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Original Article

Buckling Prediction in Steel Columns: Unveiling Insights with Artificial Neural Networks

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Abstract - *The buckling of steel columns is a critical concern in structural engineering design and analysis. Accurate prediction of buckling behavior is necessary for ensuring the integrity and safety of steel structures. Buckling phenomena in steel columns present a challenging and intricate issue within the realm of structural engineering. In the past few years, diverse Artificial Intelligence (AI) techniques have been employed to address complex problems in structural engineering. Artificial neural networks (ANNs) encompass a category within the field of AI that can learn complex patterns and relationships from datasets. This article endeavors to predict the buckling load in steel columns, addressing it as a complex problem in structural engineering. By training an ANN on a dataset that includes information about the parameters affecting buckling, such as column dimensions, material properties, and load conditions, it is possible to develop a predictive model. In this research, the behavior of steel columns under various loading conditions using Finite Element (FE) is simulated, a large amount of data for training ANNs have been generated, and multiple ANNs are trained using various architectures and training algorithms. The performance of trained ANNs is evaluated using statistical parameters such as Mean Squared Error (MSE) and coefficient of correlation (R^2). The results show that ANNs are well-suited for predicting complex and nonlinear problems such as buckling load in steel columns. The paper also discusses the importance of proper training and validation procedures and the challenges associated with extrapolation beyond the trained data range.*

Keywords - *Artificial Intelligence, Artificial Neural Networks, Buckling, Finite element, Steel columns.*

1. Introduction

The prediction of buckling behavior in steel columns plays a vital role in guaranteeing the structural integrity and safety of various engineering applications. Buckling, which refers to the sudden lateral deformation or collapse of a column under compressive loads, is a critical failure mode that engineers must accurately predict and prevent. Traditional analytical methods, such as Euler's buckling formula, have been widely used for buckling analysis. However, these methods often rely on simplified assumptions and may not capture the complex interactions between various parameters affecting buckling behavior.

The application of AI techniques in structural engineering has revolutionized the field by enhancing design, analysis, and decision-making processes [1, 2]. AI enables engineers to optimize structural designs, predict performance, and evaluate risks more accurately. AI techniques can analyze large volumes of data to identify patterns, optimize material usage, and improve structural integrity. Additionally, AI techniques can assist in structural health monitoring, detecting anomalies, and providing early warning systems for potential failures [3]. In recent years, Artificial Neural Networks (ANNs) as one of the AI techniques have emerged as powerful tools for predicting buckling in steel columns [4-6]. ANNs are computational frameworks designed to imitate the human brain, drawing inspiration from its intricate structure and functioning. They can learn from data patterns and make predictions based on learned knowledge. ANNs have gained significant attention as a result of their capability to capture complex nonlinear relationships and adapt to various input parameters.

The application of ANNs in predicting buckling behavior offers several advantages over traditional analytical methods [7-11]. ANNs can handle large and diverse datasets, allowing for a more comprehensive exploration of input parameters' effects on buckling. They can effectively learn and model the intricate interactions between parameters, enabling accurate predictions in both linear and nonlinear systems. Moreover, ANNs have the potential to generalize well to unseen data, making them valuable tools for practical engineering applications. The use of ANNs has become widespread because of their ability to produce dependable predictions, even when trained with deficient or incomplete data.

In structural engineering, several researchers have utilized ANNs to predict the buckling behavior of civil structures. For example, A research to assess the feasibility of utilizing ANNs to predict the buckling parameters of slender channel components under compression and bending loads [12]. The authors trained ANNs by inputting various parameters, including the dimensions, thickness, stiffener placement, and length of the elements. The output data comprised the buckling load. A hybrid strategy combining the finite strip technique with the equivalent nodal force approach was employed to generate training samples. The findings demonstrated that the trained algorithms exhibited a notable level of precision, with a correlation value of 98%, in predicting the buckling loads. This study also provided potential avenues for further improvement in ANN-based buckling prediction models.

In a subsequent study, examined the impact of primary parameters and various loading conditions on the ultimate torsional buckling resistance of steel I-beams with web openings [13]. Subsequently, utilizing the provided database, an ANN was employed to develop a precise formulation for predicting the ultimate lateral torsional buckling strength of steel beams. The outcomes indicated that the recommended ANN model exhibited a reasonable level of accuracy, making it a viable and practical approach for I-beams with sinusoidal web openings.

Moving on, Wu et al. [14] conducted an analytical investigation on the buckling performance of prestressed stayed beam columns. They also introduced an intelligent approach utilizing ANNs to assess the nonlinear failure mode and determine the ultimate load. The findings indicated that the utilization of the ANN technique provided accurate and reliable predictions for the failure mode and ultimate load of prestressed stayed beam columns. In another study, Tahir et al. [15] employed ANNs to estimate the buckling load of slender shell structures experiencing axial compression. A dataset comprising 516 specimens was compiled by gathering experimental data from 38 prior studies focusing on the buckling behavior of thin shell structures under axial compression. The training of the networks utilized the backpropagation algorithm and involved nine input parameters. These parameters encompassed two mechanical characteristics, six geometrical factors, the class of fabrication tolerance, and a single output parameter representing the buckling load of the specimens. In addition, Tahir and Mandal [16] performed an extensive analysis of experimental data gathered from established literature sources using ANNs. The networks were trained using 390 experimental datasets with the backpropagation algorithm. A comparison was made between the critical buckling loads predicted by the ANNs and the design guidelines provided by Eurocode 3 and the experimental buckling loads. The findings indicated that the ANNs could predict the buckling load within a 10% margin of the buckling load obtained from experiments. Consequently, these models can be considered reliable for use within the range of parameters employed during the training process.

In another research, the buckling behavior of prestressed CFRP-reinforced steel columns using ANN has been investigated by Hu et al. [17]. In this study, the finite element was employed to analyse columns subjected to axial compression load to generate 312 datasets for the training of ANN. The study identified nine significant parameters that notably impacted the buckling strength of reinforced columns using Carbon Fiber Reinforced Polymer (CFRP). These factors included the initial CFRP prestressing force, support span, eccentricity, yield strength of steel, column slenderness, elastic modulus of CFRP, initial imperfection, and boundary conditions. The research findings demonstrated that ANNs could accurately predict the buckling strength of prestressed reinforced steel columns, even when considering the complex nonlinear problem at hand.

Furthermore, in recent years, several researchers have explored the advantages and limitations of ANNs in predicting buckling behavior [18-25]. They have discussed various aspects, such as different ANN architectures, training algorithms, and the selection of input parameters. Additionally, comparative analyses have been conducted to evaluate the accuracy of ANN-based buckling load predictions compared to experimental results and theoretical models. Based on prior studies, it has been established that ANNs exhibit the potential to improve prediction accuracy, making them a valuable tool for addressing and reducing buckling risks in steel columns. Despite the promising results of using ANNs for predicting buckling load in steel columns compared to traditional methods, additional research in this area is required to assess the efficiency of ANNs. Therefore, this study aimed to focus on exploring the potential of ANNs to predict the buckling load in steel columns. The findings from this study significantly contribute to advancing the field of predictive modeling in structural engineering. Reducing the necessity for extensive physical testing provides valuable insights for engineers engaged in designing and analysing steel structures, thereby mitigating the risk of buckling failures.

2. Artificial Neural Networks

Artificial Neural Networks (ANNs) represent computational frameworks that draw inspiration from the structure and functionality of biological neurons, specifically the human brain [26-27]. ANNs consist of interconnected nodes, or artificial neurons, organized into layers. ANNs have become increasingly popular for solving real-world issues as they can address complex problems that traditional technologies cannot handle, especially those that do not have a defined algorithmic solution or have a solution that is too complicated to define. Among the various types of neural networks, the multilayer perceptron stands out as the most commonly employed one in structural engineering.

As shown in Figure 1, ANNs typically consist of three types of layers. The first layer of the network, known as the input layer, gets the initial input datasets. The input data's dimensionality dictates the input layer's size within a neural network. Intermediate layers, known as hidden layers, are located between the input and output layers in a network. They are termed as hidden because their computations are not directly observable from the outside. Hidden layers improve the network's ability to grasp complex patterns and interrelationships present within the data. ANNs can have more hidden layers, depending on the architecture chosen. The network's final layer, known as the output layer, generates the network's outputs. The number of neurons within the output layer fluctuates based on the nature of the particular problem under consideration. For example, in the case of a binary classification problem, the output layer would comprise only one neuron, while a multi-class classification problem would have multiple neurons representing different classes.

The structure of an ANN, including the number of layers and the arrangement of neurons within each layer, can differ depending on the specific problem domain and its requirements. Different architectures, such as feedforward networks, convolutional networks, recurrent networks, and deep networks, offer flexibility in capturing different types of patterns and relationships within the data.

Data preparation is the first step to developing the architecture for ANN. This includes tasks like gathering data, refining data, data normalization, and feature scaling. The data should be properly formatted and prepared to be fed into the ANN. The next step is to design the architecture of the ANN. This step entails deciding on the number of layers, the number of neurons within each layer, the activation functions that will be employed, and the connections between the neurons.

In this study, a multilayer feedforward neural network is utilized, where the neurons are arranged in layers. Each neuron in a particular layer is linked to all the neurons in the next layer. During the feedforward phase, the input data is forwarded through the network in a unidirectional manner, moving from the input layer towards the output layer. Every neuron within the network calculates a weighted sum of its inputs, employs an activation function to this summation, and then transmits the resulting value to the neurons situated in the subsequent layer. The backpropagation algorithm is widely utilized in multi-layer feed-forward networks due to its effectiveness in mathematical modeling and learning complex nonlinear relationships.

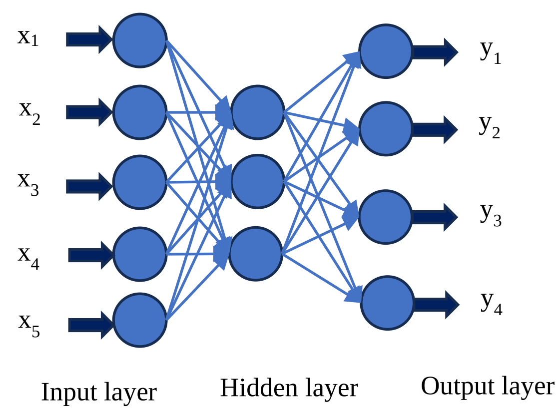

Fig. 1 Architecture of ANNs

Backpropagation serves as a fundamental algorithm for training ANNs. It encompasses computing the gradient of the error function concerning the network's weights and biases, followed by modifying these parameters to minimize the error. The gradients are calculated and propagated backwards through the network. This algorithm is evaluated based on a performance indicator, which is the least Mean Square Error (MSE). This performance index serves as the convergence criterion during the training of ANNs. It involves minimizing the average squared difference between the predicted outputs of the network and the corresponding targets in the training set, aiming to achieve a satisfactory agreement between the network's results and the training set outcomes [28].

3. Prediction of Critical Buckling Load using ANNs

The precise prediction of buckling behavior plays a crucial role in upholding various applications' structural integrity and safety. When utilizing ANNs for buckling prediction, it is routine to collect a dataset that consists of input features and their corresponding output labels, which is buckling behavior. In the occurrence of column buckling, several parameters play a crucial role. Geometric properties, which are the dimensions and shape of the column, such as length, cross-sectional area, and moment of inertia, affect its susceptibility to buckling. Longer and slender columns are more prone to buckling compared to shorter and stouter ones. Even minor imperfections in the column's geometry can have a significant influence on buckling behavior. Imperfections can cause local stress concentrations and initiate buckling at lower loads. The material characteristics of the column, including its modulus of elasticity, yield strength, and stiffness, influence its buckling behavior. Columns made of materials with lower stiffness are more susceptible to buckling. The type of support and constraints at the column ends significantly impact buckling. Columns with pinned ends have higher buckling capacity than those with fixed or clamped ends. The magnitude, direction, and distribution of applied loads on the column play a vital role in buckling. Compression loads acting along the longitudinal axis of the column increase the likelihood of buckling.

This study employed seven variables significantly impacting the critical buckling load in steel I-columns to develop ANN models. These parameters include section depth (h), the width of section (b), thickness of flange (t_f), thickness of web (t_w), slenderness ratio (L/r), the ratio of the compression flange to the thickness of flange (c/t_f), the ratio of the depth between fillets to the thickness of web (d/t_w). The output of the ANN was designated as the critical buckling load in steel I-column (P_{cr}). Table 1 presents statistical information regarding the variation of specific parameters associated with the specimens considered in the database. This study focuses on utilizing Finite Element Analysis (FEA) to simulate the performance of steel columns under diverse loading scenarios. As a result, a substantial dataset comprising 255 samples has been generated through FEA and meticulously prepared to construct models for ANNs. All datasets have been collected from simply supported columns. At first, the ANN would be trained on these datasets to establish comprehension of the relationship between the input parameters and the buckling outcome.

Among the total 255 datasets, 165 datasets were designated for training purposes, accounting for 65% of the total. Furthermore, 51 datasets were allocated for testing, making up 20% of the total, and the remaining 39 datasets, which constituted 15%, were utilized for validation. The random division of data was conducted across the three datasets, and each dataset underwent statistical analysis to ensure that it encompassed a comprehensive range of input parameters.

In this research, a feedforward Backpropagation Algorithm (BP) was applied for ANN training. During training, the network is presented with a set of training examples, and the weights and biases are adjusted iteratively using optimization algorithms like gradient descent or its variants. The training process aims to minimize the error between actual datasets and predicted results from ANN and improve the network's ability to make accurate predictions. In the BP algorithm, an input vector comprising the mentioned seven parameters is initially fed into the input layer. These input vectors generate a corresponding set of output values. Subsequently, the error, computed as the distinction between the given output and the desired output, propagates backwards through the network. The Mean Square Error (MSE) is reduced throughout this procedure, leading the ANN's output to approach the target output.

Table 1. Statistical information of datasets

Parameter	Min	Max
Section’s depth (h), mm	100	890
Section’s width (b), mm	50	424.4
Flange’s thickness (t_f), mm	6	77
Web’s thickness (t_w), mm	4.5	47.6
Slenderness ration (L/r)	30	150
Ratio of the compression flange to the thickness of flange(c/t_f),	2.75	13.4
Ratio of the depth between fillets to the thickness of the web (d/t_w).	6.05	68.5
Critical buckling load in steel I-column (P_{cr}), kN	15.7	7750

When a new sample is presented as input, a well-trained ANN is capable of producing successful results. To facilitate this, the datasets were normalized within the range of 0 to 1 and then provided as input to the input neurons of the ANN. The training process persists, continually updating and adjusting the weights until the ANN is able to generate outputs that are deemed satisfactory when compared to the target values.

This study employed numerous neural network architectures, each characterized by distinct conditions like connection weights, the quantity of hidden layers, the quantity of neurons within each layer, and the activation function type applied in both hidden and output layers. These networks were trained using available datasets to fulfill the research objectives. Based on the findings, a network with a single hidden layer demonstrated satisfactory convergence during the training of the ANN. Therefore, the network architecture decided with a 7-15-1 configuration consisting of three layers.

The first layer comprises 7 neurons in the input layer representing the seven most effective parameters on buckling load in steel beams. The second layer, known as the hidden layer, contains 15 neurons. Finally, the output layer has a single neuron corresponding to the critical buckling load. The network architecture selected for this study is illustrated in Figure 2. It should be noted that incorporating a larger number of neurons in the network increases computational complexity and time requirements. In conclusion, the 7-15-1 architecture of the ANN was chosen to achieve an optimal trade-off between compatibility cost and accuracy, providing a balance between efficiency and performance.

Additionally, the findings demonstrated that the ANN model developed with a learning rate of 0.2 and a momentum parameter of 0.7 exhibited the lowest error rate. The network employed a hyperbolic tangent activation function in both the hidden and output layers. Following that, the network was trained iteratively until the training error reached its minimum, guaranteeing stability within the network.

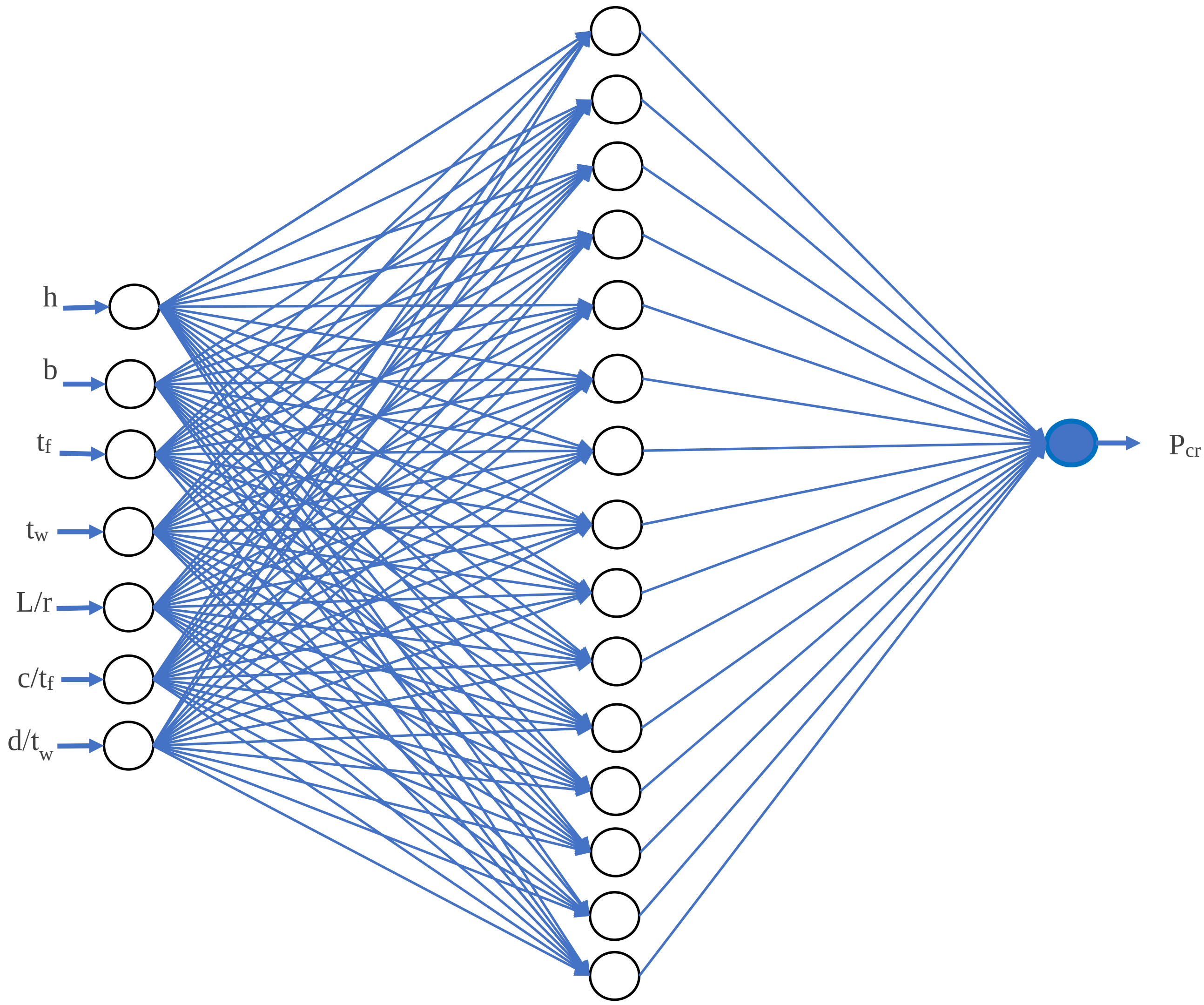

Fig. 2 Architecture of the ANN for predicting buckling load

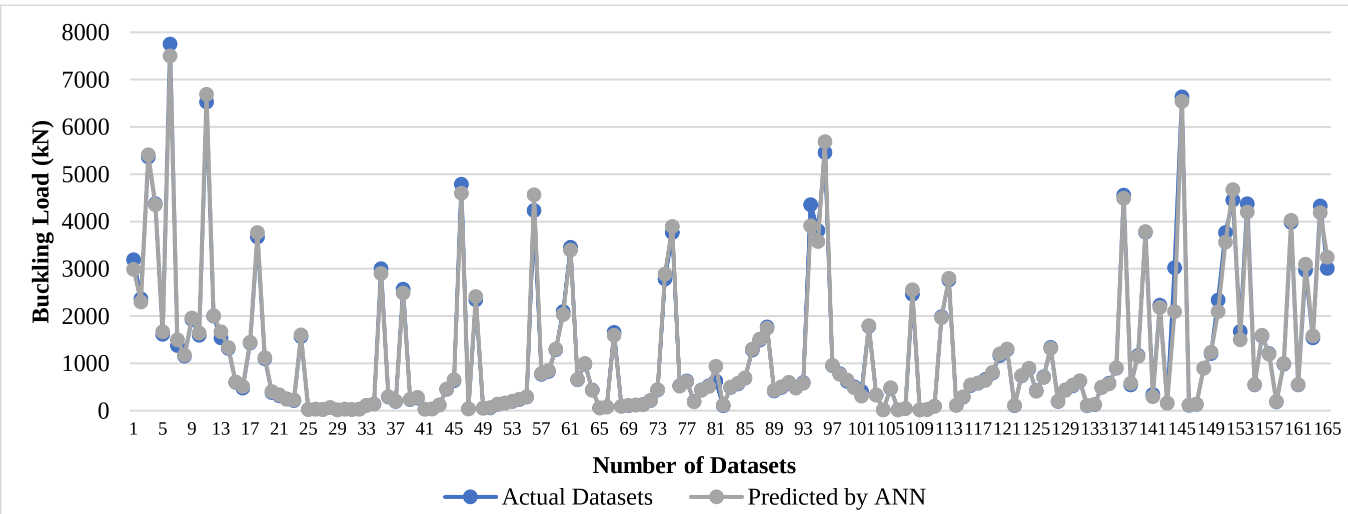

Fig. 3 Comparison of buckling load predicted by ANN and actual datasets (training sets)

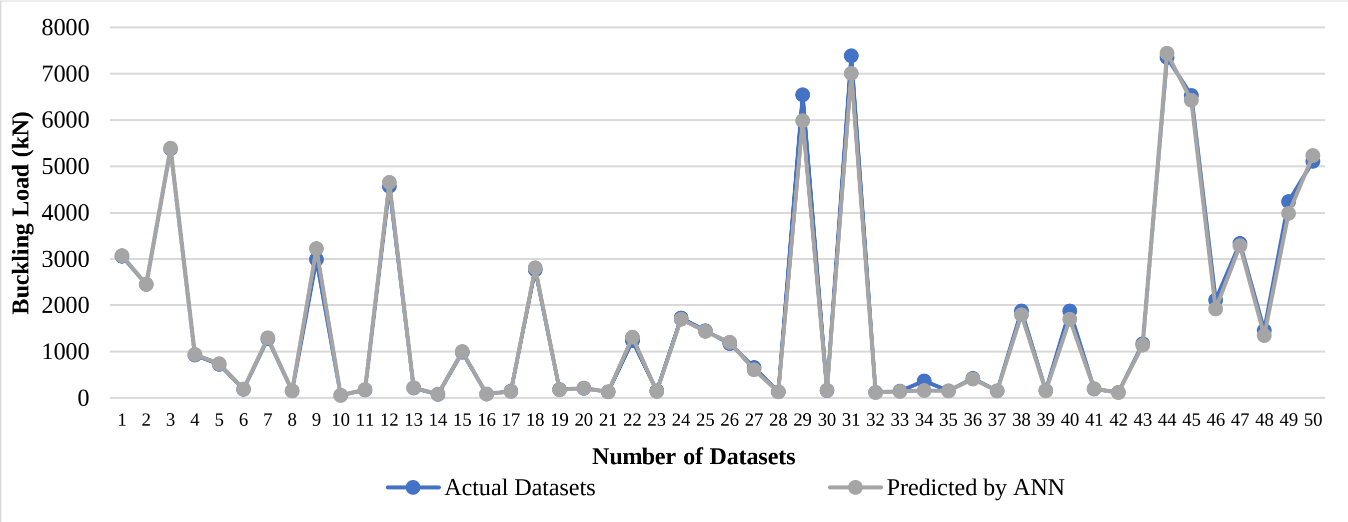

Fig. 4 Comparison of buckling load predicted by ANN and actual datasets (testing sets)

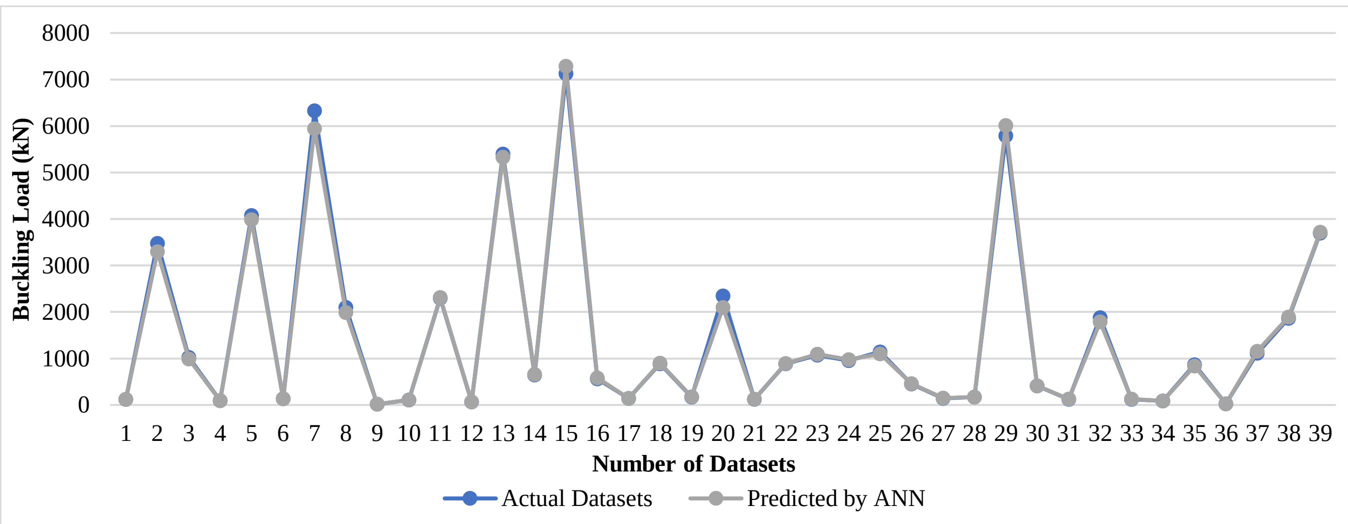

Fig. 5 Comparison of buckling load predicted by ANN and actual datasets (validation sets)

Based on the findings, the correlation coefficient for the training datasets was determined to be 0.991. Following the training process, the neural network has acquired knowledge from the samples, enabling it to predict the buckling capacity in steel columns with a Mean Squared Error (MSE) of 0.0001246.

Figure 3 presents a comparison between the predicted buckling load values generated by the ANN and the actual values for the training datasets.

Once trained, the ANN model can be employed to predict the buckling load using datasets not part of the training set. Consequently, following the completion of the network training, the testing dataset was utilized to evaluate the precision of the chosen architecture. The comparison between the predicted buckling load by the ANN and the actual datasets is depicted in Figure 4. This evaluation was conducted using 51 newly introduced datasets as testing sets for the network's predictive capabilities.

The ANN demonstrated success in predicting the buckling load of steel columns, as evidenced by a Mean Squared Error (MSE) of 0.0001572 for the testing sets, indicating a close match to the actual outputs. The correlation coefficient for the testing datasets was determined to be 0.986. These results indicated that the network accurately predicted the buckling load in most cases, as evidenced by the low error and high correlation values.

However, it should be noted that the network struggled to accurately predict the buckling load in cases with exceptionally high loading values. This limitation may be attributed to the insufficient availability of datasets within this specific range during the network's training process, which could explain its reduced accuracy in such scenarios. It is widely acknowledged that an ANN's performance can be significantly improved by training it on a diverse range of data, particularly large volumes of data.

Furthermore, the validation dataset was utilized as an additional measure to evaluate the neural network's generalization ability and to fine-tune hyperparameters such as the learning rate and quantity of hidden layers and mitigate the risk of overfitting. This tuning process aims to enhance the network's performance by optimizing these hyperparameters based on the validation outcomes. This step aimed to evaluate the reliability and accuracy of the functioning of the trained network. The comparison between the predicted buckling load by the ANN and the actual datasets for the validation datasets is illustrated in Figure 5. The validation results revealed the success of the ANN in training the relationship between the input and output data, as evidenced by an MSE of 0.001839 and a correlation coefficient of 0.982. Figure 5 illustrates that the chosen network exhibited a strong correlation between the inputs and outputs of the network, indicating its capability to capture and represent the underlying relationship effectively.

In this study, it was observed that the critical buckling load of columns, as calculated using Euler's buckling theory, significantly exceeded the practical load-carrying capacity of the columns. This disparity can be attributed to Euler's buckling theory, assuming an idealized column with perfect boundary conditions, no imperfections, and linear elastic behavior. However, real-life columns often exhibit imperfections, non-ideal boundary conditions, and nonlinear material behavior. These factors contribute to the deviation between the predicted critical load based on Euler's theory and the actual load-carrying capacity of the columns in practice.

By comparing the results of the ANN with the actual datasets, it was possible to observe the influence of input variables on the buckling load in steel columns. According to the predicted outcomes, the slenderness ratio (L/r) had a greater impact on the buckling capacity of steel columns compared to the other input parameters. The slenderness ratio is a significant parameter in the design of steel columns to assess their stability against buckling. It is important to note that when the slenderness ratio is small, the column is predominantly subjected to compressive forces and is considered short, and buckling is not a significant concern.

By the way, as the slenderness ratio increases, the column's load-carrying capacity is influenced by both its resistance to compression and its resistance to buckling. When the slenderness ratio exceeds a critical value, the column is considered long, and buckling causes the column to deflect laterally, reducing its load-carrying capacity.

The depth and width of the section were the second and third most significant input parameters in terms of their influence on the critical buckling load. According to the findings of this study, a larger depth resulted in a higher critical buckling load. This is because a greater depth provides increased resistance to bending and compressive forces, enhancing the column's stability. Similarly, a wider section tends to have a higher buckling load capacity since it offers more resistance against lateral deflection and bending moments.

According to this research, the ratio of the compression flange to the thickness of the flange (c/t_f) and the ratio of the depth between fillets to the thickness of the web (d/t_w) were identified as the fourth and fifth significant input parameters impacting the critical buckling load in steel columns. The c/t_f ratio affects the ability of the flange to resist compressive stresses. A higher c/t_f ratio indicates a wider flange relative to its thickness, which generally leads to better resistance against local buckling. Conversely, a lower c/t_f ratio implies a narrower flange in proportion to its thickness, making it more prone to local buckling failure. The d/t_w ratio affects the ability of the web to resist compressive stresses. A higher d/t_w ratio, indicating a greater depth relative to the web thickness, generally results in better resistance against local buckling. A larger d/t_w ratio indicates a slenderer web, less prone to local buckling failure. According to this study, the impact of the flange's thickness and the web's thickness on the critical local loading of steel columns was minimal. By the way, a thicker web generally provides better resistance against local buckling. Also, a thicker flange enhances the column's resistance to local buckling.

4. Conclusion

The prediction of buckling behavior in steel columns is of utmost importance in ensuring various engineering applications' structural integrity and safety. This paper presents an approach utilizing ANNs to predict the buckling load of simply supported steel columns accurately. This study focuses on developing and training ANNs using a comprehensive dataset of steel column properties and buckling load data. The seven independent variables comprising the depth and width of the section, thickness of the flange and web of the section, slenderness ratio, the ratio of the compression flange to the thickness of the flange, and the ratio of the depth between fillets to the thickness of web have been selected as input parameters of ANN. Finite element analysis from 255 different columns was used for training, testing and validation of ANN.

From the results, it was determined that ANN predicted the critical buckling load in steel columns with a very small Mean Square Error (MSE) and a high coefficient of correlation. The results demonstrated that the ANN as a computational intelligent method has the potential to give a very encouraging level of performance for the problem of buckling load prediction in steel columns based on some of its influence factors. Consequently, the approach investigated in this study shows great potential as a dependable method for accurately predicting the buckling load in steel columns.

Furthermore, this study conducted a sensitivity analysis to assess the contribution of input parameters to predict the buckling capacity in steel columns. The outcomes ascertained that the slenderness ratio (L/r) had a more pronounced influence on the buckling capacity of steel columns when compared to the other input parameters. Additionally, based on the findings of this study, it was determined that the impact of the flange thickness and web thickness on the critical local loading of steel columns was relatively less significant when compared to the other input parameters examined.

Ongoing research and advancements in this area will continue to enhance ANN-based methodologies, resulting in improved precision and efficiency in buckling load predictions. As a result, this advancement will contribute to developing structural engineering practices, ensuring structural integrity and greater safety. Integrating AI techniques in structural engineering holds great potential for advancing civil structures' efficiency, safety, and sustainability.

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