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Shear Capacity Prediction of Composite Beam–Column Joints: A Review of Analytical, Numerical, and Data-Driven Methods

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ABSTRACT: Composite beam–column joints play a critical role in the seismic performance of moment-resisting frame systems, since they transfer axial loads, bending moments, and shear forces between beams and columns under extremely nonlinear loading circumstances. Therefore, accurate estimation of these joints' shear capacity is crucial for trustworthy seismic assessment, design, and strengthening choices. Because it depends on the interaction between concrete, reinforcing bars, transverse reinforcement, embedded steel sections, bond behavior, joint geometry, and loading history, the shear-resisting mechanism in composite and steel-reinforced concrete (SRC) beam–column joints is more complicated than that of conventional reinforced concrete joints. The primary analytical, empirical, numerical, and computational techniques for estimating the shear capacity of composite beam-column joints are reviewed in this paper, with a focus on SRC joint systems. The reviewed methods are classified into four main categories: component-based analytical models, code-based and empirical approaches, finite element modelling approaches, and artificial neural network techniques using Java Neural Network Simulator (JavaNNS). Within the empirical and semi-empirical category, particular attention is given to the methods proposed by Wei Liu and Jinqing Jia and by Cheng-Cheng Chen, which have been widely used to estimate the shear strength of SRC beam–column joints based on experimental observations and key mechanical parameters.

Keywords*:* Java NNS; Shear capacity; beam-column joints; Artificial Neural Networks; Seismic Loads; Exterior joints; Interior joints; Prediction of shear capacity; Composite joints; Steel reinforced concrete (SRC) joints; Embedded steel sections in RC members.

Introduction

Composite steel-reinforced concrete (SRC) structural systems are widely used in buildings and infrastructure because they combine the compressive resistance and fire protection of concrete with the strength, stiffness, and ductility of structural steel. In seismic regions, the beam–column joint is one of the most critical zones in a moment-resisting frame because it transfers forces between beams and columns while resisting high shear stresses, repeated load reversals, cracking, bond degradation, and stiffness deterioration. Compared to a traditional reinforced concrete joint, the response of an SRC beam–column joint is more complicated. Concrete, longitudinal reinforcement, transverse reinforcement, and embedded steel sections make up the joint core. These components interact via bond, confinement, bearing, and shear-transfer mechanisms. This interaction becomes extremely nonlinear under seismic loading. In the 1980s,[1], [2] conducted the first research on SRC beam-column joints in Japan, They carried out experimental research on 15 beam-column joints of composite structures. The findings demonstrated the high bearing capacity and good ductility of the rectangular SRC beam-column joints, and the corresponding joint design and calculation formulas were proposed.

[3] investigated the effects of their suggested diaphragm scheme in seven SRC beam-column subassemblies

with H steel columns.

Full-scale joints of SRC columns and steel beams were subjected to low cyclic load experiments by [4] The results demonstrated that the SRC column-steel beam joints exhibited good seismic performance because the concrete encasement successfully contained and shielded the embedded beam, encouraging ductile behavior and high energy dissipation without premature joint failure. [5] tested five large-scale cruciform type beam-column subassemblies under cyclic loading, He examined the seismic performance of beam-column joints made of steel reinforced concrete (SRC) under unidirectional lateral cyclic loading. Greater anchorage depth of beam bars and embedded steel sections in SRC joints significantly improved shear strength, ductility, and energy dissipation, according to the authors' construction and testing of five full-scale SRC joint specimens. Strong confinement, improved seismic performance, and a delay in brittle shear failure were all made possible by these details.

[6] investigated six SRC Column-RC beam joint specimens with different axial load ratios and volumetric stirrup ratios. The findings were consistent with those of [7]**.** [8], (7) composite joint models, comprising three concrete-encased CFST column to steel beam joints and four concrete-encased CFST column to RC beam joints. The type of joint, the amount of axial load on the composite column, and whether or not the RC slab was present were the primary test parameters. From the previous searches and experimental work, Concrete compressive strength, steel section web and flange dimensions, steel yield strength, stirrup ratio, axial load ratio, joint aspect ratio, anchorage details, and whether the joint is an interior or exterior connection can all have an impact on the joint shear capacity. Traditional analytical models are useful for design and interpretation.

Existing Analytical and Numerical Models for SRC Joint Shear Strength

In structural engineering, accurately determining the shear capacity of composite column-beam joints is still a fundamental challenge, especially in areas with high seismic activity. These joints are essential parts of moment-resisting frames, and during earthquake loading, they frequently experience complex stress states. Several researchers have put forth analytical models that combine theoretical mechanics and empirical data to improve the predictive accuracy of joint behavior. Researchers create a lot of numerical methods.

1- Component-Based Analytical Models

Component-based analytical models are more suitable for SRC beam-column joints because they separate the total joint shear strength into individual resisting components. In this approach, the joint shear strength is generally expressed as:

$$V_{SRC} = V_c + V_s + V_{st} \quad (1)$$

where V_c is the concrete contribution, V_s is the contribution of the embedded steel section, and V_st is the contribution of transverse reinforcement.

This approach is mechanically reasonable for SRC joints because shear resistance is not provided by concrete alone. The concrete core forms compression struts, the embedded steel web contributes directly to shear resistance, the steel flanges assist in force transfer, and the stirrups provide confinement and additional shear resistance. [5], [7].

Cheng-Cheng Chen Method

[5] The author calculated the beam-column joint in a study that confirmed the efficacy of SRC joint detailing under seismic conditions and emphasized the critical role of steel–concrete interaction in improving joint behavior under cyclic loads.

The shear strength of SRC beam-column joints is calculated as the sum:

$$V_{src} = V_{rc} + V_{sw} + V_{slf} \quad (2)$$

Where V_{rc} is the shrear strength provided by the concrete joint area, V_{sw} is the shear strength provided by the web and V_{slf} is the shear strength provided by the flange.

-The shear strength provided by concrete joint area

For joints confined on all four faces

$V_{rc} = 1.67 \sqrt{f`_c A_j}$ (3)

For joints confined on the three faces or on two opposing faces

$V_{rc} = 1.25 \sqrt{f`_c A_j}$ (4)

For others

$V_{rc} = 1.00 \sqrt{f`_c A_j}$ (5)

Where $f`_c$ is the specified compressive strength of the concrete.

A_j is the effective area of the joint.

The effective area of the joint can be calculated by:

$A_j = b_j$ x h_j

Where b_j is the joint width and h_j is the joint depth.

The value of the b_j for a concentric joint should satisfy Eq.(5)

b_j = minimum ($b_b + h_c$, b_b + 2 X) (6)

Where X is the horizontal distance between the beam and column edges.

-Shear strength provided by the web is given as

$V_{sw} = 0.6\, F_{yw}\, d_c\, t_w$ (7)

Where F_{yw} is the yield stress of the column web, dc is the column depth, and tw is the column web thickness.

-Shear strength provided by the flange is given as

$V_{slf} = 2 \left[\frac{2}{3} (0.6\, F_{yf}\, b_f\, t_f) \right]$ (8)

Where F_{yf} is the yield stress of the column flange, b_f is the width of column flange, and t_f is the column flange thickness.

Wei Liu and Jinqing Jia Method

[7] calculated the beam-column joint shear strength as the sum:

$V_j = V_{nih} + V_{oust} + V_{sv}$ (9)

Where V_{nih} is the effective shear strength contributed by the inner concrete compression strut, V_{oust} is the effective shear strength contributed by the outer concrete compression strut and V_{sv} is the shear strength provided by the stirrups.

- The effective shear strength contributed by the inner concrete compression strut

$V_{nih} = 0.3 f_{c.inst} h_c\ (b_f - t_w)$ (10)

Where $f_{c.inst}$ is the effective inner concrete strength, b_f is the flange width and t_w is The web thickness.

- The effective shear strength contributed by the outer concrete compression strut

$V_{oust} = 0.3\, f_{c.oust}\, h_c\ b_o$ (11)

Where $f_{c.oust}$ is the effective outer concrete strength, h_c is the column depth and b_o is the width of the outer strut expressed as follows

$b_o = \min [(b_f - b_f), (b_b - b_f) + 0.5\, h_c]$ (12)

- The shear strength provided by the stirrups

$V_{sv} = A_{sv.eff}\ f_{yv}$ (13)

Where $A_{sv.eff}$ is the effective stirrups area and f_{yv} is yield stress of stirrups.

2- Code-Based and Empirical Approaches

In conventional reinforced concrete beam-column joints, code-based approaches usually evaluate the nominal joint shear strength as a function of the concrete compressive strength and the effective joint area. This design philosophy is commonly adopted in seismic design provisions for reinforced concrete joints, where the joint core is assumed to resist shear mainly through concrete compression and confinement mechanisms [9], [10].

The nominal joint shear strength may be written in the following general form:

$V_n = \gamma_j \sqrt{fc`}\ A_j$ (14)

where V_n is the nominal joint shear strength, fc` is the specified concrete compressive strength, A_j is the effective joint area, and γ_j is a coefficient related to the joint confinement condition.

The effective joint area is commonly expressed as:

$$A_j = b_j h_c \quad (15)$$

where b_j is the effective joint width and h_c is the column depth in the direction of joint shear. For concentric beam-column joints, the effective joint width may be limited as follows:

$$b_j = \min (b_c , b_\beta + h_c , b_\beta + 2x) \quad (16)$$

where b_c is the column width, b_β is the beam width, and x is the distance from the beam edge to the column edge.

The design check is generally written as:

$$V_u \leq \phi V_n \quad (17)$$

or, in terms of joint shear stress:

$$v_j = V_u / A_j \quad (18)$$

$$v_j \leq \phi \gamma_j \sqrt{f'c} \quad (19)$$

where V_u is the applied joint shear demand, v_j is the joint shear stress, and ϕ is the strength reduction factor.

These code-based expressions are straightforward and helpful for initial design, but because they do not specifically account for the embedded steel section's contribution, their direct application to SRC beam-column joints is restricted. Because of the way concrete, stirrups, reinforcing bars, and structural steel shapes interact, SRC joints have a distinct internal resistance mechanism. Consequently, rather than being a comprehensive prediction model for SRC joints, traditional RC-based equations are typically regarded as a reference or baseline method [5].

3- Finite Element Modelling Approaches

Finite element modelling has been widely used to investigate the nonlinear behavior of reinforced and composite beam-column joints under cyclic loading. Unlike closed-form analytical equations, finite element models can simulate material nonlinearity, cracking, crushing, steel yielding, confinement, bond-slip, and stiffness degradation ([11], [12]

In a finite element formulation, the equilibrium problem is generally expressed as:

$$[K]\{u\} = \{F\} \quad (20)$$

where [K] is the global stiffness matrix, {u} is the displacement vector, and {F} is the external load vector.

For nonlinear cyclic analysis, the stiffness matrix is updated during the loading process:

$$[K_t] \Delta\{u\} = \Delta\{F\} \quad (21)$$

where [K_t] is the tangent stiffness matrix, Δ{u} is the incremental displacement vector, and Δ{F} is the incremental load vector.

Concrete damage and cracking can be represented using nonlinear constitutive relationships, while steel reinforcement and embedded steel sections are commonly represented using elastoplastic stress-strain models. The steel stress may be expressed as:

$$\sigma s = Es\, \varepsilon s \qquad \text{for } \varepsilon s \leq \varepsilon y \quad (22)$$

$$\sigma s = fy \qquad \text{for } \varepsilon s > \varepsilon y \quad (23)$$

where Es is the elastic modulus of steel, εs is the steel strain, εy is the yield strain, and fy is the steel yield strength.

Finite element models are powerful because they can show stress concentration, crack pattern, steel yielding, and local damage progression. However, their accuracy depends strongly on mesh size, material models, boundary conditions, loading protocol, and the assumed bond condition between steel and concrete.

Data Driven method for Estimating SRC Joint Shear Strength

However, when there is a lot of scatter in experimental observations or when the interaction between variables is too complicated, their accuracy might be compromised. Because artificial neural networks can directly learn nonlinear relationships from experimental data, they provide a powerful computational approach in this situation. An ANN can find patterns between input variables and the measured ultimate shear capacity rather than assuming a fixed form of the shear-resisting mechanism. An ANN model for estimating the shear capacity of a composite beam-column joint can be developed using Java Neural Network Simulator (JavaNSS). The Java neural network Simulator (JavaNNS), a tool for creating neural network models, was created by the Wilhelm-Schickard-Institute for Computer Science (WSI) in Tübingen, Germany. It is based on the Stuttgart Neural Network Simulator (SNNS), created in 1989 at the Institute for Parallel and Distributed High-Performance Systems at the University of Stuttgart [13]. Java Neural Network Simulator (Java NNS) is a practical environment for building, training, and testing neural networks. It allows the user to define network topology, assign input and output patterns, select learning functions, set activation functions, control training cycles, and evaluate the behavior of the trained model. Therefore, Java NNS can be used as a transparent tool for developing an ANN model for SRC joint shear capacity prediction.

Development Procedure of the Artificial Neural Network (ANN)

Model

The behavior of composite beam-column joints under seismic loads is complicated. Because of material interactions, confinement effects, and cyclic degradation, shear capacity can be limited and inaccurately predicted using conventional methods. A powerful alternative is provided by Artificial Neural Networks (ANN), which can learn from experimental data, accurately model nonlinear relationships, and reveal hidden patterns. In order to generate more reliable and accurate joint shear capacity predictions under dynamic seismic effects, artificial neural networks (ANN) should be employed.

The Neural Network functions similarly to biological neurons and imitates the characteristics of the human brain. An arrangement of connections at different levels is called a neural network. An artificial neural network (ANN) consists of three layers: the input layer, the hidden layer, and the output layer. There are several layers of neurons. Each layer's neurons are connected by weights and biases. An input is multiplied by the matching weight prior to reaching the summing node [14]. Additionally, the artificial neuron Fig.1 . includes a bias term that is subsequently added to the summing node. Information from the external environment is collected by the input layer and sent to the hidden layer for processing and summarization. After receiving this total, the activation function uses it to identify the problem's non-linearity and generate a more precise result. The weights are changed until the prediction errors are as small as possible after comparing the actual values and the ANN results. A trained artificial neural network (ANN) can be used to predict the new input data once the network has learned enough. The Eq. (1) as well as Equ. (2) Explain how a three-layer feed-forward network operates.

$$Ha = f\ (wx,a * jx) + ba \qquad (24)$$

$$Ob = f\ (wn,b * jn) + bb \qquad (25)$$

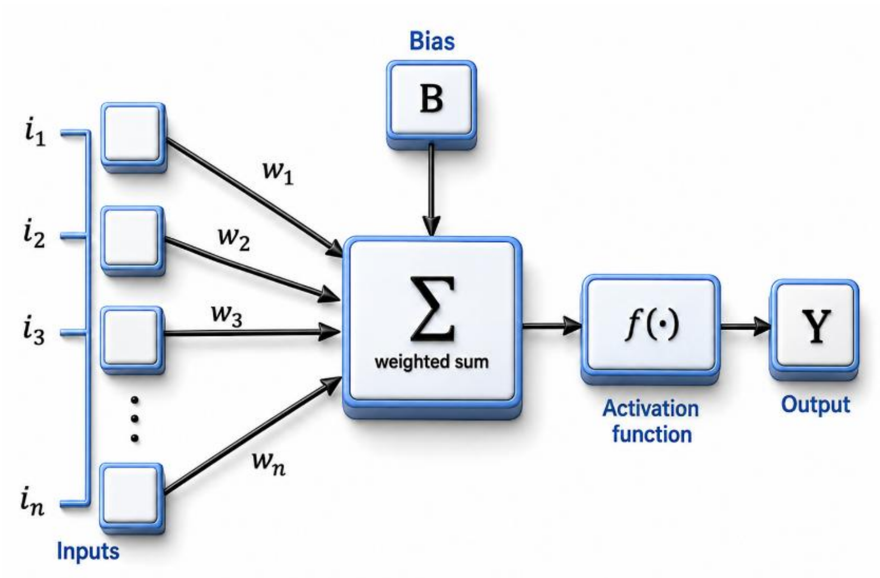

Figure 1 Structure of artificial neural network

Where H_a and O_b are the activity levels generated at the a^{th} hidden neuron and b^{th} output neuron, respectively. i_x and j_n denote the normalized data sent from the x^{th} neuron in input layer and n^{th} neuron in the hidden layer. wx,a and vn,b are the weights on the connections to the hidden layer and output layer of neurons respectively. b_a and b_b are the bias at the hidden and output layer.

The ANN is capable of solving complex problems through experience-based learning. ANN models have been used to study a variety of civil engineering issues, such as modeling the impact of RC beam size on shear strength [15], predicting the axial capacity of columns [16], predicting the shear strength of concrete beams [17], predicting the compressive strength of concrete [18], Siddique and Aggarwal, simulating the seismic response of [15], and seismic analysis [19], [20], condition assessment of RC beams [21], identification of grouting compactness in bridges [22], and distortion buckling capacity assessment of castellated steel beams [21], etc.

An ANN model with varying activation functions and hidden neuron counts will be modeled, and the ideal ANN model architecture is suggested in [23] work.

The input values of the ANN should be selected based on their notable influence on the behavior of the SRC joints in view of the main parameters mentioned earlier. yielding stress of the stirrups and steel sections, concrete compressive strength (fc'), column width (bc), column depth (dc), beam width (bb), beam depth (db), column height (which indicates the distance between the contra-flexure point along the upper and lower column's axial axis at the joint), beam length, axial compression ratio, and whether the joint was interior or exterior.

Data Input and output Preprocessing

Predicting a composite beam-column joint's shear capacity under seismic loads is the aim of the neural network model. The ANN model is intended to have an output layer with one neuron as a target and an input layer with the number of the main parameter affecting the joint shear strength as neurons. A trial-and-error method is used to determine the number of hidden layers and hidden neurons. Before training, the dataset underwent a series of preprocessing steps:

1- Normalization:

All input values were rescaled to a single range using a Min–Max normalization technique. In addition to preventing the dominance of larger numerical features, this step guaranteed stable learning.

2- Dataset Splitting:

- 70 % specimens were allocated for training.
- 30 % specimens were reserved for validation.

Hidden Layers

The available training data set dictates the number of input and output nodes, but selecting the number of hidden layers and nodes within each hidden layer can be difficult. High errors and lengthy training times are signs of "under-fitting," which can result from selecting a small number of nodes for the hidden layer. However, "overfitting" could happen if the network has too many neurons [24]. Overfitting can cause low training errors, and high validation errors.

For determining the number of hidden layers, [25] proposed that the majority of applications can use just one hidden layer. Numerous studies have been conducted to determine the optimal number of neurons in the hidden layer, but no definitive rule has yet been found. [24] provided eleven formulas for figuring out how many neurons are in hidden layers. These formulas are listed in Table 1 above (where N_i represents the number of inputs nodes, and N_o the number of outputs).

By	Formulas
Hecht-Nielsen	$2\ N_i + 1$
Shavlik	$0.1\ (N_i + N_0)$
Hush	$3\ N_i$
Rippley	$(N_i + N_0)\ /\ 2$
Wang	$2\ N_i\ /\ 3$
Blum	Between $(N_i + N_0)$
Fletcher and gross	From $2\ N_i + 1$ to $2\sqrt{N_i} + N_0$
Berry and Linoff	$< 2\ N_i$
Sigillito and Hutton	$< N_i\ /\ 2$
Kenellopoulos Wilkinson	$2\ N_i$ or $3\ N_i$
Paola	$\frac{2 + N_i\,.\,N_0 + \frac{1}{2} N_0\left(N_i^2 + N_i\right) - 3}{N_i + N_0}$

Table 1 Formulas to determine the number of neurons in hidden layers

Training Process

The neural network (ANN) model can learn the relationship between the training set and possibly apply that relationship to new inputs if it is provided with sufficient examples during the training process. The neural network architecture, training algorithm, and activation function are just a few of the many variables that have a major impact on the intricate training process. To begin training the network and achieve the intended results, these elements must be identified. A trial-and-error method is typically used to accomplish this.

Data Normalization Method

The inputs and outputs of the ANN are scaled to reduce the difference between the predicted values and the experimental results. In order to comply with the [0,1] . range, the inputs and outputs were scaled as follows [26,27]:

$$I_{si}=\frac{(I_{ni}-I_{imax})}{(I_{imax}-I_{imin})} \quad (26)$$

Where,

Isi = the scale input ranged between 0 and 1

I_{imax} = the maximum I_{ni}

I_{imin} = the minmum I_{ni}

$$Q_{us}=2 \text{ x } (\frac{Q_{ui}-Q_{umin}}{Q_{umax}-Q_{umin}}) - 1 \quad (27)$$

Where,

Q_{us} = the scale output ranged between -1 and 1

Q_{umax} = the maximum Q_{ui}

Q_{umin} = the minmum Q_{ui}

It is crucial to remember that the adopted scaling criteria for the data are determined by how the activation functions used are formulated. Therefore, the achievement of convergence in the outputs of the ANN training process will be greatly impacted by scaling. In order to create a stable and appropriate ANN model, the architecture of multiple neural networks was examined during the training process by adjusting the number of neurons in the hidden layer and the coefficients of the training function. During data training, neural network weight and bias magnitudes are adjusted to optimize ANN performance. The iterative solution algorithm for ANN selection is shown in Fig. 2. Due to the random selection of the neural network's initial weight, this model relies on a trial-and-error approach for convergence.

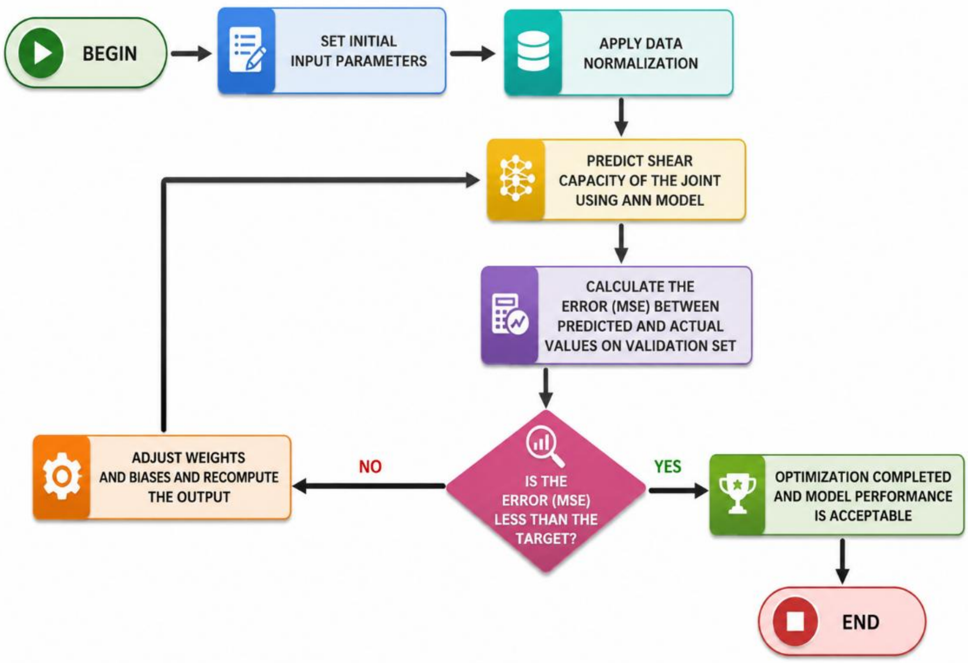

Figure 2 Flow chart of the ANN analysis of shear strength of the joint.

Activation Function

Activation functions are used by the artificial neural network to transform an input signal into an output signal. The activation function receives the sum of the products of the input weight to determine the output of the next layer in the network. Non-linear activation functions can learn and solve complex relationships between input and output data. Furthermore, activation functions must be differentiable in order to backpropagate the model's error and alter the weights to reduce errors [28]. Trails with different activation functions are conducted using

JavaNNS. Artificial neural network modeling can employ a variety of activation functions, but the logistic function (Act_Logistic), the hyperbolic tangent function (Act_TanH), and the sinusoidal function (Act_Sinus) are the most frequently used functions. The ability of these functions to depict nonlinear relationships between the input parameters and the anticipated shear capacity led to their selection. The best network configuration for enhancing training stability and prediction accuracy can also be found by comparing these activation functions.

The Backpropagation Algorithm

Networks can be categorized as either supervised, where the weight in the ANN is adjusted by running the ANN model on input cases with known outputs, or unsupervised, where output values are unknown by identifying clusters in the input data [27]. ART 1, ART 2, and the backpropagation algorithm.

The Back-propagation algorithm that yields the best results is an example of supervised learning with a single parameter, a learning rate ξ. One of the most popular techniques for training neural networks using historical data is back-propagation training[29]. There are two steps in the learning cycle of the back-propagation algorithm. In the first, inputs are propagated forward by the network until the outputs are calculated. Equation 5 indicates that the computed outputs are compared with the intended outputs from the training set to determine the error.

The Error $= Desired\ Output\ (O_d) - Neural\ Network\ Output\ (O_n)$ (28)

The error is backpropagated through the network in the second step, which modifies the network's weights to minimize the error size. Until an acceptable error is achieved, these forward and backward procedures are repeated [24]. The learning rate η is used to control the step size when weights are adjusted throughout the training process. If the learning rate is small, a long training time occurs. Whereas, if the value is high algorithm could diverge [30]. In JavaNNS the learning rate is set to 0.2 by default.

Accuracy

This methodology allows for the testing of various ANN configurations by varying the activation function, learning parameters, training strategy, number of hidden layers, and number of neurons within each hidden layer. The choice of an appropriate architecture is crucial because an extremely complex network may result in overfitting and poor generalization when applied to new data, while a very simple network might not be able to capture the nonlinear behavior of the joint [31].Because of this, developing ANNs typically involves a trial-and-evaluation process in which multiple models are trained and evaluated according to how well they predict outcomes. It should be noted that all the tested networks are trained on 50,000 cycles and a maximum error $dmax$ = 0.1. The sum squared error (SSE) will be calculated as shown in Equation 6.

Summed Square Error (SSE) = $\sum_{i=1}^{N}(O_{ti} - O_{ci})^2$ (29)

Conclusion

The reviewed methods show that the prediction of shear capacity in composite and SRC beam–column joints is a complex task because the joint resistance is governed by the interaction of several resisting mechanisms rather than by a single parameter.

Component-based analytical models break down the total joint shear capacity into the contributions of transverse reinforcement, embedded steel sections, and concrete to provide a logical mechanical framework. Because of this, these models can be used to determine the function of each resisting component and to interpret the internal force-transfer mechanism. However, the assumptions made to depict the compression strut, steel web contribution, flange action, confinement effect, and stirrup resistance have a significant impact on their accuracy.

The methods proposed by Cheng-Cheng Chen and by Wei Liu and Jinqing Jia are particularly important because they were developed based on experimental observations of SRC beam–column joints. These models provide practical expressions for estimating joint shear strength and explicitly consider some of the main resisting components. Nevertheless, empirical and semi-empirical equations are generally limited by the range of the experimental data used for their calibration. Therefore, their application to joints with different geometries, high-strength materials, different steel shapes, exterior configurations, or different loading histories should be treated with caution.

Code-based and empirical approaches offer simple and design-oriented procedures, which makes them useful for preliminary assessment and engineering practice. However, most conventional code equations were originally developed for reinforced concrete beam–column joints and do not explicitly consider the contribution of embedded steel sections. As a result, direct application of these equations to SRC joints may lead to conservative or inaccurate predictions, especially when the steel web, steel flanges, and steel–concrete interaction significantly contribute to shear resistance.

Finite element modelling provides a more detailed tool for investigating the nonlinear response of composite beam–column joints. Unlike simplified analytical equations, finite element models can simulate cracking, crushing, steel yielding, stress redistribution, bond-slip, confinement effects, and cyclic stiffness degradation. However, the reliability of finite element predictions depends on several modelling choices, including concrete constitutive models, steel material models, mesh size, boundary conditions, loading protocol, and the assumed bond condition between steel and concrete. Therefore, finite element models should be carefully validated against experimental results before being used for prediction or parametric studies.

JavaNNS-created artificial neural network models offer a viable data-driven substitute for shear capacity prediction. Nonlinear relationships between input parameters and ultimate shear capacity can be captured by ANN models without the need for a mechanical equation. This is especially helpful for SRC joints, where there is a highly nonlinear interaction between concrete strength, steel yield strength, steel section dimensions, stirrup ratio, axial load ratio, joint geometry, and connection type. However, the size, caliber, and representativeness of the available experimental database have a significant impact on how well ANN models perform. When the trained model is applied to new joint configurations, it may become overfitted due to small datasets.

Overall, there are particular benefits and drawbacks to each prediction technique. Despite being straightforward, transparent, and appropriate for design applications, analytical and empirical models might not adequately represent nonlinear parameter interaction. Although they necessitate meticulous modeling and validation, finite element models offer comprehensive insight into both local and global behavior. When there is enough experimental data available, data-driven approaches can increase prediction accuracy, but they might not be directly mechanically interpretable. Therefore, the most dependable framework for evaluating the shear capacity of composite beam–column joints in the future may be provided by a combined approach that incorporates mechanical understanding, numerical simulation, and data-driven prediction.

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