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Optimal Prediction of Shear Properties in Beam-Column Joints Using Machine Learning Approach

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ABSTRACT

The failure of shear-type beam-column joints in reinforced concrete (RC) frames during severe earthquake attacks is a critical concern. Traditional methods for determining joint shear capacity often lack accuracy due to improper consideration of governing parameters, impacting the behaviour of these joints. This study assesses the capabilities of machine learning techniques in predicting joint shear capacity and failure modes for exterior beam-column joints, considering their complex structural behaviour. An artificial neural network (ANN) model is proposed for predicting the shear strength of reinforced exterior beam-column joints. ANN, a component of artificial intelligence that learns from past experiences, is gaining popularity in civil engineering. The ANN model is developed using a dataset comprising material properties, specimen dimensions, and seismic loading conditions from previous experimental investigations. The model considers twelve input parameters to predict shear strength in exterior beam-column joints. Training and testing of the ANN model are conducted using established design codes, empirical formulas, and a specific algorithm. The results demonstrate the superiority of the proposed Shallow Feed Forward Artificial Neural Network (SFF-ANN) compared to previous approaches. The effectiveness of an Artificial Neural Network (ANN) model was quantitatively assessed in this study, with a focus on its performance in comparison to various design codes commonly used in structural engineering. The model was assessed using the coefficient of determination (R^2) and achieved R-squared values of 99%, 94%, and 98% during the training, testing, and validation stages, respectively. The study highlights the significance of beam reinforcement as a key element in estimating shear capacity for exterior RC beam-column connections. Although the proposed models exhibit a high degree of precision, future research should focus on developing improved models using expanded datasets and advanced algorithms for enhanced pattern recognition and performance.

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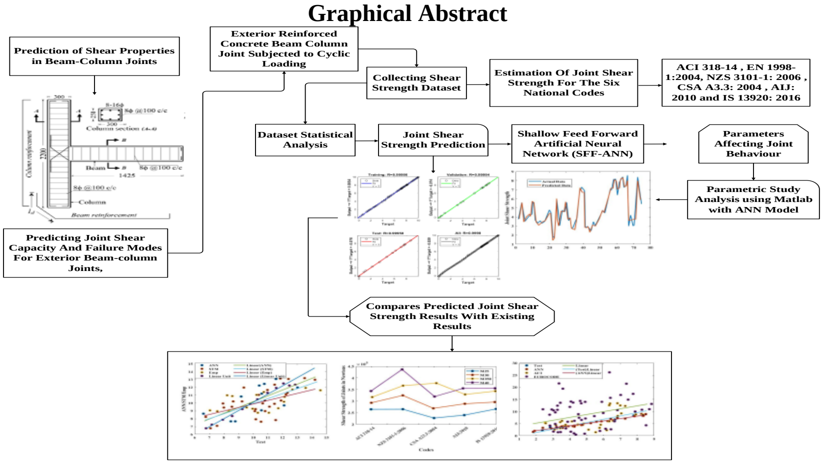
Graphical Abstract



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1. INTRODUCTION

Beam-column joints are vital components of reinforced concrete moment resisting frames (RCMRF), and they are particularly susceptible to seismic loads as failure in these joints can result in the collapse of the entire structure (1). Extensive investigations following earthquakes have emphasized the significance of beam-column joints as they significantly influence the overall seismic performance of reinforced concrete (RC) frames (2). Beam-column joints play a crucial role in maintaining the structural integrity of the system. However, during strong seismic events, these joints may experience large deformations, leading to a reduction in their capacity to carry lateral and gravity loads. This can result in partial damage or even the complete collapse of the structure (3). In modern building design, joint shear failure is a common type of failure observed in beam-column joints.

This failure mode often occurs because the joints were not designed to withstand the anticipated loads based on the capacity design principles recommended in contemporary seismic codes. Shear failure in beam-column joints, even at relatively low deformations, is a

brittle failure mode that can potentially trigger a building's collapse (4). Given the critical role of beam-column joints and their vulnerability to seismic forces, it is imperative to properly design and reinforce these joints to ensure the overall safety and integrity of structures in seismically active regions.

Determining the dimensions of the strut and cut-point regions, which are crucial for predicting the shear strength of beam-column joints, presents a significant challenge when using the Strut and Tie Model (STM) (5). The shear strength of the joint plays a vital role as the beam-column joint can become a weak link if it is not adequately considered. Previous research has employed various individual-type machine learning (ML) algorithms, such as ANN-PSO, SVM, XGBoost, and decision trees, for predicting the shear strength of reinforced concrete joints (6). Among these techniques, ANN, GEP, and fuzzy logic-based evaluations of cement strength have shown promise as efficient ML-based prediction techniques for engineering structures (7).

The resisting mechanisms provided by the beam-column joint are fundamental in enabling RC-framed buildings to withstand seismic excitations (8). In predicting the shear strength of RC joints, the deformation of Type 2 joints indirectly informs the prediction of member shear strength and follows the conservative approach recommended by ACI 352-R02 (9). Before the adoption of "earthquake-resistant" structural design in the late 1970s and early 1980s, many buildings were primarily designed to carry gravity loads, lacking sufficient shear strength, flexural capacity, and flexibility to resist strong seismic ground motions (10). In the design and seismic analysis of tall structures, lateral load-resisting systems like RC shear walls are commonly utilized. Accurately predicting the capacity of these systems is a critical aspect of the design process (11). Predicting the capacity becomes complex due to the reinforcement characteristics of concrete and the interactions between flexure and shear. Furthermore, the response of the structure during seismic activity can influence the behaviour of the joint (12).

The limited lateral force-carrying capacity of beam-column joints is influenced by the material properties used during the structure's construction, which in turn impact the overall response of the structure (13). To ensure structural safety and prevent shear failure, it is crucial to accurately forecast the shear strength of RC beam-column joints in the design process (14). With the advancement of Artificial Intelligence in recent years, there has been a paradigm shift towards applying machine learning (ML) methods for predicting the shear strength of beam-column joints (6). As part of this trend, the present research aims to analyze the shear strength prediction of beam-column joints using a neural network tool in MATLAB.

2. LITERATURE SURVEY

For the forecast of outer beam-column joint shear capacity, Alagundi and Palanisamy (2) proposed using an artificial neural network. The simulations show that the suggested model of the neural network can predict the Exterior Beam-Column joint’s shear strength. There are three effective artificial neural network methods, radial basis function neural network (RBFNN), back-propagation neural network (BPNN) and generalized regression neural network (GRNN) Zhang et al. (15) suggested identifying the failure modes and shear strengths. With the results, the testing and training phases are compared, which prove that both GRNN, BPNN and RBFNN models are powerful approaches for predicting the mode of failure and shear strength. By using ANN, Gene Expression Programming (GEP) and Network-Based Group Method of Data Handling (GMDH-NN) Naderpour et al. (16) predicted shear strength. The simulation confirms the ability of the patterns expected by, GMDH-NN, GEP and ANN which are appropriate for use as a tool in forecasting the concrete shear walls with high accuracy and shear strength. For the forecast of shear strength an artificial neural network model was proposed by Alagundi and Palanisamy (17) in the Joint of reinforced concrete exterior BC joints are themed to seismic loading; thus, the proposed ANN model can be used. For estimating the reinforced concrete shear strength, the beam-column is subordinated to regular load Marie et al. (6) proposed a framework. The simulation also reveals that the shear strength of the joint was predicted by using the Kernel regression, where the experimental values are closer than the joint shear strength which is predicted by using the parametric equation. Detailed methodologies and discussions of the two disciplines were presented by Marcos and Silva (3). Powerful digital technologies and computer systems showed dominance by presenting the regression and performance analysis through different trained neural network models.

To determine the RC beam-column joints stochastic shear strength Yu et al. (18) employed, the GPR algorithm. The simulations show that the kernel can efficiently enhance the generalization performance and prediction accuracy of the GPR Truong et al. (19) presented the Bayesian optimization (BO), BO-XGBoost hybrid model and extreme gradient boosting (XGBoost) algorithms was made and its hyperparameters were improved based on a collection of data of 320 test specimens. The suggested model exposed that the beam width, effective depth, tension reinforcement ratio, shear span-to-depth ratio and concrete compressive strength are crucial to the deep beams' shear strength. Zayan et al. (20) presented the ANN model offered a more accurate tool to compute R and capture the impacts of five primary parameters: steel reinforcement ratio, concrete compressive strength steel yield strength, steel fibre aspect ratio fibre and volumetric ratio given from trial data. The gathered results show that the first significant argument is the compressed power of the concrete. Al-Bayati (21) introduced a numerical pattern for the calculations of shear strength in the exterior and interior reinforced concrete beam-column joints that are subordinated to seismic loads. The results of 110 exteriors and 105 interiors of beam-column joints gathered from the literature, the fresh pattern is gauged. This research study contributes to the shear strength of the beam-column joint and its prediction using artificial neural networks.

Mabrouk et al. (22) evaluate the effect of using different shear reinforcement details on the punching shear behaviour of interior slab column connections. A comprehensive experimental program is conducted on sixteen specimens having the same concrete dimensions of 1100×1100×160 mm where the slab depth is chosen to be less than that stipulated by different design codes. The parameters under examination were the type of shear reinforcement arranged in a cross shape perpendicular to the column edges (single leg, multi-leg, and closed stirrups), the spacing between stirrups (25 and 50 mm), and the extended length covered by the stirrups (300 and 425 mm). Experimental results showed that slabs reinforced with multi-leg or closed stirrups, even for slabs with a thickness of 160 mm, had an increase in the shear capacity by up to 40% depending on the stirrup amount. A noticeable enhancement in ductility was also observed.

Singh and Sangle (23) presented a nonlinear static response of a vertically oriented coupled wall subjected to horizontal loading. The 3-storey vertically oriented coupled wall interconnected with coupling beams is modelled as solid elements in a finite element (FE) software named Abaqus CAE and the steel reinforcement is modelled as a wire element. For the simulation of concrete models, a concrete damaged plasticity constitutive model is taken into consideration in this research. Moreover, with the help of concrete damage plasticity parameters, the validation of two rectangular planar walls was executed with an error of less than 10%. Finally, these parameters are used for modelling and analyzed the static behaviour of coupled walls connected with coupling beams. Furthermore, the maximum unidirectional horizontal loading helped in obtaining the compression and tensile damage as well as scalar stiffness degradation.

Sfaksi et al. (24) concern a numerical study of the behaviour of reinforced masonry (RM) structures under seismic loading. These structures are made of small hollow elements with reinforcements embedded in the horizontal joints. They were dimensioned according to the rules and codes commonly used. They are subject to vertical loads due to their weight and to horizontal loads due to seismic forces introduced by the accelerograms. The software used is the non-linear analysis program Drain2D, based on the finite element method, where the shear panel element was introduced. A series of calculations were performed on several structures at different levels, excited by three major accelerograms (El Centro, Cherchell, and Kobe). Throughout the study, our main interest was to evaluate the behaviour factor, ductility, and failure mode of these structures while increasing the intensity of earthquakes introduced. The results of this present study indicate that the average values of the behaviour factor and the global ductility were of the order of $q \approx \mu \approx 3.00$. The reinforced masonry structures studied have been broken by interstage displacement.

The literature review provides valuable insights into the use of various techniques for predicting shear strength in beam-column joints. Several authors have proposed the application of artificial neural networks (ANN) to forecast the shear strength of exterior beam-column joints (2, 17). Different types of ANN models, including radial basis function neural network (RBFNN), back-propagation neural network (BPNN), and generalized regression neural network (GRNN), have shown promising results in predicting failure modes and shear strengths. Furthermore, other researchers have explored the effectiveness of machine learning algorithms such as gene expression programming (GEP) and network-based group method of data handling (GMDH-NN) in predicting shear strength (16). The application of these techniques, along with ANN, has demonstrated high accuracy in forecasting concrete shear walls and their shear strength.

Additionally, studies have utilized techniques like kernel regression, Bayesian optimization (BO), and extreme gradient boosting (XGBoost) to determine the stochastic shear strength of RC beam-column joints (3, 6, 18, 19). These techniques have shown improvements in prediction accuracy and generalization performance. Moreover, the use of artificial neural networks (ANN) has proven to be an accurate tool for computing shear strength, considering various parameters such as steel reinforcement ratio, concrete compressive strength, steel yield strength, steel fibre aspect ratio, and volumetric ratio.

Furthermore, studies have examined the behaviour of vertically oriented coupled walls under horizontal loading (23). Nonlinear static response analysis, incorporating concrete damaged plasticity constitutive models, has been conducted to assess the behaviour of these structures. The analysis includes the evaluation of compression and tensile damage, as well as scalar stiffness degradation. Lastly, a numerical study explores the behaviour of reinforced masonry structures under seismic loading (24). The study investigates the effects of vertical and horizontal loads on these structures, with a focus on behaviour factors, ductility, and failure modes. Results indicate that the average values of the behaviour factor and global ductility are approximately 3.00, and the reinforced masonry structures exhibit failure due to interstage displacement.

In conclusion, the literature review presents a diverse range of approaches and techniques employed to predict shear strength in beam-column joints and analyzed the behaviour of related structural elements. These studies contribute to the advancement of knowledge in this field and provide valuable insights for designing safer and more resilient structures.

3. RESEARCH PROBLEM DEFINITION AND MOTIVATION

Flexural strengthening garnered the majority of attention than shear strengthening in RC beams and it has received very little research. Particularly dangerous are structures exhibiting brittle failure to shear force. Shear, a sudden, unexpected structural collapse mechanism is mostly caused by this. Deep beams are subject to shear force, which has a shear span to effective depth proportion (a/d) smaller than two. The behaviours of a deep beam exposed to vertical static stress differ significantly from those of a narrow beam in both the analytical approach and design. Because of the fast and brittle fracture of RC beams caused by shear action and the absence of logical design formulas in building regulations, the behaviour and design of RC beams under shear remain a source of worry for structural engineers.

The deformations that beam-column connections experience under earthquake loading have a substantial impact on the seismic behaviour of reinforced concrete structures. Some locations fail before they should under powerful earthquakes if they are not properly planned. The researchers show several variables, such as column and beam dimensions, joint transverse reinforcement yield strength, concrete compressive strength, volumetric joint reinforcement ratio, beam longitudinal reinforcement ratios, beam eccentricity, and column axial load, affect joint shear strength. The shear strength of joint elements makes it challenging to forecast the connection between beams and columns. Machine learning (ML) approaches are being used to forecast the beam-column joint's shear strength of connections as a result of the recent advancements in AI. Shear strength is crucial while applying ML to forecast joints. Based on the outcomes of earlier experiments, the most crucial variables that impact shear strength joint were selected to develop a parametric equation to predict joint shear strength.

The Objective of the Study

- To study how different parameters impact beam-column joints' shear strength.
- To prepare data from pre-existing literature to model a neural network in MATLAB.
- Using prepared data Neural Network Model was trained and tested in MATLAB.
- To compare the analytical results extracted from MATLAB with experimental results from Pre-Existing Literature.

4. PROPOSED RESEARCH METHODOLOGY

Failure in shear is a sort of brittle failure with no warning signs, hence numerous studies have been conducted in the literature. To reduce shear failure in design techniques and preserve structural safety, it is crucial to properly forecast the strength of the RC beam-column connections. This problem can be resolved by using ML techniques, such as ANNs, as reliable modelling tools for calculating the shear strength of the joint and its connections in the beam-column. ANNs give patterns for a variety of artificial and natural phenomena, many of which are difficult to model using conventional parametric techniques. Consequently, the article proposed using Artificial Neural Network (ANN) with Shallow Feed-Forward (SFF) architecture for estimating the strength of exterior RC beam-column connections was subsequently proposed in the article. The block diagram of the proposed method is shown in Figure 1.

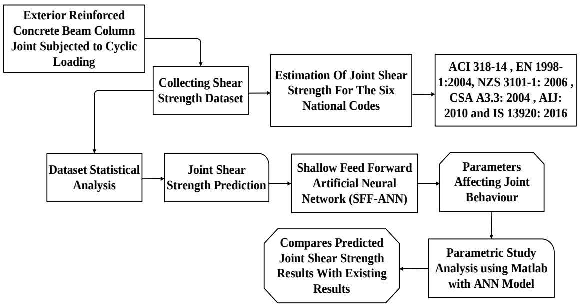


Figure 1. Block Diagram of the Proposed Work

A better understanding of the variables influencing the shear strength joint of connections in beam-column can be achieved by using machine learning analysis to look into the significance of input variables. This could result in the recommendation of useful potential methods for exploratory studies and the facilitation of lab experiments. The provisions for estimating joint shear strength for the six national codes viz., EN 1998-1:2004 (European Code EC-8), CSA A3.3:2004 (Canadian Code), IS 13920:2016 (Indian Code), NZS 3101-1:2006 (New Zealand Code), ACI 318-14 (American Code), and AIJ:2010 (Japanese Code) have been compared and evaluated in the current study using 13 experimental findings gathered from the literature. The aforementioned codes recommend different limitations on the parameters viz. confinement of joint by the effective joint depth, eccentricity between beam and column, beams, concrete compressive strength, and effective joint width. An investigation of the parameters' effects on joint shear strength revealed significant discrepancies between the code projections. The methodology equates forecast joint shear strength values with known experimental results to provide a credible design strategy.

4. 1. Experimental Program The primary objective of this study is to examine the periodic behaviour of exterior beam-column joints in reinforced concrete structures. To train, test, and validate the neural network, data sets have been prepared using experimental studies conducted by various researchers. The shear strength of these external beam-column joints is influenced by multiple factors, and a suggested approach involves utilizing an artificial neural network to predict this strength. Key inputs for the ANN model include the compressive strength of the concrete, the supports at the bottom and top of the beam, the beam-to-column depth ratio, the beam bar index, the depth and width of the joint, the yield strength of the linear support in the beam, the column load index, the joint shear reinforcement index, and the length of the beam. To assess the performance of the neural network, statistical measures such as the coefficient of correlation, root mean square error, and scatter index are employed.

In Figure 2, a typical exterior beam-column connection in an RC frame is illustrated. This region of the frame, where the beam and columns intersect, is subjected to both gravitational and lateral loads, resulting in significant shear forces, axial forces, and bending moments. The analysis considered the coupling between the beam and column in this joint region, taking into account these various forces. The beam's flexural capacity within the reference joint subassembly, as determined by geometry, reinforcing details, and material parameters, was estimated to be approximately 75 kN at the point of yielding for the longitudinal reinforcement. The dimensions of the concrete beam and column were assumed to be 230mm×230 mm, with a concrete grade of M25, while the axial load applied to the column was considered to be 1000kN. All other relevant factors were obtained from the respective codes and standards.

4. 2. Parameters Affecting Joint Behaviour Previous experimental findings have highlighted the substantial influence of material strength, both in steel and concrete, on the shear capacity of beam-column joints. Additionally, the level of confinement plays a crucial role in determining the behaviour of these joint systems. Confinement can be provided through cross supports within the joint or by incorporating the framing of cross beams and slabs into the linking area. The adequate constraint of the joint core is necessary to effectively transfer shear forces, anchor the beam reinforcement, and transmit the axial load of the column. To assess the degree of confinement, the volume of cross support in the connection region is calculated and then divided by the core volume, gross volume, or the effective volume for a single layer of transverse reinforcement. This computation yields the volumetric confinement ratio. The ratio that exhibits the strongest correlation with the results is identified as a significant contributing factor in determining the joint's strength.

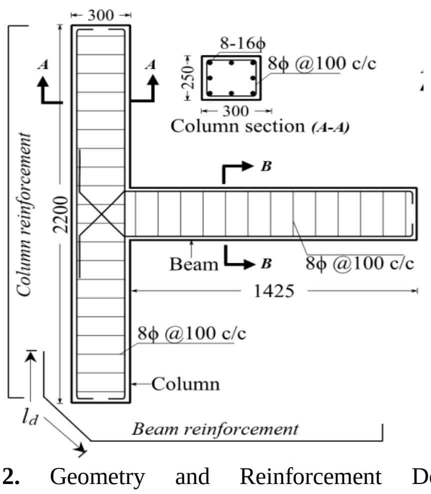


Figure 2. Geometry and Reinforcement Details (Dimensions in mm)

Furthermore, several additional parameters have been identified as influential factors impacting the shear strength of the joint. These include the eccentricity between the longitudinal beam and column center lines, the sizes of the column and beam, and the magnitude of the axial load applied to the column. Consideration of these parameters is essential for a comprehensive understanding of the joint behaviour and shear strength.

To evaluate the influence of different parameters on joint shear strength, a correlation coefficient is employed as defined in Equation 5. In this statistical approach, the independent variable x represents various parameters, while the dependent variable y represents the joint shear strength. Establishing a direct comparison between shear strength and each variable, this gain insights into their relationship. It is important to note that these correlation values provide approximate estimations of the parameters' impact on shear strength, as the correlations are expected to exhibit nonlinearity. While there may be correlations among the individual parameters, this analysis does not consider cross-correlations. The primary objective at this stage is to understand the degree of association between the parameters and joint shear strength. Interestingly, the results indicate that the joint geometry has a relatively minor influence compared to the reinforcement ratio and axial load, which exhibit high correlation coefficients. This finding highlights the significance of the reinforcement ratio and axial load in determining joint shear strength.

$$Correlation(x,y) = \frac{\sum(x-\bar{x})\cdot(y-\bar{y})}{\sqrt{\sum(x-\bar{x})^2 \cdot \sum(y-\bar{y})^2}} \tag{1}$$

The important variables that might be taken into account in the joint strength prediction are chosen when the correlation coefficients are achieved. Concrete compressive strength and volumetric joint reinforcement ratio, which shows the confinement given by the transverse reinforcement, are the two most important criteria, as was previously mentioned. As a result, values for the spacing, joint core, gross area, number of transverse reinforcing layers, and stirrup area are obtained. According to the following equations, the volumetric transverse reinforcement ratio can be calculated in three different ways by using the joint core volume, the effective confined amount as the gross bond volume and the efficient volume contains one covering of joint transverse reinforcement.

4. 2. 1. RC Beam-Column Joint Modelling The shear and compression acting forces for a typical external RC beam-column junction under seismic load are depicted in Figure 2. In the joint coreV_{jh}, the flat joint shear force can be calculated as follows:

$$V_{jh} = T_b - V_{c1} \tag{2}$$

where:

$$T_b = A_{sb} \cdot f_b \tag{3}$$

where, A_{sb} and f_b represent the area and stress of the longitudinal reinforcement of the beam, respectively, V_{c1} represents the horizontal shear of the column above the joint, and T_b illustrates the tensile force in the beam longitudinal reinforcement. The following formulas are used to compute the column shear above the joint, the beam shearV_b, and the beam flexural moment M_b.

$$V_b = \frac{A_{sb} f_b j_{bd}}{L} \tag{4}$$

$$M_b = V_b \cdot L \tag{5}$$

$$V_{c1} = \frac{L + h_c/2}{H} V_b \tag{6}$$

where, H is the height of the column, which is equal to the height between the upper and lower column inflexion points, L is the length from the beam's inflexion point to the column's face, h_c is the total height of the column cross-section, and j_{bd} is the internal moment arm of the beam cross-section, which can be calculated as follows:

$$j_{bd} = h_b - \frac{x_b}{3} - \delta_{sb} \tag{7}$$

In Equation 7, h_b is denoted as the breadth of the beam, x_b for the intensity of the contraction zone in the beam cross-section, and δ_{sb} for the distance between the closest edge of the beam cross-section and the centroid of the tensile beam reinforcement. By imposing the equilibrium of the internal forces on the beam after confirming that the concrete in compression remains within the elastic range, the value of x_b can be derived, which leads to:

$$\frac{b_b x_b^2}{2} + (A_{sb} + A'_{sb}) n_{h,b} x_b - (A_{sb} d_b + A'_{sb} \delta'_{sb}) n_{h,b} - A'_{sb} \delta'_{sb} = 0 \tag{8}$$

where, δ'_{sb} is the distance from the centroid of compressive beam reinforcement to the closest edge of the beam cross-section, b_b is the thickness of the beam cross-section at the face of the column, A'_{sb} is the area of longitudinal compressive reinforcement, d_b is the efficient breadth of the beam cross-section, and $n_{h,b}$ is the modular ratio given by:

$$n_{h,b} = \frac{E_{sb}}{E_c} \tag{9}$$

where, E_c is the concrete elastic modulus, which can be assumed to be 4700 MPa if its value is not specified, and E_{sb} is the reinforced elastic modulus of the beam reinforcement. The following method is used to compute the joint shear.

$$M_b = P(L + d^1) \tag{10}$$

where, P is the failure load (N), L is the distance from the load's application point to the column's face (mm), and d^1 is the cover (mm). The strain in the tensile support of the beam is given a value. The process is terminated, if the moment produced by the force in the beam tensile reinforcement equals the moment computed in Equation 10. If not, the assumed strain is raised gradually until the moment equals the moment specified in Equation 11. The elastic modulus of the reinforcement was estimated to be 200 GPa. The formula for shear strength joint is represented as follows:

$$V_j = T_b - V_{col} \tag{11}$$

where, T_b is the tensile force in the beam longitudinal reinforcement (N), V_{col} is the force of the shear in the upper column (N), and V_j is the joint shear force (N).

4. 3. Artificial Neural Network (ANN) Model for Shear Strength Prediction

Artificial Neural Networks (ANN) is a computational framework inspired by the learning process of the human brain. In the human brain, information is received and stored in the connections between neurons, forming a complex network. Similarly, an ANN consists of interconnected artificial neurons that can process and store information. The main goal of an ANN is to establish a relationship between input data and corresponding output, similar to how the human brain recalls information from its network of neurons. Through training, an ANN modifies its internal components to learn from the input-output patterns presented during the training process.

Once trained, an ANN can be used as a prediction model for new inputs that were not part of the training dataset. It uses the learned information from the training phase to make predictions for the missing data. However, the accuracy of these predictions is a crucial concern. To address this issue, the available data is divided into two parts: a training set and a testing set. The ANN is trained using the training set, and the predictions made by the model are compared with the known output values from the testing set. High performance in the testing phase indicates a reliable prediction model that generalizes well beyond the training data, avoiding overfitting. However, optimizing the weights in ANNs with multiple hidden layers can be challenging due to issues like vanishing gradients and convergence to local minima. Even with large datasets, these problems can limit the performance of ANNs with deep architectures, posing a bottleneck in their optimization process.

4. 3. 1. Shallow Feed Forward Neural Network

Neural network fitting occurs when a series of neurons, connected through activation functions, are accumulated. During the training of a neural network, the coefficients of the activation functions in each neuron are gradually optimized. The adjustment of biases and weights is performed to establish a relationship between the input and output values provided in the training dataset. The performance of the network is evaluated using an error function, such as mean squared error, which compares the neural network's response to the training objective. To facilitate learning during the training process, back-propagation algorithms are commonly employed. These algorithms update the weights (w) and biases (b) of each neuron in a way that minimizes the performance function (error). This minimization process involves propagating the output error backwards from the output layer to the hidden and input layers, adjusting the weights and biases accordingly.

For this work, an SNN pattern with an easy form and ideal performance containing a hidden layer and an output layer was used. Among these, the hidden layer has several neurons, whereas the output layer just has one. Figure 3 depicts the topology of the SNN model. Each output of the neuron in an SNN model's hidden layer can be described as Equation 12.

$$y_i = \sum_{i=1}^{N} w_i x_i + b_i \quad (i = 1,2,\cdots,i \leq N) \tag{12}$$

where, y_i denotes the neuron's output, N is denoted as the whole value of the hidden layer's neurons, w_i and b_i stand for the i_{th} neuron's weight and bias, respectively; and x_i stands for the input data, which is made up of $x_1, x_2, \cdots,$ and x_n. The hidden layer's neurons perform a nonlinear transformation on the input signal x_i to create the output signaly_i. The activation function within the secret covering is the Sigmond nonlinear function$\sigma(x)$, which is not readily divergent and is simple to derive during the transfer process. It can be expressed as follows:

$$\sigma(x) = \frac{1}{1+e^{-x}} \tag{13}$$

The system can obtain the creation of the SNN model as shown in the equation according to the topology of the SNN model.

$$Y = W \sum_{i=1}^{N} \sigma\left(\sum_{i=1}^{N} w_i x_i + b_i\right) + B = W \sum_{i=1}^{N} y_i + B \tag{14}$$

where, W and B represent the output layer's weight and bias, respectively. The output value Y of the SNN pattern can be produced after linear transformation from the output signal y_i of each hidden layer in the neuron, which is transferred to the output layer. The output layer's activation function is the linear function. The Mean

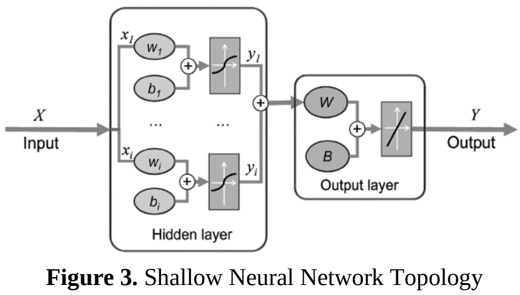


Figure 3. Shallow Neural Network Topology

Squared Error (MSE), whose minimal value denotes the best curve fit for the dataset, is used to determine when the function ends during training. To compare the MSE of the output value of the SNN pattern Y with the test data $\hat{Y}$, the weights and biases of the neurons inside the hidden and output layers are changed. Iterative training learning using the error descent along the gradient direction method is used to determine the model parameters corresponding to the minimum root of the MSE.

4. 4. Database Collection The effectiveness and validity of the proposed model in the training process rely significantly on the quantity and quality of the data available. To ensure reliable results, a comprehensive database of reinforced concrete joint tests has been meticulously compiled. The database includes detailed information on geometric dimensions, material properties, specific configurations, and the stress-strain history of the specimens.

The data collection process focuses on gathering testing results from various references, specifically targeting specimens with plain reinforced concrete. These specimens cover a wide range of parameters, such as different amounts of joint, beam, and column reinforcement, diverse material characteristics, varying column axial loads, eccentricities, and transversely framed beams. It is important to note that retrofitted specimens have been excluded from the database to maintain consistency and relevance.

Table 1 in this section summarized the results of 120 specimens tested by Hanson et al. (25), Karayannis et al. (26) and Salim et al. (27). In all of these experimental studies where joints in beam-column are subordinated to monotonic or cyclic load until one of the collapse types of failure in the joint or beam yielding followed by joint failure is presented.

TABLE 1. Dataset Collection 1

Investigator		fc′, ksi	fyc, ksi	fyb, ksi	Lb, in.	hb, in.	bb, in.	ρ	ρ′	Lc, in.	hc, in.	bc, in.	ρc	P/fc′ Ag	γj TEST
Hanson et al. (25)	Specimen ID	3.3	64.8	51	120	20	12	0.02	0.01	137	15	15	0.05	0.86	11.6
Pantelides et al. (28)	Unit 3	4.9	68.1	66.5	63	16	16	0.02	0.02	166	16	16	0.02	0.1	10.8
	Unit 4	4.9	68.1	66.5	63	16	16	0.02	0.02	166	16	16	0.02	0.25	12.4
	Unit 6	4.9	68.1	66.5	63	16	16	0.02	0.02	166	16	16	0.02	0.25	11.7
	Unit 5	4.6	68.1	66.5	63	16	16	0.02	0.02	166	16	16	0.02	0.1	10.4
Wong et al. (29)	BS-L	4.48	75.6	75.4	52	17.7	10.2	0.01	0.01	98.1	11.8	11.8	0.02	0.15	8.13
	BS-U	4.5	75.6	75.4	52	17.7	10.2	0.01	0.01	98.1	11.8	11.8	0.02	0.15	8.78
	BS-LL	6.12	75.6	75.4	52	17.7	10.2	0.01	0.01	98.1	11.8	11.8	0.02	0.15	8.8
	BS-L-LS	4.58	75.6	75.4	52	17.7	10.2	0.01	0.01	98.1	11.8	11.8	0.02	0.15	8.79
	BS-L-V2T10	4.73	75.6	75.4	52	17.7	10.2	0.01	0.01	98.1	11.8	11.8	0.02	0.15	10
	BS-L-V4T10	4.1	75.6	75.4	52	17.7	10.2	0.01	0.01	98.1	11.8	11.8	0.02	0.15	10.8
	BS-L-600	5.28	0	75.4	52	23.6	10.2	0.01	0.01	98.1	11.8	11.8	0.02	0.15	6.74
Ghobarah et al. (30)	T1	4.48	61.7	61.6	65.8	15.8	9.84	0.01	0.01	108	15.7	9.84	0.02	0.19	12.1
	T2	4.48	61.7	61.6	65.8	15.8	9.84	0.01	0.01	112	15.7	9.84	0.02	0.1	12.2
Karayannis et al. (26)	B0	4.59	84.3	84.3	39.4	11.8	7.87	0.01	0.01	59	11.8	7.87	0.01	0.05	8.18
	C0	4.59	84.3	84.3	39.4	11.8	7.87	0.01	0.01	59	11.8	7.87	0.01	0.05	8.6
Tsonos et al. (31)	L1	2.61	66.8	70.5	35.4	11.8	7.88	0.01	0.01	55.1	7.87	7.87	0.02	0.21	10.2
	L2	2.61	66.8	70.5	35.4	11.8	7.88	0.01	0.01	55.1	7.87	7.87	0.02	0.21	11.6
	O1	2.61	66.8	70.5	35.4	11.8	7.88	0.01	0.01	55.1	7.87	7.87	0.02	0.21	10.2
Antonopoulos et al. (32)	C1	2.82	66.8	84.8	39.4	11.8	7.87	0.01	0.01	50.9	7.87	7.87	0.02	0.06	7.04
	C2	3.44	66.8	84.8	39.4	11.8	7.87	0.01	0.01	50.9	7.87	7.87	0.02	0.05	7.31
Sarsam et al. (33)	EX2	7.5	61.6	80	56	12	5.98	0.01	0.01	60	8.03	6.18	0.03	0.19	9.15

Filiatrault et al. (34)	S1	4.93	69	69	78.8	17.7	13.8	0.01	0.01	118	13.8	13.7	0.03	0.08	12
Hoffschild et al. (35)	—	3.82	65.4	83.2	32.2	7.9	6.5	0.01	0.01	99.8	7.48	7.48	0.01	0.13	10.5
Park et al. (36)	UJ2-EW	3.96	68.1	72.2	96	30	16	0.01	0.01	145	18	18	0.03	0.17	8.76
	UJ2-NS	3.96	68.1	72.2	96	30	16	0.01	0.01	145	18	18	0.03	0.15	8.37
	UJ1-EW	4.3	70	68	96	18	16	0.02	0.02	145	18	18	0.03	0.31	14.4
	UJ1-NS	4.3	70	68	96	18	16	0.02	0.02	145	18	18	0.03	0.31	13.1
Hassan et al. (37)	UJ2-EW	4.43	70	77	96	30	16	0.01	0.01	145	18	18	0.03	0.45	9.97
	UJ2-NS	4.43	70	77	96	30	16	0.01	0.01	145	18	18	0.03	0.45	9.47
	BJ1-EW	4.41	70	77	96	18	16	0.02	0.02	145	18	18	0.03	0.45	11.4
	BJ1-NS	4.41	70	77	96	18	16	0.02	0.02	145	18	18	0.03	0.45	10.8
Salim et al. (27)	S1	4.39	68.1	66.8	35.8	11.8	5.91	0.02	0.01	74.8	7.09	7.09	0.02	0.09	8.59

The following factors are taken into consideration for the neural network's inputs in the current study: Joint width (b_j), Joint depth (h_c), Compressive strength of concrete (f_c), Beam Reinforcement at the Top (T_{Ast}), Beam Reinforcement at the Bottom (B_{Ast}), Beam length (L), Yield strength of beam bars (f_{yb}), Joint Shear Reinforcement Index (φ_s), Column Axial Load Level (P_y), Beam Bar Index (x_b), Beam-Column depth ratio (h_b/h_c) andτ. Table 2 displays the experiment analysis of the 53 data that were obtained for this investigation. The MATLAB scripting language is used to construct an object-oriented framework to collect certain joint specimen properties. A gathering of sample assets and measured outcomes, such as concrete strength, joint type, joint reinforcement ratio, etc., constitute an instance of the experiment class.

TABLE 2. Dataset Collection 2

S. no.	b_j	h_c	f_c	T_{Ast}	B_{Ast}	L	f_{yb}	φ_s	P_y	x_b	h_b/h_c	τ
1	280	300	31	0.806	0.806	1500	520	0	0	0.1538	1.5	3.75
2	280	300	33	0.806	0.806	1500	520	0.0819	0	0.1538	1.5	4.631
3	280	300	42	0.806	0.806	1500	520	0.1442	0	0.1538	1.5	5.7024
4	280	300	36	0.6045	0.6045	1500	520	0	0	0.1154	2	3.381
5	280	300	42	0.6045	0.6045	1500	520	0.0928	0	0.1154	2	4.2857
6	280	300	30	0.6045	0.6045	1500	520	0.2184	0	0.1154	2	4.0714
7	200	200	35	0.5234	0.5234	900	510	0.6602	0.1429	0.1333	1.5	4.3
8	200	200	35	0.5134	0.5134	900	495	1.0322	0.1429	0.0933	1.5	4.1
9	200	200	22	0.77	0.77	900	495	1.2184	0.2273	0.14	1.5	5.8
10	200	200	22	0.77	0.77	900	495	0.9767	0.2273	0.14	1.5	5.55
11	200	300	34	0.755	0.755	1000	580	0.2603	0.05	0.24	1	3.6333
12	200	300	34	0.755	0.755	1000	580	0.6764	0.05	0.24	1	3.45
13	200	300	32	0.785	0.785	1000	580	0	0.05	0.3	1	3.35
14	200	300	32	0.785	0.785	1000	580	0.0854	0.05	0.3	1	3.65
15	100	200	21	0.785	0.785	1000	470	0	0.1	0.2	1	3.3
16	100	200	21	0.785	0.785	1000	470	0.2564	0.1	0.2	1	3.6
17	100	200	21	0.785	0.785	1000	470	0.5179	0.1	0.2	1	3.6
18	100	200	23	1.18	1.18	1000	470	0	0.1	0.3	1	4.2

19	100	200	23	1.18	1.18	1000	470	0.245	0.1	0.3	1	4.85
20	100	200	23	1.18	1.18	1000	470	0.4949	0.1	0.3	1	4.4
21	200	200	36	0.2617	0.2617	1000	574	0	0.0486	0.0667	1.5	1.8
22	200	200	36	0.2617	0.2617	1000	574	1.0212	0.0486	0.0667	1.5	1.9
23	280	300	34	1.209	1.209	1500	520	0	0.1607	0.2308	1	6.0119
24	280	300	31	0.806	0.806	1500	520	0	0.1605	0.1538	1.5	3.75
25	280	300	36	0.6045	0.6045	1500	520	0	0.1607	0.1154	2	3.381
26	280	300	33	0.806	0.806	1500	520	0.1692	0.1605	0.1538	1.5	4.75
27	280	300	28	0.806	0.806	1500	520	0.3673	0.1607	0.1538	1.5	4.7976
28	280	300	33	0.806	0.806	1500	520	0.0819	0.1605	0.1538	1.5	4.631
29	280	300	42	0.806	0.806	1500	520	0.1442	0.1607	0.1538	1.5	5.7024
30	280	300	31	0.806	0.806	1500	520	0	0.1502	0.1538	1.5	3.7619
31	280	300	31	0.806	0.806	1500	520	0	0.1502	0.1538	1.5	4.0595
32	215	230	19	0.7137	0.7137	1375	300	0.2185	0.0798	0.2091	1.4348	2.8311
33	250	250	26	0.5491	0.5491	1375	300	0.7136	0.0615	0.1455	1.32	2.832
34	350	350	24	0.7272	0.7272	1780	417	1.5629	0	0.18	1.1429	3.4612
35	350	350	20	0.7272	0.7272	1780	417	1.7121	0	0.18	1.1429	3.6816
36	370	420	67	1.3639	1.3639	1900	430	1.0651	0.0188	0.2917	1.0714	6.4157
37	370	420	69	1.3639	1.3639	1900	430	1.3075	0.0183	0.2917	1.0714	7.2844
38	370	420	71	1.3639	1.3639	1900	430	1.1358	0.0178	0.2917	1.0714	6.9498
39	370	420	73	1.3639	1.3639	1900	430	1.1202	0.0173	0.2917	1.0714	6.686
40	200	200	16	0.77	0.77	1100	585	0	0.0719	0.14	1.5	2.925
41	200	200	19	0.77	0.77	1100	585	0	0.0605	0.14	1.5	2.875
42	200	200	15	0.77	0.77	1100	585	0.0839	0.0767	0.14	1.5	3.1
44	275	300	39	0.7856	0.7856	850	570	0	0	0.12	1.6667	2.3273
45	275	300	39	0.7856	0.7856	850	570	0	0.0932	0.12	1.6667	2.7152
46	275	300	37	0.7856	0.7856	850	570	0	0.1867	0.12	1.6667	3.3455
47	275	300	39	0.7856	0.7856	850	570	0	0	0.12	1.6667	2.9576
48	275	300	40	0.7856	0.7856	850	570	0	0.0909	0.12	1.6667	3.1515
49	275	300	38	0.7856	0.7856	850	570	0	0.1914	0.12	1.6667	3.6
50	275	300	43	0.7856	0.7856	850	485	0.2005	0	0.12	1.6667	4.1939
51	275	300	43	0.7856	0.7856	850	485	0.2005	0.0846	0.12	1.6667	4.6545
52	275	300	43	0.7856	0.7856	850	485	0.2005	0.1691	0.12	1.6667	4.7636
53	275	300	43	1.2872	1.2872	850	515	0.2005	0	0.1536	1.6667	4.4485

5. EXPERIMENTATION AND RESULTS DISCUSSION

The suggested ANN model is created via MATLAB code and operates in MATLAB. The codes are developed in MATLAB with its toolbox. The dataset (input and output) used in this section is the same as the regression models' dataset. A popular training algorithm (so-called "Trainlm" (34)) that updates weight and bias values according to Levenberg-Marquardt optimization is used. Activation functions for the hidden and output layers are hyperbolic tangent sigmoid (Tansig) and linear transfer function (Purelin), respectively. To achieve the best-performing model, a single ANN architecture is built with the hidden layer neurons set through experimentation (trial and error). Gradient descent is utilized to minimize error in the current study's backpropagation-type training procedure, which is used in shallow feed-forward with a single hidden layer. Using the Levenberg-Marquardt algorithm, the network is trained. The achievement of the ANN model is quantified using statistical metrics.

In Figure 4, the analysis focuses on the shear strength of beam-column joints according to various concrete grades. Specifically, this study employs grade M25 concrete and compares it with other grades such as M35, M40, and M30 across six different codes. The analysis aims to determine the shear strength of beam-column joints for each concrete grade within these codes. The results of this analysis reveal that the shear strength of M25 grade concrete in the beam-column joint is calculated as 2.6. This value indicates improved ductility and stiffness in the anchorage system, which can be attributed to reduced crack width and the formation of multiple cracks in the joint. Based on the findings, it can be concluded that the ACI 318-14 code provides a more suitable prediction for shear strength in the beam-column joint.

5. 1. Models Evaluation Measures To evaluate the constructed prediction models, a mathematical technique commonly employed in research to study machine learning models was utilized in this study. Several mathematical measures were employed to assess the accuracy of the models, including measures that aimed to minimize the discrepancy between the observed and predicted shear strength and others that aimed to identify the best-fit model. Eight evaluation measures were employed to accurately assess the anticipated accuracy of the models. These measures included the determination coefficient, Mean Square Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). In evaluating the models, better performance is indicated by lower values of MSE and higher values of the determination coefficient (R^2), which should be closer to 1. By employing these evaluation measures, the study aimed to provide a comprehensive and accurate assessment of the predictive accuracy of the models.

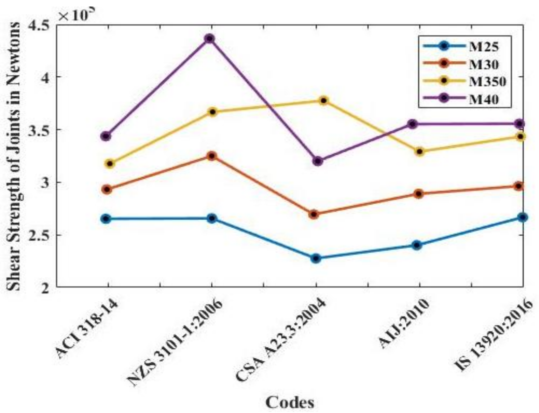


Figure 4. Shear Strength of Joint with Several Codes

Figure 5 illustrates the Mean Squared Error (MSE) curve, which provides valuable insights into the training process. Initially, the error exhibits a rapid decline, indicating effective learning. As the training progresses, the rate of error reduction slows down. Notably, the MSEs of the validation data and test data follow a similar pattern to that of the training data, indicating the model's consistency and reliability. The minimum MSE value for the validation performance, reaching 0.00010534, is achieved after 13 training iterations. Importantly, no significant overfitting is observed up to this point, which is evident from the similar characteristics of the error in the test set and validation set. Consequently, the training results of this model can be considered reasonable and promising. The performance analysis for prediction accuracy is illustrated in Figure 6.

To evaluate the influence of different parameters on joint shear strength, a correlation coefficient is employed as defined in Equation 5. In this statistical approach, the

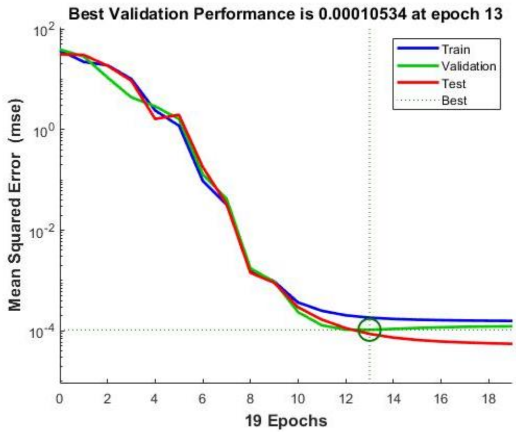
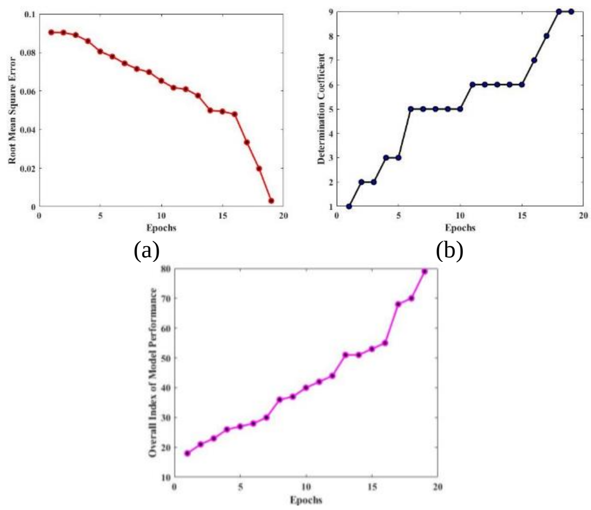


Figure 5. Mean Square Error Performance Analysis



(a) (b)

(c)

Figure 6. Performance Analysis for Prediction Accuracy

independent variable x represents various parameters, while the dependent variable y represents the joint shear strength. Establishing a direct comparison between shear strength and each variable, this gain insights into their relationship. It is important to note that these correlation values provide approximate estimations of the parameters' impact on shear strength, as the correlations are expected to exhibit nonlinearity. While there may be correlations among the individual parameters, this analysis does not consider cross-correlations. The primary objective at this stage is to understand the degree of association between the parameters and joint shear strength.

Interestingly, the results indicate that the joint geometry has a relatively minor influence compared to the reinforcement ratio and axial load, which exhibit high correlation coefficients. This finding highlights the significance of the reinforcement ratio and axial load in determining joint shear strength.

The Levenberg-Marquardt method was used to train an optimised feed-forward neural network for each response parameter. Table 3 illustrates this neural network training and testing procedure with different initial, stooped, and target value parameters. To prevent overfitting, where the network perfectly matches the training data but performs poorly on the testing set, the number of epochs is kept to a minimum during the development of the optimal topology of the networks. Seven trained neural networks were used as experimental data and the findings of the FE study.

In Figure 7, the comparison between predicted and actual responses is displayed for different parameters of the response curves. The data points forming clusters along the diagonal line indicate the accuracy of the trained neural networks. The validation set was utilized to assess the generalizability of the model and to prevent overfitting by halting the training process. The R-squared (R^2) value measures the proportion of variance in the response variable that can be predicted by the trained artificial neural network. In this study, the R^2 values range from 0.92 to 0.99, indicating a high level of prediction accuracy. The ANN model achieves R-squared values of 99%, 94%, and 98% for the training, testing, and validation sets, respectively, across all the data. These results demonstrate the robust performance of the ANN model in accurately predicting the responses, providing a reliable tool for estimating the desired parameters.

TABLE 3. Testing and Training of Neural network model

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	14	1000
Elapsed Time	-	00:00:00	-
Performance	22.8	0.0323	0
Gradient	65.6	0.0182	1e-07
Mu	0.001	0.001	1e+10
Validation Checks	0	6	6

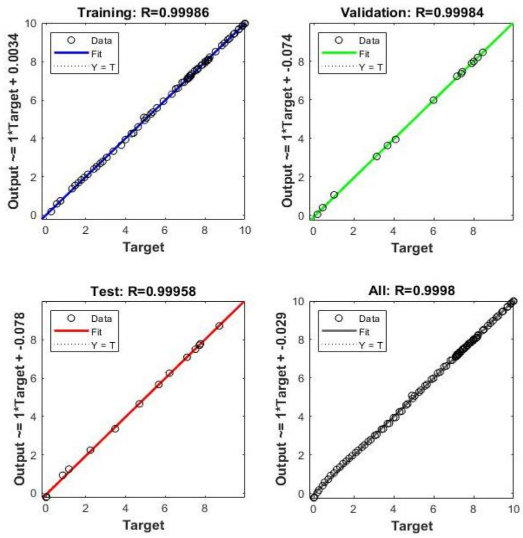


Figure 7. Target Data versus Predicted Response in the Training, Validation, and Test Sets

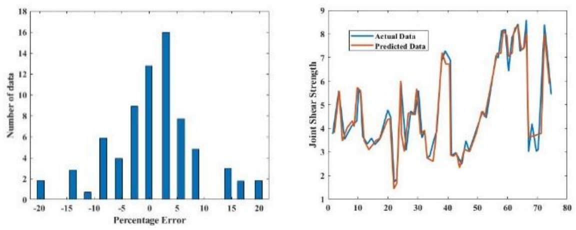
To ensure the superior robustness of the neural network model compared to traditional fitting methods, a random sampling method was employed for data set segmentation. Moreover, the Levenberg-Marquardt method was utilized for training the Self-Organizing Neural Network (SNN). The results, as presented in Table 4, highlight the overall superiority of ANN training and testing compared to other algorithms. This demonstrates that the proposed ANN model exhibits excellent alignment with experimental test results when compared to alternative models. Furthermore, the empirical model demonstrates improved performance compared to the results obtained from existing codes, emphasizing its effectiveness and accuracy.

TABLE 4. Results for Test Dataset with Existing Techniques

Test	ANN	STM	Emp
11.6	13.16	10.1	11.4
10.8	12.46	11.5	11
12.4	12.69	12.8	11.6
11.7	12.69	12.4	11.6
10.4	12.33	11.1	11
8.13	9.13	9.16	8.98
8.78	9.14	9.17	8.98
8.8	9.44	10.4	8.98
8.79	9.15	9.25	8.98

10	9.19	9.37	8.98
10.8	9.04	8.83	8.98
6.74	8.55	8.11	7.78
12.1	11.44	12	11.3
12.2	11.32	10.7	11
8.18	7.83	9.79	11
8.6	7.83	9.62	11
10.2	10.20	7.99	9.21
11.6	10.20	7.79	9.21
10.2	10.20	7.79	9.21
7.04	7.13	6.79	8.98
7.31	7.36	7.27	8.98
9.15	10.72	11.9	9.15
12	9.88	10.4	9.7
10.5	8.96	10.8	10.7
8.76	7.77	8.81	8.57
8.37	7.66	8.79	8.52
14.4	11.82	13.2	12
13.1	11.82	13.2	12
9.97	9.48	10.2	9.55
9.47	9.48	10.4	9.55
11.4	11.66	10.1	9.06
10.8	11.66	10.2	9.06
8.59	9.31	9.34	8.52

In Figure 8, several plots depict the analysis of the full data set, including the correlation coefficient (CC) plot comparing actual values with predicted values, the error histogram, and the graph illustrating predicted versus accurate shear strength values. Figure 8a presents the CC plot, where a correlation coefficient of 98.24% demonstrates a strong correlation between the predicted values and the actual values. This indicates that the ANN model's predictions align well with the true values. Figure 8b displays an error histogram, showcasing the distribution of errors between the predicted and actual shear strength values. Approximately 85% of the predictions made by the ANN model fall within a 9% margin of error. This suggests that the model performs well in accurately estimating the shear strength values, with a relatively small margin of error for the majority of predictions. These visualizations highlight the effectiveness of the ANN model in capturing the correlation between predicted and actual shear strength values and demonstrate its ability to generate accurate predictions for the full data set.



(a) (b)

Figure 8. CC Plot for Actual and Predicted Values

In Figure 9, a performance analysis graph is presented, comparing precision and recall for concrete cracking, spalling, rebar exposure, and rebar buckling. The objective was to evaluate the network's performance as the percentage of modules varied and to analyse its impact on the model's effectiveness. The curve precision-recall (PR) was employed for this assessment, as shown in Figure 9.

For the cracking model, the obtained values range from 0.764 to 0.831. Notably, the proposed SFF-ANN network achieves an accuracy that is 8.8% higher compared to other models, indicating its improved performance in predicting concrete cracking. The PR curve provides insights into the precision and recall achieved by the model, offering a comprehensive evaluation of its performance across different scenarios. The results demonstrate the superiority of the SFF-ANN network in accurately predicting concrete cracking, leading to enhanced accuracy and improved performance compared to alternative models.

In Figure 10, a comparison analysis is presented, comparing the performance of the Artificial Neural

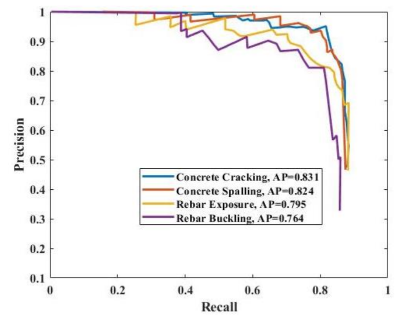
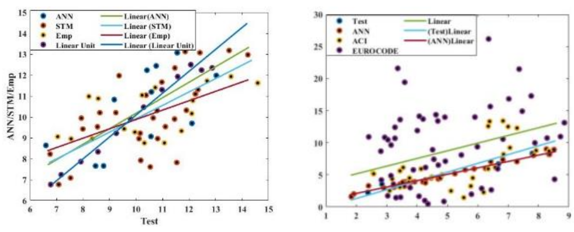


Figure 9. Precision Vs Recall Performance Graph



(a) (b)

Figure 10. Comparison Analysis of ANN with Two Datasets

Network (ANN) with the Strut and Tie Model (STM) and Empirical Model (Emp). Figure 10(a) focuses on the analysis of the ANN test data using dataset 1. The plot showcases the regression lines for the three models, representing the line of best fit that minimizes the total error of the model. It is important for the relationship between variables to be linear, and this can be visually assessed through a scatter plot. In this case, the data points exhibit a distribution implying a linear relationship. In Figure 10(b), a comparative analysis is conducted using dataset 2, and the regression plot is determined for the ANN, ACI, and Eurocode models. The scatter plot in this case does not align in a straight line but appears more scattered. This indicates that in the comparative study of ANN, the collected dataset performs better when compared to dataset 2. These visualizations in Figure 10 provide insights into the comparative performance of the ANN model against the Strut and Tie Model (STM) and Empirical Model (Emp.). The results suggest that the ANN model shows promising performance, particularly when compared to the specific datasets analyzed in this study.

6. RESEARCH CONCLUSION

The article successfully developed an artificial neural network (ANN) model using artificial intelligence technology to assess the reinforced concrete shear ability of external beam-column (BC) joints. Experimental data from various literature works were gathered and assembled to create an input and output data set for the ANN model. The proposed ANN model outperformed other models and empirical formulas provided in design codes in terms of precision and accuracy.

- The ANN-based model, implemented in MATLAB, can effectively predict the shear strength of external BC joints made of reinforced concrete.
- Five main parameters, namely joint aspect ratio, joint transverse reinforcement, concrete compressive strength, beam reinforcement ratio, and joint width, were used to develop the ANN model.
- The ANN model's effectiveness was quantitatively assessed using the coefficient of determination (R^2), with R-squared values of 99%, 94%, and 98% obtained during the training, testing, and validation stages, respectively.
- Comparison of the ANN model results with experimental data showed strong agreement and better alignment compared to results calculated using various design codes such as ACI 318-14, EN 1998-1:2004, NZS 3101-1:2006, CSA A3.3:2004, AIJ:2010, and IS 13920:2016.
- The proposed SFF-ANN model, which combines the ANN model with experimental data, is considered an efficient tool for predicting the shear strength of interior joints exposed to cyclic loading.

In conclusion, this research contributes to the scientific field by introducing an ANN model that outperforms existing empirical formulas and design codes in accurately predicting the shear strength of reinforced concrete external BC joints. The study's findings have significant practical implications, as the developed model can be applied to real-world projects, providing engineers with a reliable tool for assessing the performance and structural integrity of external BC joints. This joint shear strength prediction model can be readily implemented into joint response models for the evaluation of earthquake performance and inelastic responses of building frames.

Consequently, the proposed model holds tremendous potential as a valuable resource for researchers and reinforced concrete engineers, enabling them to make precise estimations of the joint shear strength of beam-column connections. This model proves particularly advantageous in two key aspects: it operates within the input data ranges established in this study, ensuring accuracy, and it significantly reduces both time and cost compared to the construction of alternative numerical schemes. As such, this model emerges as an efficient and cost-effective tool for professionals in the field, streamlining the estimation process while maintaining reliability. Further research should focus on gathering field data and conducting comparative studies to validate the model's predictions and explore its applicability in diverse structural configurations.

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Persian Abstract

چکیده

شکست اتصالات تیر و ستون نوع برشی در قاب های بتن مسلح (RC) در هنگام حملات شدید زلزله یک نگرانی حیاتی است. روش های سنتی برای تعیین ظرفیت برشی اتصال اغلب به دلیل در نظر گرفتن نادرست پارامترهای حاکم بر رفتار این اتصالات، دقت کافی ندارند. این مطالعه قابلیت‌های تکنیک‌های یادگیری ماشین را در پیش‌بینی ظرفیت برشی مشترک و حالت‌های شکست برای اتصالات تیر–ستون خارجی، با توجه به رفتار ساختاری پیچیده آن‌ها ارزیابی می‌کند. یک مدل شبکه عصبی مصنوعی (ANN) برای پیش‌بینی مقاومت برشی اتصالات تیر–ستون خارجی تقویت‌شده پیشنهاد شده‌استANN ،. جزء هوش مصنوعی که از تجربیات گذشته درس می گیرد، در مهندسی عمران محبوبیت پیدا می کند. مدل ANN با استفاده از مجموعه داده ای شامل خواص مواد، ابعاد نمونه و شرایط بارگذاری لرزه ای از تحقیقات تجربی قبلی توسعه یافته است. این مدل دوازده پارامتر ورودی را برای پیش‌بینی مقاومت برشی در اتصالات تیر–ستون خارجی در نظر می‌گیرد. آموزش و آزمایش مدل ANN با استفاده از کدهای طراحی ایجاد شده، فرمول های تجربی و یک الگوریتم خاص انجام می شود. نتایج نشان‌دهنده برتری شبکه عصبی مصنوعی پیش‌روی کم عمق (SFF-ANN) در مقایسه با رویکردهای قبلی است. اثربخشی یک مدل شبکه عصبی مصنوعی(ANN) به صورت کمی در این مطالعه با تمرکز بر عملکرد آن در مقایسه با کدهای طراحی مختلف که معمولاً در مهندسی سازه استفاده می‌شوند، ارزیابی شد. مدل با استفاده از ضریب تعیین (R^2) ارزیابی شد و مقادیر R-squared به ترتیب ۹۹٪، ۹٤٪ و ۹۸٪ در طول مراحل آموزش، آزمایش و اعتبارسنجی به دست آمد. این مطالعه اهمیت تقویت تیر را به عنوان یک عنصر کلیدی در برآورد ظرفیت برشی برای اتصالات تیر–ستون RC خارجی برجسته می‌کند. اگرچه مدل‌های پیشنهادی درجه بالایی از دقت را نشان می‌دهند، تحقیقات آینده باید بر روی توسعه مدل‌های بهبودیافته با استفاده از مجموعه داده‌های توسعه‌یافته و الگوریتم‌های پیشرفته برای تشخیص و عملکرد بهتر الگو تمرکز کند