.50	12.30	0.00	2.53
Range	25.26	4.90	29.24	20.00	6.84
Mean	13.88	17.73	18.36	4.14	5.03
Median	13.16	17.77	17.30	3.00	5.08
Standard deviation	6.44	1.56	4.52	3.93	0.90

Fig 1. Pearson correlation heatmap of input variables and the structural number (SN). Yellow indicates strong positive correlations, dark blue indicates strong negative correlations, and gray represents weak or near-zero correlations.



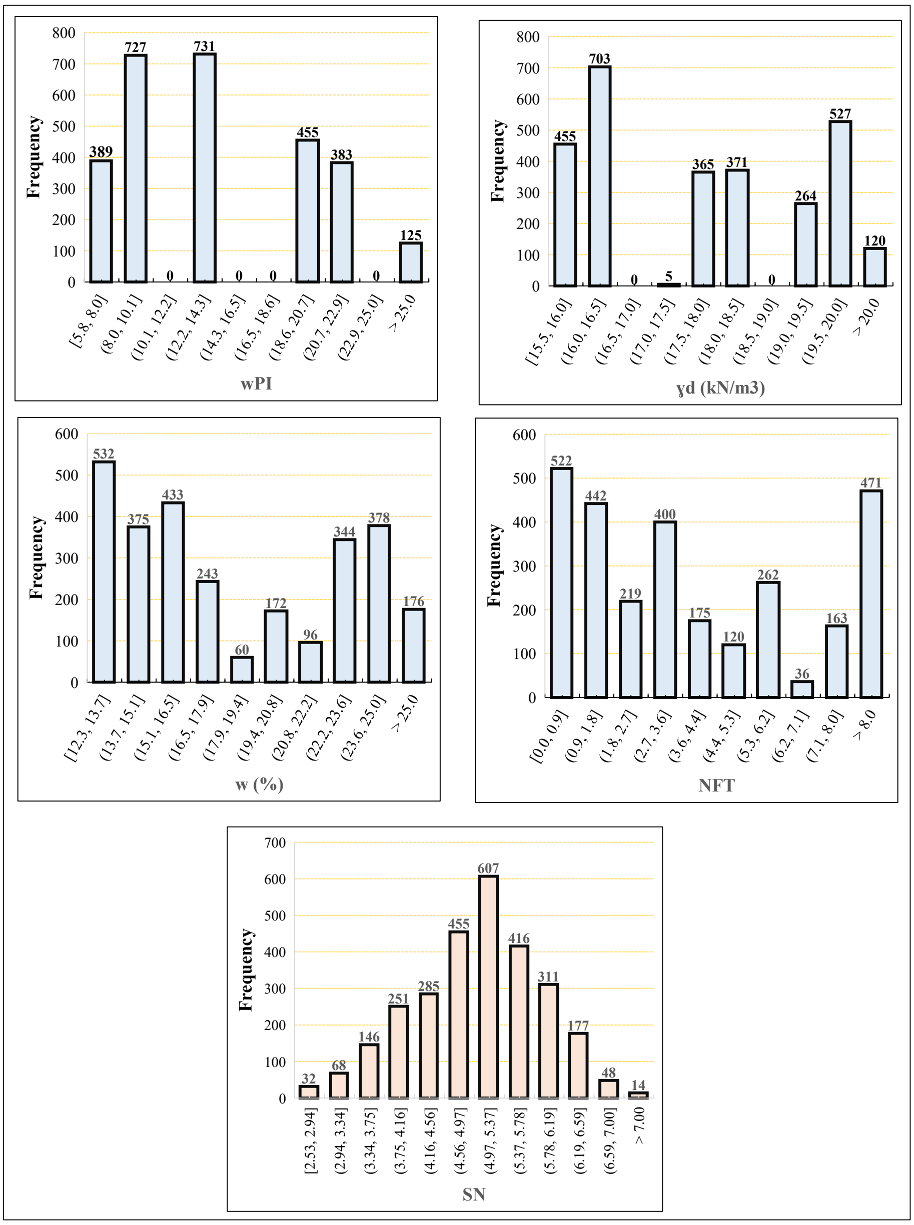


Fig 2. Histograms of wPI, γd, w, NFT, and SN showing the frequency distribution of observations. The plots highlight the spread, central tendency, and variability of the dataset, as well as potential skewness, clusters, or outliers.

2.2. Creation and Development of the ANN Model

The artificial neural network model in this study was developed and trained using the Levenberg–Marquardt algorithm due to its efficiency in handling nonlinear optimization problems. A feed-forward architecture was employed, consisting of an input layer, a hidden layer, and an output layer, with neurons interconnected through weights, biases, and activation functions (Arunvivek et al., 2025; Barkhordari et al., 2022; Khan et al., 2022; Li et al., 2023; Qi et al., 2023).

Each input node corresponded to an independent variable, ensuring comprehensive representation of the dataset and allowing the model to capture complex relationships among subgrade soil properties and environmental factors. To prevent overfitting and enhance computational efficiency, the architecture was kept simple with a single hidden layer, while the number of neurons was determined through experimental trials to achieve an optimal balance between learning capacity and generalization.

After testing several configurations, a hidden layer of 10 neurons demonstrated the best predictive performance. The network training was stopped once generalization was achieved, as indicated by increasing mean squared error (MSE) on the validation set.

Model performance was evaluated using correlation coefficients and error metrics such as MSE and ensuring reliable prediction of the target variable. The final ANN architecture and workflow are illustrated in Fig. 3. while the regression plots and performance indices, including training, validation and testing R-values, are presented in results and discussion section.

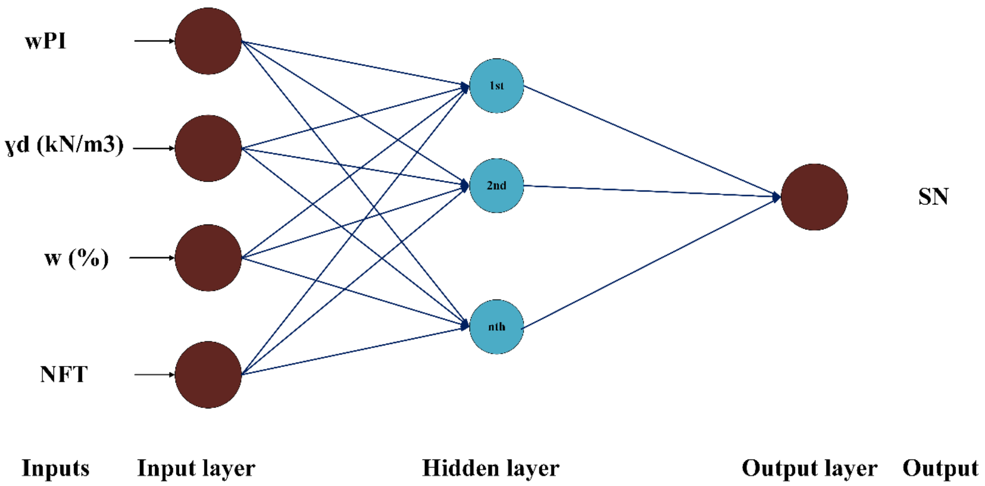


Fig 3. Architecture of the artificial neural network (ANN) model used in this study

3. Results and Discussion

To evaluate the predictive performance of the developed ANN, regression analyses were conducted for the training, validation, testing, and overall datasets (Fig. 4). The network achieved high coefficients of determination (R^2), with values of 0.951 for training, 0.948 for validation, 0.930 for testing, and 0.949 overall. The close agreement between predicted and actual values across all subsets indicates that the ANN effectively captured the nonlinear interactions among soil properties and environmental factors influencing the structural number. These findings confirm the robustness and reliability of the ANN as a predictive tool for flexible pavement design.

Model training performance is presented in Fig. 5, where the best validation performance was achieved at Epoch 114 with a minimum mean squared error (MSE) of 0.074116. Training was stopped automatically at this point to prevent overfitting. The convergence of the training, validation, and testing curves demonstrates that the network generalized effectively without significant loss of accuracy. The error distribution is shown in Fig. 6. Most residuals are concentrated around zero and exhibit a nearly symmetric pattern across the training, validation, and testing subsets. This distribution further supports the accuracy and stability of the ANN predictions.

The overall status of the network during training is summarized in Fig. 7, where the gradient, Mu, and validation checks were monitored over 120 epochs. The gradient decreased steadily and stabilized at 0.068 by the final epoch, indicating effective convergence of the optimization process. The parameter Mu, which regulates the adaptation of the Levenberg–Marquardt algorithm, reduced to 1×10^{-5}, reflecting stable training behavior. Additionally, the validation checks reached a maximum of six, at which point training was stopped to prevent overfitting. These results confirm that the training process was efficient and well-regularized, ensuring a balance between accuracy and generalization capability.

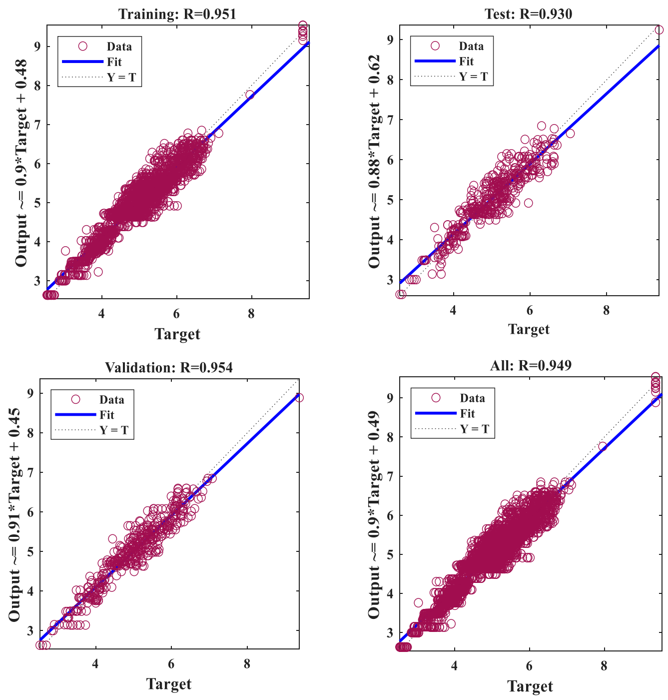


Fig. 4. Regression plots of the developed ANN model for overall training, testing, and validation datasets. The high R values demonstrate the strong agreement between predicted and actual values of SN

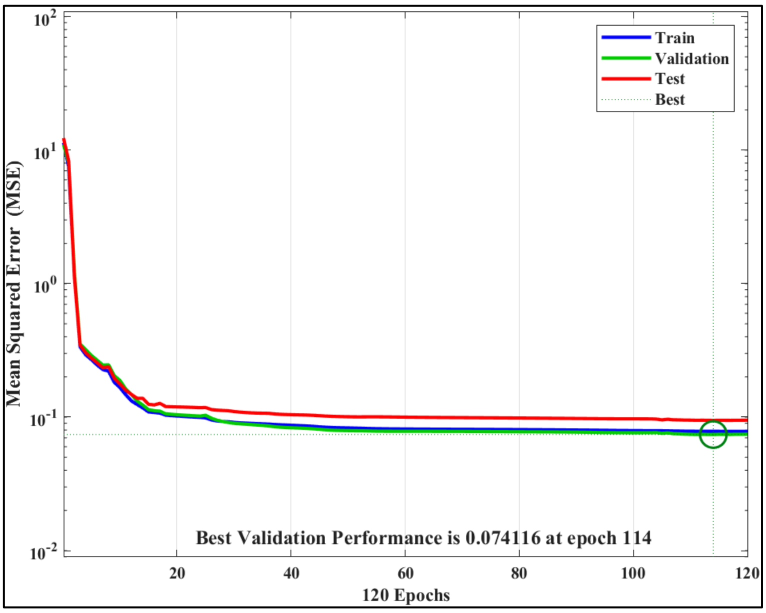


Fig. 5. Training performance of the ANN model showing mean squared error (MSE) variation with epochs for training, validation, and testing subsets. The best validation performance (MSE = 0.074116) was achieved at Epoch 114

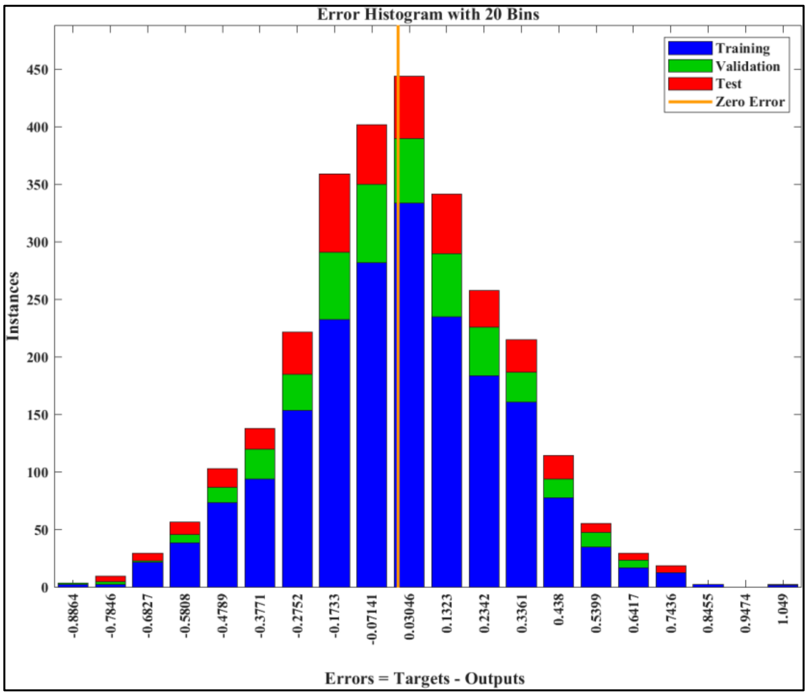


Fig. 6. Error histogram of the ANN predictions for training, validation, and testing subsets. Most residuals are concentrated around zero, confirming the accuracy and stability of the model.

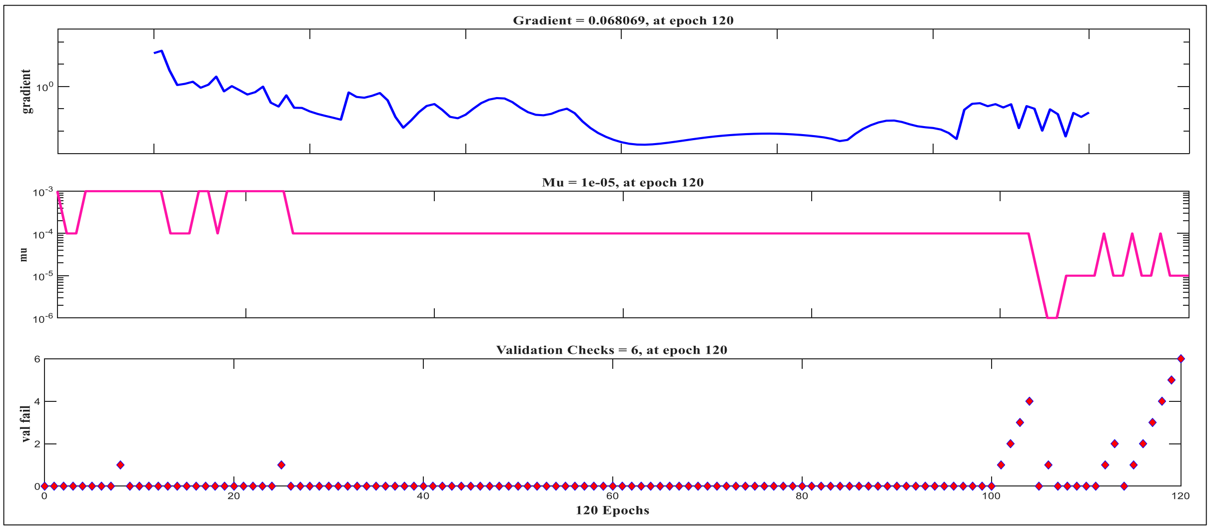


Fig. 7. Overall status of the ANN training process showing; top gradient, middle Mu, and bottom validation check over 120 epochs. The decreasing gradient, stable Mu, and limited validation checks indicate effective convergence and well-regularized training.

4. Conclusion

This study developed an artificial neural network (ANN) model to predict the structural number (SN) of flexible pavements using fundamental subgrade soil properties and environmental conditions. By utilizing moisture content (w), dry unit weight (γd), weighted plasticity index (wPI), and freeze–thaw cycles (NFT) as input variables, the model successfully replaced costly resilient modulus (MR) and CBR tests traditionally required in the AASHTO design procedure. The ANN, trained with the Levenberg–Marquardt algorithm and optimized with a single hidden layer of 10 neurons, demonstrated excellent performance, achieving R values above 0.930 across training, validation, and testing subsets.

The results indicate that the ANN successfully captured the nonlinear relationships between soil properties and pavement structural capacity. Convergence of the training and validation curves, along with error distributions centered around zero, confirmed that the model generalized well without overfitting. These findings are in agreement with the study by Ziar (2025), which evaluated four machine learning algorithms for predicting structural numbers and identified gradient boosting as the most effective model (Ziar, 2025). Both studies highlight that machine learning techniques can reliably predict pavement structural capacity using readily available subgrade properties and environmental factors, reducing reliance on time-consuming and expensive laboratory tests.

Overall, the results demonstrate that machine learning approaches, including ANN, offer practical, accurate, and cost-effective tools for flexible pavement design, supporting more efficient and informed decision-making in pavement engineering.

Looking ahead, future studies should broaden the current modeling framework by incorporating variable traffic levels. While this work relied on a fixed traffic load and predefined design parameters, in practice the cumulative number of equivalent single axle loads (ESALs) differs significantly across roadway classes. Integrating a wider spectrum of traffic conditions would improve the versatility and applicability of ANN-based predictions in diverse pavement design contexts.

In addition, because of the limited availability of base and subbase layer data, this study concentrated on the overall structural number, which is largely governed by subgrade behavior. Expanding the model to include layer-specific properties of base and subbase materials would allow for more refined predictions of each pavement component's contribution to SN. Such enhancements would pave the way for a more detailed, accurate, and optimized pavement design framework driven by machine learning.

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