Predicting Shear Capacity of RC Beams Strengthened with NSM FRP Using Neural Networks

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***Abstract*— This research aims to predict the shear capacity of NSM FRP beams using the neural network method. The study investigates the key considerations and the necessary analysis for this prediction. NSM FRP beams are reinforced concrete beams that are strengthened with near-surface mounted (NSM) fiber-reinforced polymer (FRP) composites. Accurately predicting their shear capacity is important for ensuring their safety and reliability in real-world applications. The neural network method is a machine learning approach that is increasingly used in engineering analysis and design. The study explores how this method can be used to predict the shear capacity of NSM FRP beams and what factors should be taken into account in this analysis. The research also discusses the analytical approach required for this prediction, highlighting the necessary steps for obtaining accurate results. Overall, this study provides valuable insights into the use of the neural network method for predicting the shear capacity of NSM FRP beams. The findings can help inform future research and practical applications in the field of structural engineering, contributing to the development of safer and more reliable structures.**

Keywords*— *Structural engineering, NSM FRP, Machine learning, Deep learning, Prediction, Data mining, Data process, Neural Network, Neural Designer, Orange Data Mining.

I. Introduction (*Heading 1*)

According to De Lorenzis and Nanni, 2001[1] the Near-Surface Mounted (NSM) method can be traced back to the 1940s, where steel rebars were inserted into pre-cut grooves for bridge repair in Sweden. Despite the increasing popularity of Near-Surface Mounted method and Near-Surface Mounted Fiber Reinforced Polymers (NSM FRP), research on this method has been limited until recently (Rizzo and De Lorenzis, 2009[2]). NSM FRP systems have been found to enhance the shear strength and capacity of structural members, with potential increases of up to 106%, according to multiple studies including Wiwatrojanagul et al. (2012)[3] and Abdelmohaymen and Salem (2022)[4]. The prediction of shear capacity for reinforced concrete beams that have undergone shear strengthening using NSM FRP is a highly intricate task, as evidenced by the current body of research (Perera et al. 2010[5] and Perera et al. 2014 [6]).

The artificial intelligence and machine learning methods, which have recently been widely used in many different disciplines. It will be used as tools for predicting the shear capacities of beams strengthened with NSM FRP metod. To ensure precise and accurate predictions, suitable machine learning models will be employed in Neural Designer and Orange Data Mining software. These Artificial Intelligence models will be based on data that is collected from various experimental studies conducted to determine shear capacity.

A. *Statement of the Problem*

There are several notable formulations that have been proposed to predict the shear contribution of NSM FRP. These include Kotynia (2007)[7], Singh et al. (2012)[8], Dias and Barros (2013)[9], Islam (2009)[10], De Lorenzis and Nanni (2001)[1], Paretti and Nanni (2004)[11], Bianco et al. (2014)[12], and Mofidi et al. (2016)[13]. Although in some cases, the predictions of shear contribution of NSM FRP come close to the experimental results, when the comparative data results based on the article of Ke et al., 2023[14] are considered, predictions of the shear contribution of NSM FRP that are based on the formulations may not reflect completely accurate and precise actual results.

Beginning from this point, in order to illustrate an accurate prediction approach of the shear contribution of NSM FRP that can overlap with the experimental results, Neural Network which is a machine learning algorithm will be used for prediction. Machine learning algorithms have been used for the predictions for several years. The use of machine learning techniques in structural engineering has gained popularity in recent years due to the increasing availability of large datasets and advances in computing power.

However, there are only a few studies that have utilised machine learning algorithms to predict the shear capacity of RC beams reinforced with NSM FRP. Some of these studies does not include up-to-date recent experimental data, while others have not specifically focused on analysing shear contribution of NSM FRP systems or investigated the application of machine learning algorithms for predictive purposes.

B. Statement of the Purpose

The main purpose of this research is by reviewing the existing experimental literature on the role of NSM FRP reinforcement in shear capacity of beams, to achieve accurate and reliable shear capacity predictions, the study proposes utilising Neural Network Model to subject AI to the input variables and their corresponding output values in predicting shear capacity. In order to attain the subsequent three objectives:

1. An extensive literature search and data collection of experimental studies will be conducted to explore the impact of the NSM FRP application on the shear capacity of reinforced concrete beams;

2. Experimenting and evaluating appropriate machine learning techniques and applying the collected experimental data to these methods;

3. Comparison and explanation the shear capacity of beams obtained through machine learning methods with the experimental data to evaluate the effectiveness and accuracy of the utilised techniques.

In this review, the key factors will be identified that influence the prediction of shear capacity in NSM FRP beams for the first objective. These factors include the sizes of concrete, steel, and FRP materials used, the utilisation rate of these materials, and their technical characteristics, such as ratio of strengthening or elasticity modulus of FRP. These parameters will help to build up of a pattern for developing an understanding on various artificial intelligence models to predict these beams' capacity and how the shear capacity works.

The second objective is to conduct model trials, which involve using a portion of the gathered data as training data and comparing it with the remaining data. During this experimental process, two critical factors come into play: understanding the operating principle of artificial intelligence and determining the margin of error, which indicates the difference between the predicted data and the remaining data.

The third goal is to evaluate the accuracy of the predicted data in relation to the experimental data and existing studies' formulations, as well as to elucidate how different artificial intelligence models estimate shear contributions from various NSM FRP types differently. This entails examining how different machine learning models estimate the contributions of different NSM FRP types and comparing the results with previous studies to gain a comprehensive understanding of these models' functioning.

II. The Literature Review

Comprehending the factors that influence the shear strength of reinforced concrete (RC) beams is essential when evaluating the effectiveness of Near- Surface Mounted (NSM) Fiber Reinforced Polymer (FRP) methods in increasing the beams' shear capacity. Specifically, an understanding of the interplay between structural members that bear shear forces is necessary. To gain insight into how concrete, shear strengthening stirrups, and FRP reinforcement contribute to resisting shear forces in RC beams, each parameter must be carefully considered.

On the other hand, to supplement such formulas, it is equally imperative to engage in empirical research. Unlike design formulas, which are based on assumptions, such studies provide illustrations of the actual situation. As such, they are indispensable for achieving a more accurate understanding of the subject matter at hand.

A. Present Equations for Shear Capacity

This section provides an in-depth analysis of the various characteristics and parameters that contribute to the shear capacity of structural members. Specifically, the parameters that impact the ability of a member to withstand shear forces are thoroughly examined and summarised.

According to this formula (1) can be seen in Section 6.2.1 (6.1) of Eurocode 2 (EC2) (2004)[15], the total capacity working against shear forces;

$$V_R = V_{ccd} + V_{Rd,s} + V_{td}\,* \tag{1}$$

In this formula, the subsequent symbols are; V_{ccd} is the shear contribution of concrete, $V_{R,s}$ is the shear contribution of shear strengthening steel stirrups and V_{td}* is the shear contribution of the tensile reinforcement in case of an inclined chord.

Based on the experimental data collected and analyzed, it was observed that none of the tested specimens contained inclined tensile reinforcement. Consequently, the original formula was modified by removing this parameter and incorporating the contribution of NSM FRP, as described in Perera et al. (2014)[6]. The resulting updated formula (2) is presented below.

$$V_{Rd} = V_c + V_s + V_f \tag{2}$$

In this formula, the subsequent symbols are; V_{Rd} is the total shear resistance of the structural member, V_c is the shear contribution of concrete, V_s is the shear contribution of shear strengthening steel stirrups and V_f is the shear contribution of FRP.

B. Artificial Intelligence, Deep learning and Neural Network

Artificial Intelligence (AI) is a cross-disciplinary domain of computer science that aims to create intelligent machines capable of performing tasks that traditionally demand human intelligence. Various techniques, such as machine learning, deep learning, natural language processing, computer vision, and expert systems, are utilized in AI systems, to enable machines to learn, reason, and adapt. AI has become increasingly important in recent years, with applications in fields such as finance, healthcare, and engineering.

The use of Artificial Intelligence in the field of structural engineering is not uncommon; however, the number of studies investigating the contribution of the NSM FRP method to shear capacity through deep learning is still limited. This is thought to be due to the significant difference between the disciplines of data analysis and structural engineering.

To unite the two disciplines which are structural engineering and machine learning at a common mathematical point and offer a new solution, the methodology should be gathered under two different topics. The first one is to investigate the physical and mathematical understanding of how the NSM FRP method contributes to the shear capacity of beams from the perspective of structural engineering, and the second one is to determine which deep learning methods are suitable for solving the problem from the perspective of data science, or which types of deep learning methods should be selected.

Deep learning offers a significant advantage over traditional machine learning methods, as it is capable of autonomously identifying feature representations from data, thereby eliminating the need for human intervention in hand-engineering features. This feature makes it highly effective in applications that involve a vast amount of complex and high-dimensional data.

A type of deep learning is the Neural Network, which is also known as an artificial neural network. Neural networks have three basic parts or sections, each consisting of nodes: the input layer, hidden layer(s), and output layer. Neural networks are specific and are built to solve a particular type of problem, such as classification, pattern recognition, prediction, forecasting, and estimation. Real-world examples of neural network applications include medical diagnosis, handwriting recognition, stock market prediction, real estate appraisal, and image recognition. Although there are other machine learning techniques such as linear regression or logistic regression, these types of machine learning methods are better able to analyse and provide results for linear equation solutions. However, the machine learning method that can predict FRPs should be suitable for exponential and trigonometric mathematical problems and complex equations.

In summary, to summarise the working principle of machine learning and deep learning systems for prediction, it would require providing all experimental data to the system as input, dividing the data into training and test data (which will be explained later), sending the training data to the training model (deep learning), and comparing the predictions based on trained data, made by the model, with the target test data.

III. Methodology

A. Research and Data Preparation

For the approach towards solving the problem, academic experimental studies investigating the shear capacity of beams strengthened by the NSM FRP method and the contribution of the NSM FRP method to the shear capacity were reviewed. In this way, the aim was to obtain the necessary datasets for the deep learning method to be applied later. Furthermore, how these experimental data were accepted and what experimental setups they had or aimed for were analysed.

After analysing and scrutinising the experimental and results sections of the collected research and articles, data with unsuitable failure types were eliminated from the existing experimental data. The reason for this was that in some of these experiments, and certain test specimens failed in flexure before reaching the FRP applications' shear capacity. By examining the experimental results, these test specimens were removed from the planned data set.

As a result of the research, 20 experimental publications that investigated the NSM FRP method and the parameter data affecting the shear capacity of this method were collected. These data were then saved for later application in deep learning.

Additionally, two cumulative articles were found that included some or all of these experimental studies. These publications and articles are 'Application of artificial intelligence techniques to predict the performance of RC beams shear strengthened with NSM FRP rods. Formulation of design equations' by Perera (2014)16] and 'Shear strengthening of RC beams with NSM FRP. II: Assessment of strength models' by Ke et al. (2022)[17].

Based on these sources, the characteristic properties of materials, all existing reinforcements and their ratios, beam dimensions, and the shear capacities obtained from these various experiments were transferred to an Excel file for later application in deep learning. Some unspecified parameters were filled in by checking the cumulative datasets found in the articles. Parameters that could not be found in these sources were obtained through manual calculations, if possible.

Furthermore, to ensure the completeness and accuracy of the collected data, cross-checking and verification were conducted between the different sources. Any discrepancies were resolved through careful analysis and discussion.

In summary, by collecting and integrating data from various sources, a comprehensive dataset was created to facilitate the application of Neural Network in Neural Designer and Orange Data Mining to predict the shear capacity of beams strengthened by the NSM FRP method.

B. Deep Learning Applications

In order to predict shear capacities and gather data, an investigation was conducted into software programs that could implement neural network deep learning methods. Through this investigation, it was researched how the experimental data could be inputted into the neural network. It was discovered that the obtained data needed to be introduced to different software programs in different ways and that the dataset needed to be compatible with the programming language of the program. As a result of the research, three software programs were identified that work with neural networks, each having its own interface and working methodology.

The first program, Neural Designer, is designed solely for creating and generating neural networks, with the ability to provide detailed parameter relationships. The second software is Orange Data Mining, which supports the working principle of data processing visually through its interface and operates with a widget-based system.

In terms of the number of hidden layers that can be added to the neural network, both Orange Data Mining and Neural Designer allow for multiple layers. However, while Orange Data Mining may have a more effective visual interface for conceptualising the modelling scheme compared to Neural Designer, it remains more restrictive in comparison to Neural Designer, which is solely based on neural network prediction.

It should be noted that avoiding overfitting in machine learning applications is crucial. Overfitting occurs when a model fits the training data too closely and becomes unable to generalise to new data. Using fewer features to reduce the error rate is a common method to prevent overfitting. Reducing the number of features can help simplify the model and prevent overfitting.

1) *Neural Designer*

Neural Designer is a software application that allows for the design and training of neural network models, enabling prediction and classification. Neural Designer supports a wide range of neural network models, including feedforward neural networks, recurrent neural networks, convolutional neural networks, and deep learning networks.

In the beginning, the variables, referred to as features, are first placed in columns, and the samples obtained from experiments are placed in rows in the dataset, which is then saved in a format that the software can read. When the dataset is loaded, the software automatically detects and applies the data from the spreadsheet to the system.

As is the case with most predictive software, it is necessary to select the numerical data that needs to be predicted as the target. In the research, the target data is the shear capacity.

In the second step, the data set needs to be divided into three sub-sections under the two main columns. In Neural Designer, these sub-sections are divided into training samples, selection samples, and test samples .

The selection samples are dataset used during the training of the model. It is a subset separated from the training sample and is used to monitor the training performance of the model. During training, the model is optimised on the training sample data and its performance is monitored using the selection sample data. The selection sample is used to control the problem of overfitting of the model, which refers to the situation where the model fits the Training sample data very well but performs poorly with new data. The Selection sample is used to ensure that the model does not overfit to the Training sample data and performs well with more general data.

After this step, neural network hidden layers and features are optimized to the extent preferred, and to prevent the overfitting problem, the input variable parameters are simplified by eliminating the features that have the least impact or can be calculated with the help of other features by examining the correlation coefficients between the variables and the targeted values. Also, based on the results, this topic has been extensively examined in section titled 'Results and Critical Discussion'.

2) *Orange Data Mining*

Orange Data Mining is an open source software package that uses the Python programming language. It provides users with an interactive interface for exploring data, building predictive models, and conducting data mining operations. This software package combines many different data mining components, allowing users to create a workflow using a drag and drop method. These components include data input and output, data pre-processing, feature engineering, modelling, and evaluation.

Initially, the variables, referred to as features, are placed in columns and the samples obtained from experiments are placed in rows in the dataset, which is then saved in a format that the software can read. Subsequently, the feature to be predicted is assigned as the target by selecting it from the loaded dataset in the program. Specifically, for this study, the column containing the shear capacity values of the beam is selected as the target outcome.

The second step involves splitting the dataset into two parts. One part is intended to be used for the planned machine learning process, while the remaining dataset is set aside for calculating the error rate by comparing it with the data generated by the machine learning. Typically, a certain percentage of the dataset, with variations allowed, is allocated as train data for machine learning, while the remaining percentage is set aside as test data to be used for evaluating the training process.

In general, 80% of the dataset is assigned as train data, while 20% is assigned as test data. Although the ratio may vary, typically, around 80% of the data set is allocated as training data for machine learning, while the remaining 20% is set aside as test data to measure the performance of the trained model.

From this point on, in order to prevent overfitting errors as mentioned in the previous section, which is applicable to all machine learning and deep learning applications, the number of variable features given to the system should be reduced. This can be achieved by adding the "correlations" widget between the "data sampler" widget that separates the data into training and test data and the "Neural Network" widget that builds the training model.

IV. Results and Critical Discussion

A. Data Set, Inputs and the Target and their correlation

As previously discussed in the previous chapter on any neural network analysis, the preparation of the data set and the relationship between the input variables and the target value are both crucial and difficult to understand. One reason for this is the multi-layered nature of the model, which creates many multi-dimensional planes, while the other reason is that in this study, the target value is influenced by all input variables.

Based on the input target correlations, the ratio of fiber reinforced polymer (FRP) (ρf) seems to have a negative correlation with the target value of Vexp, while the distance (s) between FRPs appears to have a positive correlation. Based on engineering knowledge, it can inevitably be said that the opposite of this relationship is expected. However, when these variables were entered into these two software programs without changing the samples and features found in both Perera (2014)[16] and Ke et al. (2022)[17] studies, the signs of these variables in the correlation table were the opposite of what should have been.

The apparent reason is that, when the majority of input values are concentrated within a certain range while target values are scattered outside of this range, the input-target correlation may appear negative (Fig. 1). It is entirely related to the dataset, in which there is a high usage of FRP in beams with small dimensions, low concrete quality, and relatively low steel reinforcement, while there is a low usage of FRP in beams with large dimensions, high concrete quality, and high steel reinforcement.

A more detailed explanation is that, even though the ratio of FRP (ρf) may increase in our dataset of 149 samples, the usage and quality of both steel and concrete materials may have changed, causing the target data to appear decreased. This decrease in target data can make the relationship between the two parameters appear negative. It should also be noted that, although the input-target relationship considers only the relationship between two values, the target value is influenced by all inputs and has a relationship with them.

This approach indicates that the system fell into a misconception by only looking at the sample distribution, without being trained yet.

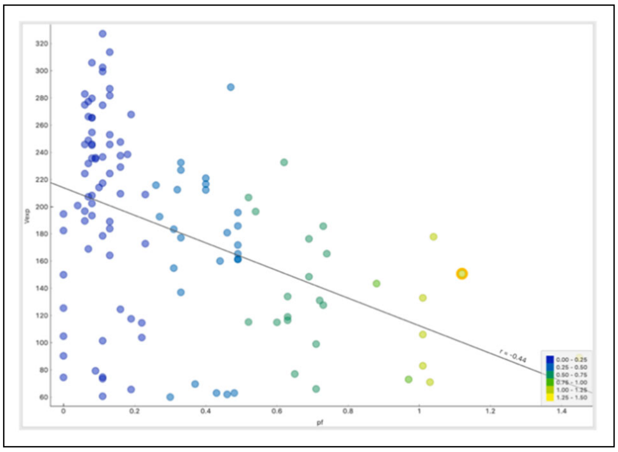

Fig. 1. The chart illustrates the sample distribution of the characteristics ρf and Vexp (pre-trained data)

However, similarly to Perera et al. [16], the model created for prediction in this study was trained using a neural network in Neural Designer and the impact on the target value (*Vexp*) was checked using the 'Calculate Model Input Importance' command. The results obtained by this study showed a positive relationship between the ratio of FRP (ρ_f) and the target value (*Vexp*), as well as an inverse relationship with the FRP distance s (Fig. 2). This demonstrates that the model understands the current state of the system and provides a correct approach accordingly.

Although it is no longer applicable for the current model, the research conducted found that in the book "A primer for soft modelling"[18] which discusses different forms of opposing correlations and their reasons, the section titled "A Digression on Suppressor Effects and Redundancy" analyses the reasons for this correlation and provides possible explanations related to the relationship between inputs and the target. Furthermore, Shmueli (2011)[19] covers various approaches concerning this subject.

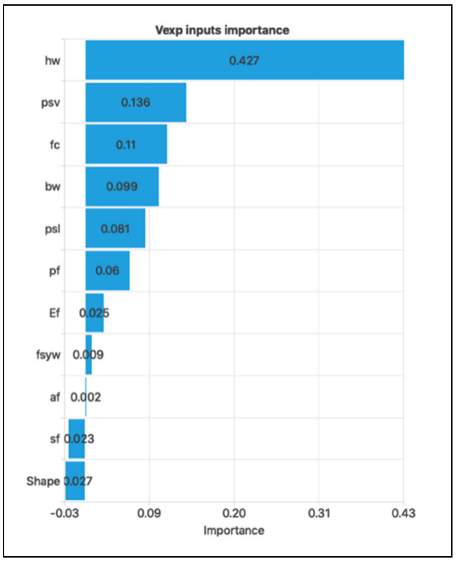

Fig. 2. Input importance for the target data (post-trained data)

B. Results

1) Information on the Prediction Modesl and Settings for Results

Firstly, all collected features and the targeted feature were entered into the dataset as variables, without examining whether they are repetitive or their relationships with each other, for the purpose of being inputted into the spreadsheet. These variables were determined as 17, including shape, b_w, h, d, a/d, ρ_{sl}, f_c, E_{sv}, ρ_{sv}, $f_{s,yw}$, s_{sv}, E_f, ρ_f, s_f, f_f, a_f, and the eighteenth variable, V_{exp}, was added to the dataset for prediction purposes. Data samples that experienced flexural failure from the twenty different experiments were eliminated, and 149 different experiment samples and their corresponding features were added to the dataset. Following this step, examining the input-target correlations in order to observe the relationship between the features and the target data that needs to be predicted. It should be noted that, as explained in the previous section, the relationships between these variables should be checked after the training process, and the input-target relationship should be examined.

In order to determine the importance of variables and how they contribute to the results after the casting process based: *Case 0* includes all variables in the feature combination, *Case 1* includes 11 features that contain the variables shape, h, b_w, ρ_l, f_c, ρ_{sw}, $f_{sy,w}$, Ef, ρ_f, s_f, α_f, *Case 2* includes 10 features that contain the variables shape, , b_w, ρ_l, f_c, ρ_{sw}, $f_{sy,w}$, Ef, ρ_f, α_f. Furthermore, two distinct predictions were made based on the shapes of the data, namely *Case 1-T* and *Case 1-R*. However, due to the limited amount of data used for training the model, these cases were considerably less successful compared to *Case 0*, *Case 1*, and *Case 2*.

The reason for leaving out the selection possibilities for *Case 2*, as the variable simplification has reached the limit value, which tends to increase the error rate.

2) Comparing the Results of the Cases

As observed from the results, the *Case 0* is a guide that contains 17 variables from a data analysis perspective, when all features are inputted, *Case 0* provides a good fitting for the model's training data, but it is weaker in terms of prediction on the test data. This point exemplifies why there is a need to reduce the number of features.

On the contrary, although diminishing the quantity of characteristics can enhance the forecast's performance to a certain extent, surpassing this limit will result in a reduction of the training model's success and forecasting ability. The coefficient of determination (R^2) indicates how well the linear regression line fits the data points. R^2 values closer to 1 indicate a better fit of the regression line to the data, which means that the predicted outcomes are more accurate and closer to the actual values.

Another point to be mentioned is the overall mean error percentage which includes test and trained data error. Although the overall mean error percentage illustrates a rough idea about the model's performance, this value does not fully demonstrate the success of the training system. This is because the success of the prediction model also can be understood by the mean test error. Therefore, this demonstrates that overfitting has been avoided and the system can provide good results on test data that comes from external sources.

Comparing the prediction of *Case 1* (which yields the most successful result among the other cases with reduced features), and the prediction of *Case 0* and *Case 2*, although the training data results for *Case 0* and *Case 2* are slightly more successful than *Case 1*, when the test data predictions of the two cases are compared, *Case 0* and *Case 2* are further away from the regression line compared to *Case 1* and have yielded a less successful outcome on both NN softwares.

It is worth noting that, upon reviewing the results, certain data points consistently produced unsatisfactory outcomes across all experiments. Moreover, in certain instances, beams possessing identical features exhibited differences in their shear capacity. These inconsistencies in the gathered experimental data could potentially result from variations in material quality, production techniques, labour, or experimental conditions, and are thought to be the underlying cause of these discrepancies.

In comparison to Orange Data Mining (ODM), Neural Designer (ND) provides more adjustment options for data analyse and predictions and produces more successful results. This is due to the fact that Neural Designer is a software specifically designed for Neural Networks, providing high adjustment flexibility, and has the ability to provide selecting data choice for model architecture, which is a feature not available in ODM, resulting in better artificial intelligence capabilities.

When examining the distribution of two different results and datasets, a detailed approach is required. The statistical terms of R^2, R, and slope briefly summarise the measurement of linearity and strength of the relationship between two variables which are experimental and predicted data.

While the R^2 value is representing the proportion of variability in the dependent variable that can be explained by the independent variable and showing how much of the dependent variable's variance can be explained by the independent variable, R measures the strength of the linear relationship between two variables which is also known as the Pearson correlation coefficient and ranges from -1 to 1.

A positive R value indicates that the variables increase together, while a negative value indicates that one decreases as the other increases. When the R value is close to 1, it indicates a strong linear relationship between the variables, and the model is successful.

Slope measures the effect of a one-unit increase in the independent variable on the dependent variable. It determines the height and direction of a linear curve. Slope is the m coefficient in the linear equation ($y = mx + b$). As the value of the slope increases, an increase in the independent variable has a greater effect on the dependent variable.

For a successful model, the R^2 value is generally expected to be between 0.7 and 1, indicating that the model fits the data well. The R value is typically expected to be between 0.5 and 1, indicating a strong linear relationship between the variables and a successful model. The sign and expected value range of the slope are also important for a successful model.

It is clearly evident that the neural model generated with ND *Case 1* has yielded highly successful and consistent performance across all results and is the selected model for the research.

The comparison of the values from ODM and ND can be seen in Figure 3, which displays the prediction results of *Case 1* from each software:

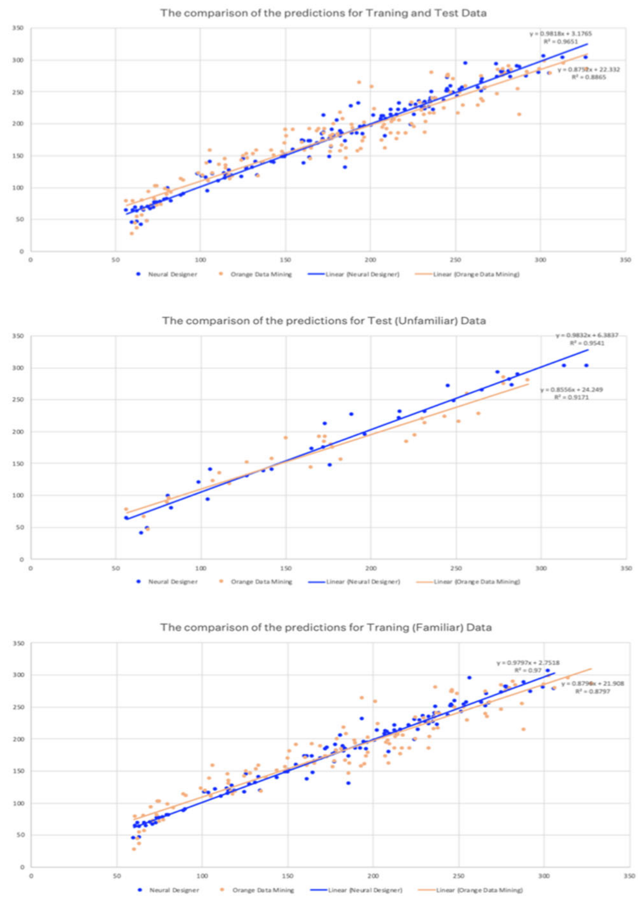

Fig. 3. V_{pre}/V_{exp} graphs of ND and ODM results

3) Details of the Case 1 Model on Neural Desıgner and the Associated Prediction

The most successful neural network model in terms of the training process among the existing cases is *Case 1* from the predictions of Neural Designer. As mentioned before, when the variables are given to Neural Designer, the trial-and-error method is used to find the most suitable number of neurons. At the end of this process (Fig. 4), our network architecture consists of 11 scaling layer with 11 neurons, perceptron layer with 9 neurons and 1 neuron, unscaling layer with 1 neuron, and bounding layer with 1 neuron.

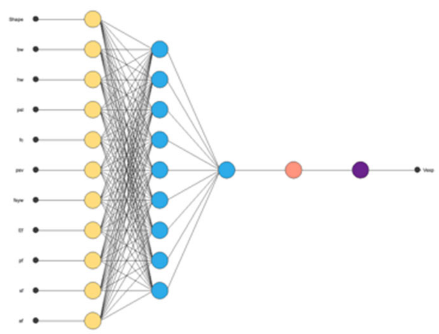

Fig. 4. Network architecture

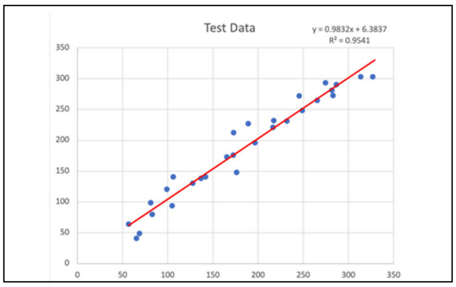

Fig. 5. *Vpre*/*Vexp* of test data (Unfamiliar data)

Fig. 6. *Vpre*/*Vexp* of training data (Familiar data)

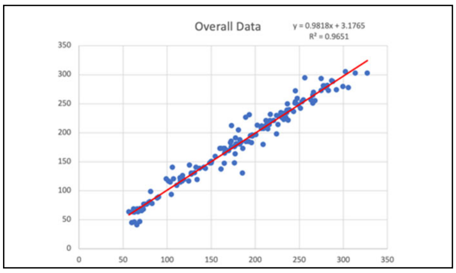

Fig. 7. *Vpre*/*Vexp* of overall data

Case 1	
The coefficient of determination (R2) (Overall)	0.9651
Max percentage error (%)	14.4078
Mean percentage error (%)	4.79554

Fig. 8. Table of error statistics for *Case 1*

	Minimum	Maximum	Mean	Deviation
Absolute error	0.535446	38.9875	12.9767	12.1808
Relative error	0.00197874	0.144078	0.0479554	0.0450142
Percentage error	0.197874	14.4078	4.79554	4.50142

Fig. 9. Error statistics

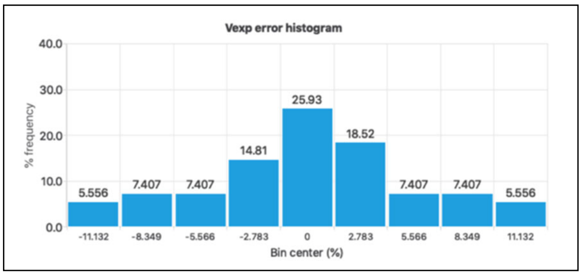

Fig. 10. Error histogram chart

As a result of this training model, the informative results of testing analysis can be seen in Fig. 5, 6, and 7.

When comparing the R^2 values for the test and training data, which are 0.9541 and 0.97 respectively, we can see that these values are quite close to each other and similar. This suggests that the model works similarly for these two different data sets (training and test data), indicating successful prediction. Although some samples show deviation from the regression line (Fig. 5, 6, and 7), the results for most of the samples in both test and training data follow successful regression lines. It should also be noted that some discrepancies and deviations are expected under experimental conditions, and considering that experimental data is used, such deviation is acceptable for this prediction model (Fig. 9). This deviation and mean percentage error rates are consistently observed to be in agreement with each other.

Examining the error rates provides clear information about the model's performance and prediction ability. One of these methods is to examine the error histogram. According to the model's error histogram (Fig. 10), approximately 60% of the data results fall below a 5% error rate, while approximately 90% fall below a 10% error rate. The predictions are clustered around an error rate close to 0. Samples with relatively high error rates appear to be around 10%, and the maximum error percentage from these values is 14%. However, this does not change the fact that there is an average error rate of approximately 4.8% across the entire model.

V. Conclusion and Recommendations

Technical formulations and experimental research specific to the relevant discipline are crucial for understanding and implementing the model in future work. For instance, in this study, the working principle of NSM FRP cannot be understood without fully grasping the NSM FRP topic or shear capacity and obtaining a significant amount of experimental data on these topics. Without meeting these conditions, it is impossible to create an effective prediction model and obtain results.

If the A.I. software used in this research had the ability to group inputs and disconnect the correlation between inputs, it is thought that the predicted data could match the actual values perfectly. This can be seen as follows: Since it is unknown how the system creates correlations between inputs in the hidden layer after training, it is not possible to know whether there are correlation probabilities between some inputs or not, which can cause deviations. For instance, although there is no linear or inverse relationship between the tensile strength of stirrup steel and the elastic modulus of FRP, the system may try to establish a relationship between them based on the data, leading to less efficient predictions. To prevent this, if a sufficiently large sample size is provided, there may be no need to specify this relationship, but currently, this does not seem very likely as there are not many experimental studies available.

In addition, it is not possible to enter certain formulas into these programs and start a training process based on them. This hinders the improvement of the working methods of the formulations with the existing experimental data. For this reason, research should be conducted in the fields of A.I. and coding using programming languages such as Python that is highly adjustable.

Another point is that, while one of these programs has the feature of generating expressions for programming (which is not available in the other software), it cannot provide a suitable formalisation, formalisation-based solution or approach for NSM FRP analysis. However, such studies can lead to NN-based add-ons and updates in structural analysis programs. It is obvious that, to ensure that the resulting predictions are lower than the ultimate values, there will also be a need for reduction coefficients specified in certain codes.

In this study, various FRP formulations and independent FRP contribution estimations were not compared. This is because, although total experimental capacity values were available, experimental data providing separate contributions of the components could not be obtained for the majority of the samples. Therefore, since it is not possible to group the contributions of each material based on predicted values, formulation comparison could not be made.

Furthermore, it should be noted that this approach is based on a model created with a small number of samples, which means that the ranges of the inputs are limited and the model is generated based on the specific set of samples. Therefore, a more comprehensive research study could be conducted to create a model that captures the real-world scenario by using a large number of samples which will be developed specifically for this purpose only.

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