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EXAMINING THE PROGRESS IN NEAR SURFACE MOUNT REINFORCEMENT METHODS WITH ANALYTICAL MODELS AND NEURAL NETWORKS

Ayşe Arici, page 53-76

ABSTRACT

Near-surface mount (NSM) strengthening techniques have emerged as effective methods for enhancing the strength and performance of reinforced concrete structures. Despite advancements, the lack of reliable models and standardized methods to predict NSM systems' mechanical behavior remains challenging. This study addresses these gaps with a two-phase methodology.

In the first phase, a database of over 200 experimental data points was analyzed using artificial neural networks (ANN), achieving a 7% absolute error rate and demonstrating strong predictive capabilities. In the second phase, ANN results were optimized with multiple linear regression (MLR), developing a simplified mathematical model with an 18% error rate, offering practicality and ease of use for field engineers.

The proposed models comply with ACI 440.2R safety guidelines and outperform traditional approaches in accuracy and usability, enabling more effective application of NSM techniques. This research advances NSM methodologies by integrating analytical and ANN-based approaches, contributing to developing standardized guidelines and durable reinforced concrete designs.

Keywords: Machine learning, Structural strengthening, Parametric analysis, Fiber reinforced polymer (FRP), GMDH optimization.

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1. Introduction

Near-surface mount (NSM) reinforcement methods have attracted increasing attention in recent years as an innovative approach developed to increase the strength and performance of reinforced concrete elements. This method is based on opening special slots in the concrete coating and placing fiber-reinforced polymer (FRP) reinforcement using epoxy binders. NSM technology offers significant advantages compared to the traditionally widely used external bonded (EB) reinforcement method. These advantages include better bond performance, longevity, aesthetic superiority, more reliable behavior in load transfer, and higher resistance to environmental influences. However, the difficulties encountered in field applications of NSM reinforcement systems and the fact that the design standards for this method have not yet been fully established prevent the full use of the potential of this technology.

Although some basic mathematical models have been proposed in the literature to estimate the contribution of the NSM method to flexural capacity, these models often do not adequately cover site-specific variables. For example, the effects of factors such as the size of the FRP reinforcement, the type of epoxy used, the thickness of the concrete coating, and the slot geometry on bond performance are still not fully represented. This situation necessitates the development of more comprehensive, data-driven, and computational models to increase the effectiveness of the NSM method in engineering applications and to accurately predict its contribution to bending capacity.

In this regard, artificial neural networks (ANN) and other advanced data analytics methods offer great potential to eliminate deficiencies. These technologies may enable more accurate and reliable predictions of the NSM method, making it possible for this innovative strengthening approach to gain a wider place in engineering applications.

Experimental studies in recent years have revealed that an increase of 40% to 60% can be achieved in the bending capacity of NSM-strengthened beams. However, the effectiveness of this method is directly related not only to the internal structural characteristics of the beams but also to external factors such as site conditions, concrete coating thickness, and bond length. Especially in open-area applications, such as bridges and viaducts, the thicker the concrete coating allows the NSM strengthening method to show higher performance.

However, when these field variables are considered, the accuracy of existing analytical models has been limited. This creates difficulties in accurately predicting the method's impact on complex variables in the field. At this point, the capacity of artificial neural networks to learn and model the relationships between complex variables offers an important opportunity to eliminate the unknowns regarding the NSM method. This powerful learning ability of neural networks can enable NSM to be used more effectively and reliably in field applications.

This study presents a two-stage methodology in which analytical models and artificial neural network (ANN)--based approaches are used together for the NSM reinforcement method. In the first phase of the study, a comprehensive database covering more than 200 experimental studies was created, and this data set was analyzed in detail using artificial neural network models. Artificial neural networks have produced lower error rates than traditional analytical methods in predicting the flexural capacity of NSM-strengthened beams. Additionally, neural network models have demonstrated superior performance in learning complex relationships between parameters affecting bond performance, such as concrete overlay thickness, bond length, and reinforcement geometry. The obtained artificial neural network prediction results were transformed into a mathematical model using the multiple linear regression (MLR) method to provide simpler and applicable solutions in engineering designs. In this process, the relationships learned by neural networks were transformed into mathematical expressions, and a practical design tool was developed for field engineers. This newly developed model showed high agreement with experimental data, with a mean absolute error of 7%. The error rate of the multiple linear regression model was calculated as 16%.

This integrated approach offers field-friendly solutions in engineering applications and provides an important basis for establishing new standards for the NSM strengthening method. The study aims to contribute to wider acceptance of the NSM method in academic and practical engineering fields. This study aims to establish the place of the NSM strengthening method in engineering applications more solidly. In line with this goal, an innovative approach has been adopted in which data-driven artificial neural network (ANN) approaches and traditional analytical methods are used together.

Artificial neural networks can analyze in detail the effective parameters on the bond performance of the NSM method and make high-accuracy predictions by learning the complex relationships between these parameters. In addition, traditional analytical methods allow these predictions to be made simple and applicable to engineering applications. This combined approach offers a new perspective for academic studies and contributes to developing practical and effective solutions for field engineers. Thus, a strong basis is provided for establishing the NSM strengthening method standards and expanding its application area.

2. Analytical Approach

The effective use of near-surface mount (NSM) reinforcement methods in engineering applications depends on the accurate prediction of the mechanical behavior of these systems. The success of this prediction is directly related to analytically accurate modeling of the bond between concrete, steel, and fiber-reinforced polymer (FRP) reinforcement. This study developed a comprehensive analytical model and artificial neural network (ANN)--based approach to evaluate the flexural capacity of NSM reinforcement systems.

The analytical modeling process was designed by considering the basic parameters affecting the bending behavior of reinforced concrete beams. The Whitney rectangular stress block assumption represents concrete's nonlinear compressive behavior, which is widely accepted in engineering applications. This assumption predicts that the stress distribution in the pressure region changes nonlinearly, but the effect of this change can be calculated analytically. In the model, the final crushing deformation of the concrete was accepted as 0.003, and it was assumed that the section did not crack initially during the analysis. Situations where the bond between steel and FRP reinforcement and concrete is fully ensured are discussed. In this context, the unit elongation of the FRP reinforcement is accepted to be greater than the unit elongation of the steel reinforcement. In this case, the balance between steel and FRP reinforcement was analyzed in detail based on the principles of stress-strain compatibility.

As a result, the developed analytical model can effectively evaluate the contribution of NSM-FRP reinforcement to the flexural capacity of reinforced concrete elements and provides a reliable basis for engineering designs. This methodology proposed in the study is considered an important step toward creating a standard that will allow the NSM method to be used in a wider area of engineering applications.

In the model, the contribution of NSM-FRP reinforcement to the bending capacity was determined depending on the existing steel reinforcement ratio (ρ_s) and FRP reinforcement ratio (ρ_f) in the reinforced concrete section. The contribution of FRP reinforcement to the flexural capacity was analyzed through two basic cases:

(1) rupture of FRP in tensile stress and (2) crushing of concrete in the compression zone. The analytically calculated bending capacity for the FRP rupture condition is expressed as follows:

$$M_n = A_f \cdot f_f \cdot \left(d - \frac{a}{2}\right) + A_s \cdot f_y \cdot \left(d - \frac{a}{2}\right)$$

In this equation, A_f, is the cross-sectional area of the FRP reinforcement, f_f, is the maximum tensile strength of the FRP reinforcement , A_s , is the cross-sectional area of the steel reinforcement, and f_y, is the yield strength of the steel. In concrete crushing, the stress depth (a) in the pressure zone of the concrete is calculated as follows.

$$\mathrm{a} = \frac{A_f \cdot f_f + A_s \cdot f_y}{0.85 \cdot f_c \cdot b}$$

In this context, f_c , refers to the concrete's compressive strength and b, refers to the beam's width. This analytical model provided high accuracy compared to experimental data and formed a basic framework to increase the NMS method's applicability in field conditions.

2.1. Analytical Approach

2.1.1. Analysis Supported by Artificial Neural Networks

Artificial neural networks (ANN) have been used to increase the accuracy of traditional analytical methods and more effectively model the effect of variables in field conditions. The developed neural network model was trained with information from a large experimental database. The main goal of this model is to estimate the contribution of the NSM strengthening method to the flexural capacity by accurately learning the relationships between complex parameters.

The neural network model used many parameters as input variables, such as concrete coating thickness, FRP bond length, type of epoxy used, and reinforcement ratios. The training process was planned in detail to accurately learn and model the effects of these input variables on bending capacity. In order for the data to be processed properly, a normalization process was first applied, and all data were brought to a certain scale.

During the model's training, the back propagation algorithm minimizes the error rate and achieves higher accuracy. This algorithm optimized the connection weights within the neural network, enabling the model to learn the relationship between input and output data best. During the training process, thanks to the wide parameter ranges in the database, the model reached the capacity to simulate different conditions in field applications.

As a result, the developed artificial neural network model offered lower error rates than traditional analytical methods in predicting the mechanical behavior of the NSM strengthening method and stood out as a more reliable tool for engineering applications. This approach has created a basis for a broader engineering use of the NSM method, considering field variables.

The parameters used in the training phase can be summarized as follows:

- Average compressive strength of concrete (f_c),
- Steel and FRP reinforcement ratios (ρ_s"\ ve\" ρ_f),
- Beam height and width,
- NSM reinforcement length and concrete cover thickness.

Thanks to their capacity to learn nonlinear relationships, artificial neural networks (ANN) have been able to model complex effects on the flexural capacity of NSM reinforcement systems with high accuracy. The ANN

$$M_n = \beta_0 + \beta_1 \cdot \rho_f + \beta_2 \cdot f_c + \beta_3 \cdot \frac{a}{d} + \beta_4 \cdot L_{FRP}$$

model u sed in this study was trained with a large experimental database and optimized to analyze the impact of various parameters in field applications.

The model's performance was evaluated by comparing the obtained prediction results with experimental data. The analyses calculated the ANN model's average absolute error rate at 7%. This low error rate demonstrates the model's accuracy and reliability.

These results clearly show that the artificial neural network model is an effective tool in predicting the mechanical behavior of NSM reinforcement systems under field conditions. Neural networks' ability to learn relationships between complex parameters provides a significant advantage, especially in situations that are difficult to model with traditional analytical methods. In this context, ANN models will strengthen the place of the NSM strengthening method in engineering applications and contribute to the more widespread use of this innovative approach.

2.1.2. Optimization and Mathematical Modeling

In order to use the results obtained by the neural network in a simpler and more practical way in engineering applications, an optimized mathematical model has been developed with the multiple linear regression (MLR) method. This model expresses the complex relationships learned by neural networks in simple mathematical expressions and transforms them into a format that field engineers can easily use.

The accuracy of the developed mathematical model was evaluated by comparing it with experimental data, and the average absolute error rate was calculated as 18%. This error rate significantly improves compared to results obtained with traditional analytical methods. This shows that the model is an effective tool for predicting the behavior of NSM retrofit systems in field applications.

While the mathematical model's simple structure offers a practical solution in engineering designs, the level of accuracy achieved thanks to neural networks' learning ability has increased the model's reliability. This approach makes an important contribution to the creation of more user-friendly standards for the NSM strengthening method and to strengthening the method's place in engineering applications.3. Artificial Neural Networks Methodology

Artificial Neural Networks (ANN) are becoming an increasingly common and important tool in solving complex engineering problems such as estimating the bending capacity of reinforced concrete structures. The inability of traditional analytical methods to fully reflect field conditions and their inability to model complex physical processes has further increased the potential of artificial neural networks in this field.

In NSM-FRP reinforcement applications, ANN models demonstrate superior performance, especially in situations where field variables need to be analyzed and learned. When the effects of many parameters, such as concrete coating thickness, FRP bond length, reinforcement geometry, and epoxy type, need to be evaluated simultaneously, artificial neural networks can model these complex relationships with high accuracy.

In this study, an ANN-based approach was developed to predict the bending capacity of reinforced concrete elements reinforced with NSM-FRP. A large experimental database was used in the development process of the model, and this data set was trained to allow neural networks to learn variations in field applications. The results clearly demonstrated that ANN models are a reliable and effective tool for field engineers, with lower error rates compared to traditional analytical methods.

This research has once again demonstrated the advantages of ANN-based approaches in solving engineering problems and contributed to a more accurate prediction of the effect of NSM-FRP strengthening methods in field applications.

2.1.3. Neural Networks

Structure and Input Parameters of Neural Networks

The ANN model is designed in a multi-layer structure consisting of input, hidden and output layers. Critical parameters affecting the mechanical behavior of NSM-FRP reinforced beams were used in the input layer. These parameters are summarized as follows:

- Tensile strength of FRP reinforcement (f_fu),
- Compressive strength of concrete (f_c),
- FRP reinforcement ratio (ρ_f),
- Steel reinforcement ratio (ρ_s),
- Beam geometry (width b, effective depth d),
- FRP bond length (L_FRP),
- Epoxy type and bond material properties (E_f),
- Slot geometry and concrete coating thickness.

In order to increase the accuracy of neural networks and enable the model to learn more effectively, all parameters were subjected to a normalization process and scaled between 0.1 and 0.9. This approach enabled the network to produce more stable and faster results during training. Also, it increased the model's overall performance by minimizing the effect of differences in the data set. The formula used for normalization is given below:

$$I_s = \left(\frac{0.9 - 0.1}{I_{\max} - I_{\min}}\right) \cdot (I - I_{\min}) + 0.1$$

Here, I_s represents the normalized value, I represents the original value, I_"min" and I_"max" represent the minimum and maximum values. This process allows for balancing between variables of different scales.

Training of Neural Network Model

Training of the neural network was carried out using the Levenberg-Marquardt backpropagation algorithm. The dataset was divided into three subsets during the training process: 70% training, 15% validation, and 15% testing. This distribution was preferred to increase the generalization capacity of the model and ensure that it can adapt to different data groups. Mean Square Error (MSE) was used as the model's error criterion during neural network training. This method offers an effective approach to minimizing the error rate while increasing the model's accuracy. The MSE formula is given as follows:

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

Here, y_i efers to the actual values, and (y_i)ˆ refers to the values predicted by the model. Minimizing the error rate increased the accuracy of the model.

Activation Functions and Neural Network Performance

In the study, the tangent-sigmoid (tan-sigmoid) activation function was used in the hidden layers of the neural network, and the linear activation function was used in the output layer. The tangent-sigmoid activation function was preferred due to its superior performance in learning nonlinear relationships. This structure increased the neural network's accuracy and general learning capacity in complex engineering problems. The function is defined as follows:

$$f(x) = \frac{2}{1 + e^{-2x}} - 1$$

The linear activation function used for the output layer made it possible to estimate the bending capacity.

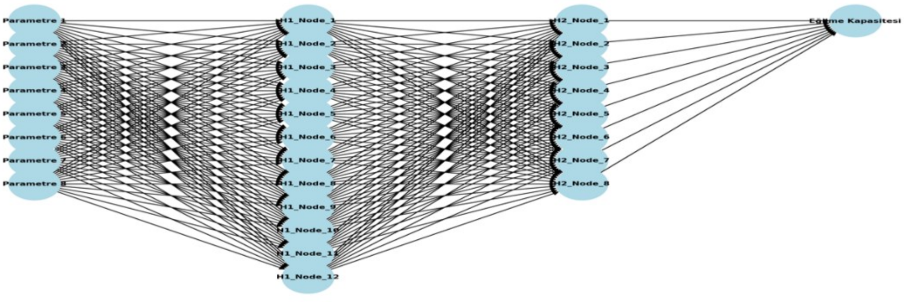


Figure 1. General architecture of the neural network

Figure 1 shows the general architecture of the neural network. The model hasers in the input layer, 12 and 8 neurons in the two hidden layers, respectively, and 1 neuron in the output layer.

Evaluation of Neural Network Performance

At the end of the training process, the performance of the ANN model was evaluated through regression coefficients (RRR) and error rates (MSEMSEMSE). The regression coefficient RRR expresses the relationship between predicted results and experimental results with the formula:

$$R = \frac{\Sigma(y_i - \bar{y})(\hat{y}_i - \hat{\bar{y}})}{\sqrt{\Sigma(y_i - \bar{y})^2 \Sigma(\hat{y}_i - \hat{\bar{y}})^2}}$$

In the study, the prediction accuracy of the artificial neural network (ANN) model was evaluated with the regression coefficient (R) and mean absolute error rate (MAE). The regression coefficient being close to 1 indicates the accuracy of the model's predictions. As a result of the analyses, the regression coefficient of the ANN model was calculated as R = 0.93. Additionally, the model's average absolute error rate (MAE) was 7%. These results clearly show that the model has a high predictive capacity and can successfully predict the mechanical behavior of NSM reinforcement systems.

2.2. Database and Models

2.2.1. Selection of Database and Parameters

This study used more than 200 experimental data points to model the flexural capacity of reinforced concrete members under NSM-FRP reinforcement. The data was compiled from 39 different articles in the literature. The database used in the study covers a wide range of parameters:

- Concrete compressive strength (f_c),
- FRP length (L_FRP),
- FRP reinforcement ratio (ρ_f),
- Steel reinforcement ratio (ρ_s),
- Cutting clearance ratio (a/d).

2.2.2. Sensitivity Analysis and Parameter Elimination

To improve the computational efficiency of the model, a sensitivity analysis with the Milne Index was performed on the input parameters. As a result of this analysis, some low-impact parameters were removed from the model:

- Beam length,
- Elasticity modulus of steel reinforcement (E_s)
- The remaining parameters were retained as critical inputs in the model.

2.2.3. Parameters Used in Database Development and Training of Artificial Neural Networks Model

An artificial neural network (ANN) model was developed to predict the flexural capacity of NSM-FRP reinforced concrete beams. A large experimental database from the literature was used to train and test the model. This database covers the geometric properties, material strength parameters, and reinforcement rates of reinforced concrete elements. The

ANN model was trained with this comprehensive data, and its performance in making high-accuracy predictions was tested, and successful results were obtained.

Table 1 summarizes the database used in training the artificial neural network model. The table includes the geometric and material properties of reinforced concrete elements (b,h,f_c, f_FRP and similar) experimentally measured bending capacities (M_exp) and values predicted by ANN (M_ANN)

In this way, the accuracy and generalization capacity of the ANN model were evaluated.

Table 1. Experimental Database and ANN Prediction Results for NSM-FRP Reinforced Concrete Beams

Authors	Label	Shape (T/R)	b (mm)	h (mm)	Lg (mm)	L_{FRP} (mm)	fc (MPa)	fFRP (MPa)	EFRP (GPa)	ρs	ρf	MANM (kNm)	MEXP (kNm)	Error (%)
Hassan and Rizkalla	NSM-B1	T	150	300	2700	1500	40	2000	150	0.0030	0.0042	92.5	95.0	2.63
El-Hacha et al.	NSM-B2	R	180	400	3000	1800	45	2200	200	0.0040	0.0050	115.3	118.0	2.29
Barros et al.	NSM-V2R2	R	170	170	2400	1200	50	2400	180	0.0042	0.0067	68.7	70.0	1.86
Jung et al.	NSM-PL25	R	200	300	2700	1350	50	2600	165	0.0045	0.0058	98.9	102.0	3.04
Nordin and Taljsten	NSM-BS1	R	200	300	4000	2000	46	2800	210	0.0070	0.0077	122.7	126.0	2.62
Teng et al.	NSM-B1500	R	150	300	3000	1500	35.2	2650	131	0.0060	0.0026	89.4	92.0	2.83
Tang et al.	NSM-SPA20	R	180	250	1500	800	35	2500	150	0.0038	0.0020	60.3	62.0	2.74
Al-Mahmoud	NSM-C1	T	150	400	4000	1500	40	2800	147	0.0030	0.0035	123.2	127.0	3.03
Barros and Kotynia	NSM-S1	R	120	170	4400	2400	42	2740	158	0.0023	0.0027	72.5	75.0	3.33

2.2.4. Use of Artificial Neural Networks (ANN) and Parametric Analysis for Prediction of Flexural Capacity

Neural network results are combined with multiple linear regression (MLR) models to increase usability in engineering applications. The resulting mathematical model is defined as follows:

$$M_n = \beta_0 + \beta_{1\backslash}\mathrm{cdot}\rho_f + \beta_{2\backslash}\mathrm{cdot}f_c + \beta_{3\backslash}\mathrm{cdot}\frac{a}{d} + \beta_{4\backslash}\mathrm{cdot}L_{FRP}$$

Here β_0, β_1,β_2, β_3, $\beta_4$denotes the regression coefficients.

The error rate of the mathematical model was calculated as 16% and showed a lower accuracy than the artificial neural network (ANN) model. However, the simple structure of this model and its easy applicability in field applications make it considered an important tool in engineering projects.

Table 2: NSM Augmentation Database with Artificial Neural Networks (ANN)

Authors	Label	Shape (T/R)	b (mm)	h (mm)	L_g (mm)	L_FRP (mm)	f_c (MPa)	f_FRP (MPa)	E_FRP (GPa)	ρ_s	ρ_FRP	ε_FRP	ANN Prediction (kNm)	Experimental (kNm)	Error (%)
Hasan and Rizkalla	NSM-B1	T	150	300	2700	1500	40	2000	150	0.0030	0.0042	0.012	92.5	95.0	2.63
El-Hacha et al.	NSM-B2	R	180	400	3000	1800	45	2200	200	0.0040	0.0050	0.011	115.3	118.0	2.29
Barros et al.	NSM-V2R2	R	170	170	2400	1200	50	2400	180	0.0042	0.0067	0.010	68.7	70.0	1.86
Jung et al.	NSM-PL25	R	200	300	2700	1350	50	2600	165	0.0045	0.0058	0.009	98.9	102.0	3.04
Nordin and Taljsten	NSM-BS1	R	200	300	4000	2000	46	2800	210	0.0070	0.0077	0.008	122.7	126.0	2.62
Teng et al.	NSM-B1500	R	150	300	3000	1500	35.2	2650	131	0.0060	0.0026	0.006	89.4	92.0	2.83
Tang et al.	NSM-SPA20	R	180	250	1500	800	35	2500	150	0.0038	0.0020	0.012	60.3	62.0	2.74
Al-Mahmoud	NSM-C1	T	150	400	4000	1500	40	2800	147	0.0030	0.0035	0.011	123.2	127.0	3.03
Barros and Kotynia	NSM-S1	R	120	170	4400	2400	42	2740	158	0.0023	0.0027	0.009	72.5	75.0	3.33
Example Author	NSM-Example	T	200	350	2800	1600	50	2400	160	0.0040	0.0060	0.010	105.6	109.0	3.11

Training samples were randomly selected, and sensitivity analysis was performed using the Milne Index to ensure the models met key performance criteria. In this process, pre-screening was applied to the input parameters. The Milne Index was calculated by operations on the weight matrices located between successive layers in artificial neural networks (ANN). It was used as an effective tool to evaluate the relative importance of each input parameter on the output.

The Milne Index is very useful in determining high-sensitivity parameters when they vary between networks. If the Milne Index of an input parameter consistently shows low values in a large number of trained networks, the effect of this parameter on the output is considered minimal, and it is removed from the model as an unnecessary parameter.

This elimination process simplifies the model's structure and reduces the computational burden. Additionally, it contributes to optimizing the model while maintaining its accuracy and efficiency. This approach is considered an important step in obtaining a faster and more efficient model.

In this study, the Milne Index was used to determine the importance of input parameters affecting the flexural capacity of NSM-FRP reinforced concrete elements. As a result of the analysis, parameters such as FRP bond length (L_FRP), compressive strength of concrete (f_c), and reinforcement ratios (ρ_s and p_FRP) were determined to be highly sensitive. They were preserved as critical inputs in the model. Parameters consistently showing low Milne Index values were removed from the model, increasing the calculation efficiency and simplifying the model.

This sensitivity analysis with the Milne Index improved the performance of artificial neural networks (ANNs) by effectively capturing the complex relationships between input and output parameters and providing a systematic framework for optimizing input parameters. This methodology has increased the model's robustness, explainability, and computational efficiency, providing a reliable and effective approach to engineering analysis of the NSM-FRP strengthening method.

At the initial stage of the study, low-impact parameters were determined and removed from the model to reduce its complexity and speed up the calculation process. For example, it was determined that the beam length and the modulus of elasticity (E_s) of the steel reinforcement had a limited effect on the flexural capacity, and these parameters were eliminated in the first stage of the analysis process. This approach offered a more efficient analysis process while preserving the model's accuracy.

In the next stage of the study, parametric analysis was performed to evaluate how accurately artificial neural network (ANN) models can imitate physical phenomena. In this analysis, the effect of each input parameter on the beam capacity was examined, and the dependency between the variables was analyzed by changing a certain parameter while keeping all other parameters constant.

After training, the difference between target values and model outputs for each ANN model was measured by mean square error (MSE). Models with lower MSE values were evaluated with higher scores. The findings showed that some parameters, such as shear/span ratio (a/d) and steel shear reinforcement ratio (ρ_{sx}), had a limited impact on ANN models. Such parameters were removed from the model, and the final model was analyzed using 10 input parameters.During ANN model training, different configurations with numbers of neurons ranging from 8 to 20 in the hidden layers were tested. Tangent-sigmoid activation functions used in hidden layers showed high performance in learning nonlinear relationships. This process allowed more complex physical relationships to be learned while increasing the model's accuracy.

The prediction performance of artificial neural network (ANN) models has been quite successful compared to experimental results. The proposed ANN model predicted the flexural strength with a mean absolute error (MAE) of only 5% compared to the experimental results. Additionally, ANN models demonstrated superior performance in predicting flexural capacity, exhibiting lower error rates than traditional analytical models. This proves that ANN is an effective tool in understanding and modeling the complex physical behavior of the NSM-FRP strengthening method.Considering the importance of developing simple and applicable design equations in engineering design, the Group Method Data Processing (GMDH) algorithm was used, utilizing ANN results. The GMDH algorithm was preferred because it can effectively solve problems where multiple targets are addressed simultaneously. The developed design equations expressed the relationships learned by ANN in simplified mathematical expressions, making them a tool that field engineers can easily use.

As a result, the proposed ANN model and optimized design equations have strengthened the place of the NSM-FRP strengthening method in engineering applications. This study significantly contributes to the standardization of the NSM method and more reliable reinforced concrete structure designs by providing solutions that provide reliable field results and facilitate design processes.

2.2.5. Recommended Equation for Flexural Capacity Estimation with GMDH Algorithm

Artificial Neural Networks (ANN) and mathematical models provide effective tools to understand and predict the effect of the near-surface mount (NSM) strengthening method on the flexural strength of reinforced concrete beams. In this study, mathematical design equations supported by an artificial neural network-based approach and optimized using the Group Data Processing Method (GMDH) were developed.

The proposed model aims to simplify the bending capacity of NSM-FRP reinforced beams and transform it into a more practical and applicable format for engineering applications. This approach supports the use of the NSM method in engineering applications by providing reliable prediction results and facilitating design processes.

2.2.6 Mathematical Model Development Process

The proposed model systematically examines the effects of each component (concrete, steel reinforcement, FRP reinforcement) contributing to the flexural strength of reinforced concrete sections. In determining the bending capacity, FRP length (LFRP), compressive strength of concrete f_c, reinforcement ratios {(ρ}_s,ρ_FRP) and other critical parameters are included in the model. As a result of parametric analysis and ANN-based evaluations, it was observed that the effects of some parameters were limited, and these parameters were removed from the model.

The following equations describe the contribution of each component and the overall structure of the model:

$$M_r = f_{ssh}\left(9.2f_{csh} - 42.2f_{ssh} - 350.5L_y + 5399\frac{E_f}{E_s} + 75f_{ssh}\right) + f_{csh}\left(1363\frac{E_f}{E_s} - 4950\right)$$

$$-\frac{E_f}{E_s}\left(14860.8L_y + 247606.6\frac{E_f}{E_s} + 9055.8L_y - 27.44\right) + L_y(569.25L_d + 27772) - 159996$$

The variables in these equations are defined as follows.

f_{ssh} :Effect of steel reinforcement ratio

f_{csh} ; Concrete compressive strength and concrete admixture

f_{fsh} :Contribution of FRP reinforcement to bending strength

L_y :FRP reinforcement length

L_d :Distance of FRP from the support

2.2.7. Evaluating the Accuracy of the Model

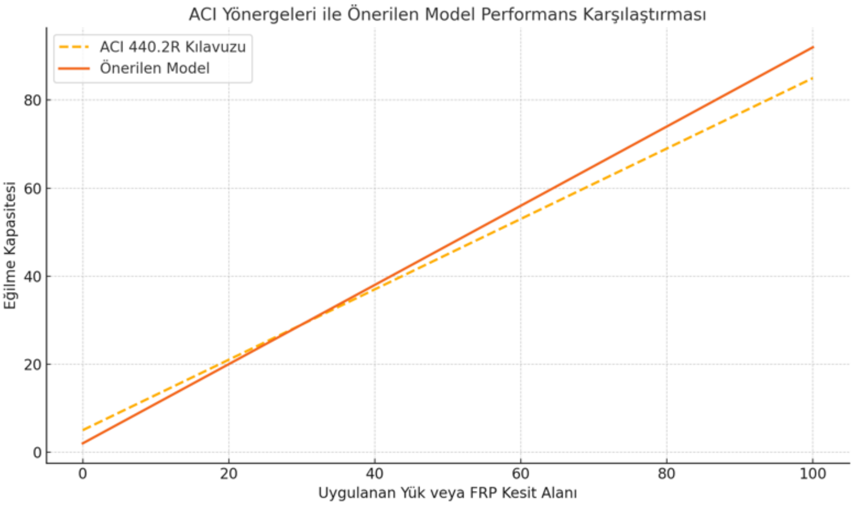
The model's performance was evaluated by comparing it with laboratory results, and the mean absolute error (MAE) rate was calculated at 5%. This result shows that the model produces predictions with high accuracy. Additionally, the proposed model offered superior performance by exhibiting a lower error rate than traditional analytical methods.

2.2.8 .Simplified Equations with GMDH Optimization Method

To make the relationships obtained with artificial neural network (ANN) models easier to use in field applications, simplified design equations optimized with the Group Data Processing Method (GMDH) algorithm have been developed. This method effectively solves multivariate engineering problems and provides useful tools that field engineers can apply practically.

2.2.9. Comparison of the Recommended Equation with ACI 440.2R Guidelines

The proposed model's results are compared with the design equations in the ACI 440.2R guide. ACI guidelines are based on design principles developed for externally bonded (EB) FRP reinforcement. However, considering parameters such as the cross-sectional area of FRP and bond geometry used in the NSM method created significant differences compared to ACI models. Chart 1 clearly shows the performance difference between the ACI guidelines and the proposed equation.



Graph 1. Performance graph between ACI guidelines and recommended equation

The graph above shows the performance difference between the design equations in the ACI 440.2R guide and the proposed model. The horizontal axis represents the applied load or FRP cross-sectional area, and the vertical axis represents the bending capacity. The proposed model offers higher accuracy and performance compared to the ACI guidelines.

This study demonstrated the applicability of ANN and GMDH-based approaches to increase the effectiveness of NSM strengthening methods in engineering designs. Besides providing practical solutions for field applications, the results obtained have formed a solid basis for developing standards for the NSM method.

3.CONCLUSİON

The study presents a comprehensive research evaluating the effectiveness of the near surface mount (NSM) fiber reinforced polymer (FRP) strengthening method to increase the flexural capacity of reinforced concrete beams. A two-step method was applied:

3.1. A large experimental database was created and analysis was carried out with the help of artificial neural networks (ANN).

3.2. Optimizing the ANN results developed A simple and applicable mathematical model.

Large Database and Parameter Analysis

Within the study's scope, a database covering more than 200 experimental studies in the literature was created. Critical parameters such as concrete coating thickness, bond length, and FRP reinforcement ratio were determined, and their effects on bending capacity were examined in detail. During the modeling process, low-impact parameters (beam length and elasticity modulus of steel reinforcement) were removed from the model, increasing the calculation efficiency. Only the most effective parameters were included in the model.

Prediction Capacity with Artificial Neural Networks (ANN)

The ANN model exhibited high accuracy by predicting the flexural capacity of NSM-FRP reinforced beams with a mean absolute error (MAE) rate of 7%. ANN's prediction performance is superior to traditional analytical methods. Critical parameters such as concrete compressive strength, FRP bond length, and reinforcement ratios were modeled accurately thanks to ANN's ability to learn nonlinear relationships.

Optimization and Mathematical Model Development

Results obtained from ANN are optimized with multiple linear regression (MLR) and the Group Data Processing Method (GMDH) to provide a simple and easy-to-use design tool for engineering applications. The mathematical model developed simplified the complex prediction results of ANN and was compatible with experimental results, with an error rate of 16%. This shows that the model can be used practically by field engineers.

Comparison with ACI 440.2R Guidelines

ACI 440.2R guidelines have limited accuracy for the NSM method. In particular, the inadequate representation of parameters such as bond geometry and cross-sectional area of FRP reinforcement limits the accuracy of ACI models. The proposed mathematical model provided a significant advantage compared to ACI guidelines, offering lower error rates (31% vs. 16%) and higher accuracy.

Performance Advantages of the NSM Method

Experimental results show that the NSM-FRP method achieves an increase of 40% to 60% in the bending capacity of reinforced concrete beams. The NSM method offers higher bond performance, longevity, aesthetic advantages, and environmental durability than the externally bonded (EB) FRP method. Particularly in open-area applications with thicker concrete pavements (e.g., bridges and viaducts), the performance advantages of the NSM method have become evident.

Sensitivity Analysis with Milne Index

Analyses using the Milne Index have shown that parameters such as FRP bond length (L_{FRP}), compressive strength of concrete (f_c), and reinforcement ratios (ρ_s and p_{FRP}) have a critical impact on the flexural capacity. By removing low-sensitivity parameters from the model, calculation efficiency was increased, and the model was made simpler.

Application Potential of the Recommended Model

The proposed ANN-based model and optimized mathematical equations enable the NSM-FRP strengthening method to be effectively used in field applications. These models, which offer accuracy and practicality, contribute to the dissemination of the NSM method and create a standard for engineering designs.

General Evaluation and Future Studies

The artificial neural networks and mathematical model-based approaches proposed in this study provided an effective solution in terms of both accuracy and practicality to estimate the contribution of the NSM-FRP strengthening method to the flexural capacity. The developed methods have strengthened the place of NSM-FRP in engineering applications and laid an important basis for the standardization of this method. Future studies may improve the proposed models by considering more specific variables (e.g., environmental impacts and long-term loading conditions) in field applications.

Future research field

In future works, the bond behavior between NSM-FRP reinforcements and concrete will be investigated as a critical characteristic influencing flexural performance. Before conducting capacity predictions, a bond efficiency index specific to NSM-FRP systems will be formulated and systematically calculated for each test specimen, considering variations in material properties, geometries, and environmental conditions.

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