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DATA DRIVEN METHODS FOR UNCERTAINTY PROPAGATION IN PREDICTING BRITTLE RESPONSES OF REINFORCED CONCRETE STRUCTURES

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Abstract

Predicting the brittle response of reinforced concrete (RC) members remains a significant challenge, especially for continuous or indeterminate beams where shear-critical behavior introduces considerable uncertainty. While professional tools like SAP2000 and research platforms such as ABAQUS offer trade-offs between usability and precision, they face notable limitations—ranging from underestimating failure modes to requiring substantial computational resources. This study introduces a hybrid Artificial Neural Network–Finite Element Analysis (ANN–FEA) methodology as a computationally efficient, data-driven alternative for the analysis and design of shear-critical RC structures. The approach integrates ANN-based failure prediction models, trained on experimental data, with segment-wise nonlinear pushover analysis. A curated dataset of 315 RC beams was used to develop and calibrate eight ANN configurations, among which the BWS-7 model achieved the highest predictive accuracy. The ANN–FEA method was validated against experimental results and benchmarked through a case study involving indeterminate RC beams subjected to axial and transverse loading. The results demonstrate that the ANN–FEA model closely matches experimental outcomes, achieves accuracy comparable to ABAQUS, and outperforms SAP2000 in detecting brittle failure. This work advances uncertainty quantification in RC analysis and offers a practical tool for structural assessment under complex loading conditions.

Keywords: Reinforced Concrete Beams, Multi-span, Design Tools, Artificial Neural Network.

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1 INTRODUCTION

Since the mid-20th century, the rapid expansion of concrete construction has significantly transformed the role and technical responsibilities of structural engineers [1-5]. These professionals are tasked with ensuring the structural safety, serviceability, and cost-effectiveness of reinforced concrete (RC) buildings. In recent years, research has increasingly focused on developing predictive models that capture the brittle behavior of RC frame elements. Such analytical tools have become essential for a variety of applications, including: (i) designing new RC structures in compliance with modern codes; (ii) reassessing existing structures based on updated regulations; (iii) evaluating structural performance; (iv) identifying design inconsistencies between the planning and construction phases; and (v) supporting forensic investigations of structural failures [1-5].

In professional engineering practice, various national and international design codes are commonly used to assess the structural performance of complex RC members, particularly columns subjected to axial loads at the ultimate limit state (ULS). Prominent among these are the American ACI 318 [6], the European Eurocode 2 (EC2) [7], the Japanese JSCE [8], New Zealand's NZS 3101.1:2006 [9], the Korean KBSC [10], and the Canadian CSA A23.3 [11]. These standards typically rely on analytical models grounded in truss-based representations and strut-and-tie mechanisms, often supplemented by cross-sectional analysis methods to characterize structural behavior at ULS. An alternative to these conventional approaches is the Compressive Force Path (CFP) method, which provides a distinct framework for evaluating RC member behavior [12].

To meet these evolving challenges, the field has gradually integrated a variety of advanced analytical methods over the past decades [13-15]. Today, structural engineers depend on sophisticated computational tools both to design new RC structures in compliance with modern regulatory frameworks and to reassess existing structures according to current standards [6-11]. This transition has marked the emergence of a new era in high-fidelity modeling and simulation—enhancing the ability to predict brittle failure mechanisms but also requiring substantial computational resources and specialized expertise [16-20].

However, nonlinear finite element analysis (NLFEA) tools such as ABAQUS [13] and ADINA [15] are primarily used in research settings due to their complexity and computational demands. In contrast, software commonly used in the design industry—such as SAP2000 and ETABS [14]—is typically employed for practical structural analysis and design tasks. While these tools are generally reliable for predicting flexural (ductile) failure modes, they often fall short in accurately capturing shear (brittle) failure mechanisms [1-5]. Given that shear failures are usually sudden and catastrophic, occurring with little to no prior indication, it is essential for structural analysis software to provide accurate predictions of such failure modes. Reliable forecasting is critical to developing safe and cost-effective design strategies that preserve the structural integrity and resilience of RC frame systems. Conversely, inaccurate predictions can result in unsafe designs by overestimating the load-bearing capacity and ductility of structural elements.

Recent advancements in artificial intelligence have significantly influenced civil engineering practice and education, highlighting the transformative potential of machine learning and large language models in structural analysis and design workflows [21-24]. In recent years, soft computing (SC) techniques—particularly Artificial Neural Networks (ANNs)—have emerged as a promising alternative to traditional finite element (FE) methods for structural analysis [25-30]. This advancement has led to the development of hybrid ANN–FEA models, which integrate neural networks with finite element analysis to enhance prediction accuracy and computational efficiency [28, 31-33]. The proposed ANN–FEA approach consists of three main steps, as illustrated in Figure 1:

- **Step 1**: ANN models are trained using experimental datasets. These models function as failure criteria specifically designed to predict shear failure in individual RC members, such as beams and columns, as established in the authors' prior studies [27, 32, 34-39].
- **Step 2**: The structural system is systematically divided into discrete segments based on the locations of peak bending moments and points of contraflexure, or between successive contraflexure points. This segmentation emulates the behavior of supported beam elements and enables localized structural analysis [31, 32].
- **Step 3**: During nonlinear pushover analysis, the trained ANN models are employed as failure indicators. The analysis terminates once the applied load exceeds the predicted shear capacity of any segment, ensuring accurate detection of potential failure.

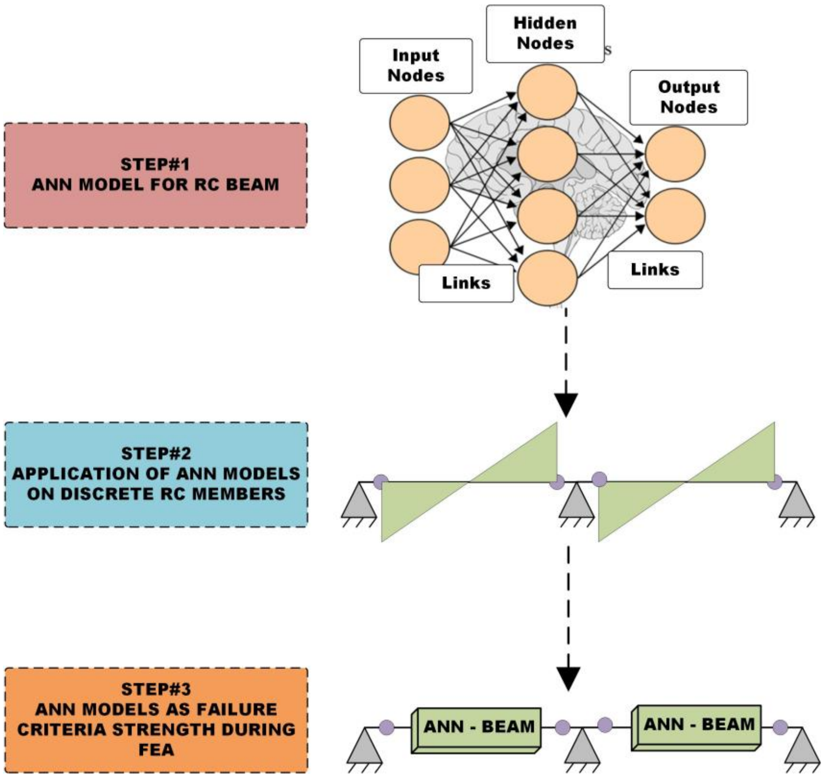


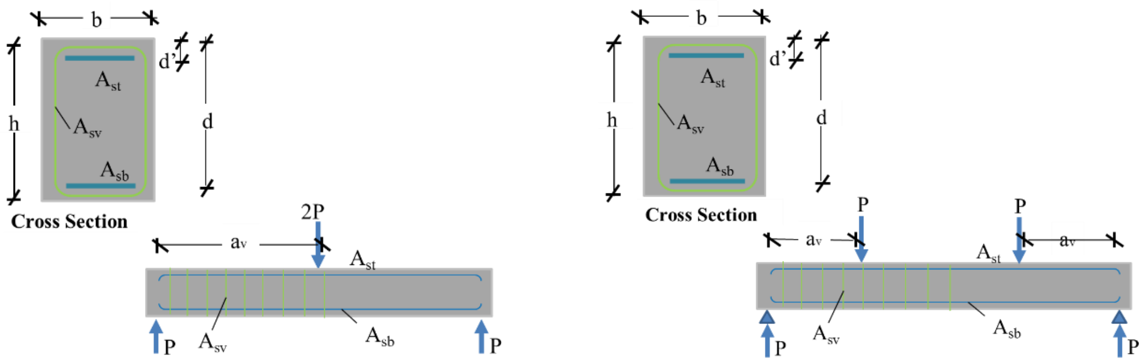
Figure 1: Overview of the proposed ANN–FEA hybrid methodology for reinforced concrete (RC) continuous beams [31, 32].

The proposed ANN–FEA structural analysis methodology demonstrates strong effectiveness in both the design of new RC structures and the assessment of existing ones. Moreover, it enhances the predictive capabilities of current structural analysis software used in professional practice [31, 32]. This study emphasizes the key strengths of the ANN–FEA approach, particularly its ability to simulate the behavior of indeterminate RC structural systems, including beams that fail in flexure or shear. The predictions generated by the ANN–FEA method are compared with those from ABAQUS [13], a high-fidelity finite element analysis tool widely used in research, and SAP2000 [14], a popular commercial software used in engineering practice. These predictions are further validated against experimental data. Following this validation, a parametric study is carried out to evaluate the method's performance. The results indicate that the ANN–FEA approach yields brittle failure predictions that closely align with experimental and ABAQUS outcomes. In contrast, SAP2000 fails to capture brittle shear failure accurately, as it does not terminate the analysis when such failure occurs due to inherent software limitations.

2 EXPERIMENTAL DATABASE OF RC BEAMS WITH STIRRUPS (BWS)

A comprehensive database of RC beam specimens with stirrups (BWS) was compiled to support the current study. The dataset consists of 315 beams tested under either three-point or four-point loading configurations, as illustrated in Figure 2. This curated database systematically captures key design parameters that influence the load-carrying capacity and failure modes of RC beams at the ULS. It includes detailed information on material properties, geometric dimensions, reinforcement details, and loading conditions—enabling in-depth analysis of structural behavior under extreme loading scenarios.

The database serves as a critical foundation for predictive modeling and performance evaluation, facilitating the development of safer and more efficient structural designs. Key features of the dataset include: Material properties; Geometric dimensions; Reinforcement configurations; Loading conditions; Observed failure modes; Measured load-carrying capacity. Table 1 presents statistical summaries for these parameters. Among the 315 specimens, 204 (65%) failed in shear, while the remaining 111 (35%) failed in flexure.



(a) (b)

Figure 2: Experimental setup for RC Beams with Stirrups BWS: (a) three-point loading configuration, (b) four-point loading configuration.

ID	Quantity	Unit	Range (Min–Max)	Avg.	COV	St. Dev
1	b	mm	100 – 510	207.27	0.33	67.64
2	d	mm	113 – 975	342.87	0.46	157.03
3	a_v/d		1 – 7	3.43	0.39	1.35
4	ρ_l	(%)	0.18 – 5.60	2.35	0.45	1.05
5	f_{yl}	MPa	250 – 880	411.33	0.19	77.88
6	f_c	MPa	12 – 125	44.51	0.5	22.41
7	ρ_w	(%)	0.08 – 2.25	0.56	0.86	0.48
8	f_{yw}	MPa	225 – 875	399.4	0.28	112.62
9	M_f	kN·mm	2648 – 1738423	283485	1.34	378729
10	V_u	kN	4 – 760	185.54	0.72	134.25

Table 1: Statistical information for BWS.

2.1 Correlation Coefficient of the Parameters

Pearson's correlation coefficient (R), computed using Eq. (1) [40], is used to quantify the strength and direction of the linear relationship between variables in the dataset. Figure 3 illustrates the correlation values between the shear capacity (V_u) and each input parameter included in the BWS database.

$$r = \frac{n\sum xy - \left(\sum x\right)\left(\sum y\right)}{\sqrt{n\sum x^2 - \left(\sum x\right)^2}\sqrt{n\sum y^2 - \left(\sum y\right)^2}} \tag{1}$$

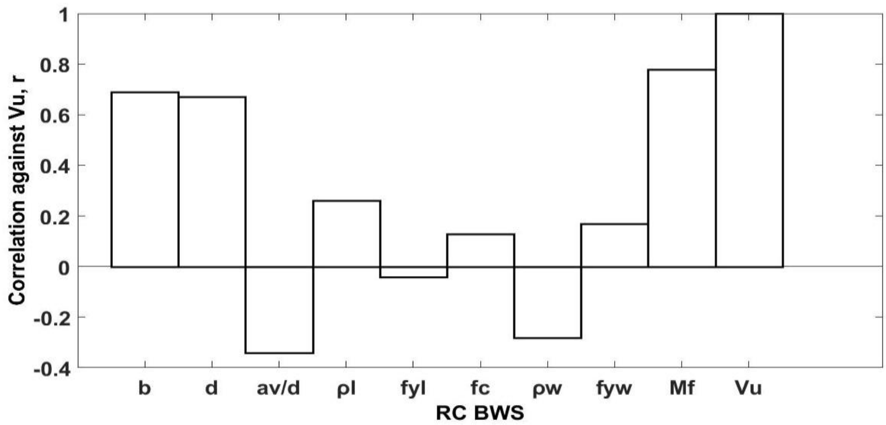


Figure 3: Pearson correlation coefficient r between the shear capacity V_U and each of the parameters including itself, for the RC beams with stirrups (BWS).

3 ARTIFICIAL NEURAL NETWORK MODELING FOR SHEAR CAPACITY PREDICTION

Artificial Neural Networks are widely used in machine learning and data mining for their ability to learn patterns and predict outputs from input data. An ANN consists of a system of interconnected nodes, or neurons, as shown in Figure 4, and is inspired by the structure and functioning of biological neural networks in the human brain [27, 32, 34, 35]. Unlike traditional computational models, ANNs do not require predefined assumptions about the underlying relationships between variables. This flexibility allows them to effectively capture and model complex, nonlinear interactions within real-world data. During training, ANNs can also uncover hidden patterns and trends, making them especially useful in large datasets due to their parallel processing capabilities.

An ANN typically consists of three main components: an input layer, one or more hidden layers, and an output layer. The core mathematical operation of a single neuron within the network is described in Eq. (2), where the output is determined by the weighted sum of inputs and a bias term, passed through an activation function. Eq. (2) describes the output of a single artificial neuron in the network, not the response of the entire ANN model. The predictive capability of the network depends on three key parameters: the input values, the connection weights, and the bias term.

$$O = f\left(\sum x_i w_i + b\right) \tag{2}$$

During training, the network uses the backpropagation algorithm in conjunction with the delta rule to iteratively adjust the weights, minimizing the difference between the predicted outputs and the actual target values from the training data. As illustrated in Figure 4, this adjustment process flows backward through the network—from the output layer to the input layer. The optimization procedure, governed by the minimization of the mean squared error (*MSE*) as expressed in Eq. (3), continues until the error converges below a specified tolerance threshold, thereby enhancing the model's predictive accuracy [27, 32, 34, 35].

$$E(w)=\frac{1}{2}\sum_{i}(T-O)^{2} \tag{3}$$

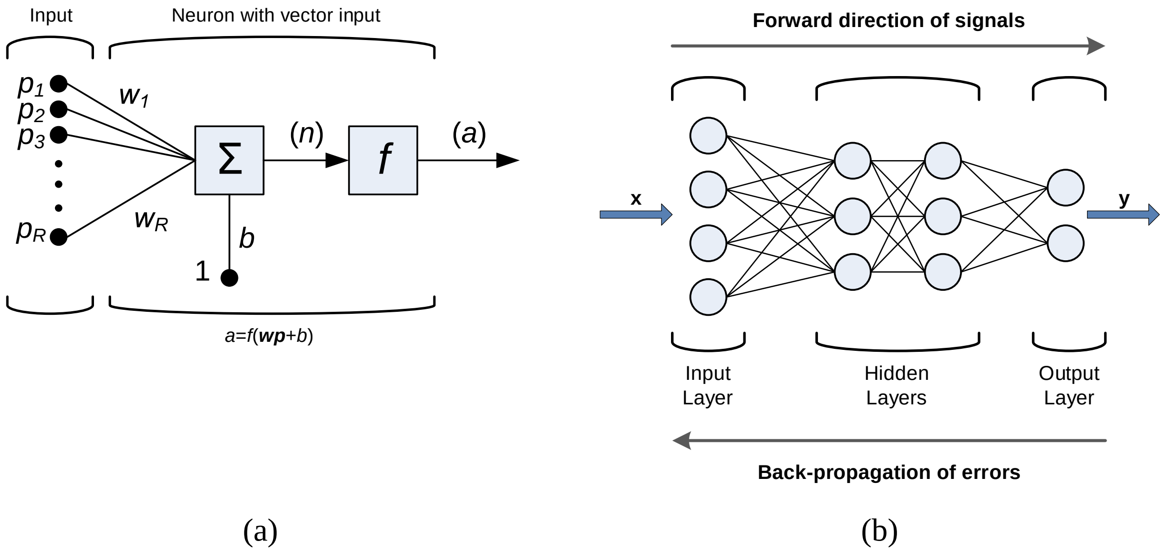


Figure 4. (a) Structure of a single artificial neuron with multiple weighted inputs, bias, and activation function. (b) Feedforward ANN architecture showing input, hidden, and output layers with backpropagation of errors.

In this study, input variables were normalized using Eq. (4), which scales values to a range of 0.2 to 0.8, deviating from the conventional 0 to 1 range commonly found in the literature [27, 32, 34, 35]. This modified normalization approach was adopted to prevent saturation in activation functions—particularly in sigmoid or tanh-based networks—by avoiding input values near the function's boundaries. Maintaining input values within this narrower range helps preserve gradient activity during training, thereby improving numerical stability and accelerating convergence.

$$X=\left(\frac{0.6}{\Delta}\right)x+\left(0.8-\left(\frac{0.6}{\Delta}\right)x_{\max}\right) \tag{4}$$

3.1 Calibration of Proposed ANN Model

In this study, an ANN was employed to estimate the strength characteristics of reinforced concrete. The modeling process began with the division of the dataset: 60% of the data was used for training, while the remaining 40% was equally split into validation and testing subsets (20% each).

The ANN was constructed using the training data, and its performance was evaluated by comparing predicted results with experimental values. This evaluation used statistical metrics such as mean absolute error (*MAE*), root mean square error (*RMSE*), and the Pearson's correlation coefficient (*R*) to assess accuracy and reliability [40]. The modeling workflow is illustrated in Figure 4 (a) and (b).

A multi-layer feedforward backpropagation ANN architecture was adopted for this study. The network was trained using the Levenberg–Marquardt optimization algorithm and employed a logistic sigmoid activation function in the hidden layers. Once the input and output variables were transformed into numerical arrays (datasets), the supervised learning process was initiated.

To test the model's generalization ability, new material combinations and proportions were introduced during the testing phase. The model's ability to accurately predict outcomes for previously unseen data highlights its effectiveness in capturing the complex physical behavior of RC elements. This approach ensures that both input and output responses are appropriately learned and validated within the training domain.

3.2 ANN model development

To evaluate the predictive performance of different input configurations and network structures, eight distinct ANN models were developed and tested for estimating the load-carrying capacity of RC beams with stirrups (BWS). Each model, labeled BWS-1 through BWS-8, was designed using varying combinations of input parameters and network architectures, as detailed in Table 2. The goal of this approach was to identify the most effective model configuration in terms of accuracy, generalization, and alignment with physical behavior. These models incorporated a range of geometric, material, and derived parameters, while the architectures varied in terms of the number of input neurons, hidden layers, and neurons per layer. By systematically comparing the results of these eight configurations, the study aims to determine the optimal ANN structure for reliable prediction of shear strength in RC beam elements.

ANN label	Parameters considered	No. of parameters	Network architecture
BWS-1	b, d, a_v/d, ρ_l, f_{yl}, f_c, ρ_w, f_{yw}	8	8-16-16-1
BWS-2	b, d, a_v/d, M_f, f_c, ρ_w, f_{yw}	7	7-14-14-1
BWS-3	b/d, a_v/d, $M_f/f_c bd^2$, ρ_w, f_{yw}	5	5-10-10-1
BWS-4	b/d, a_v/d, ρ_w/ρ_l, f_c/f_{yw}	4	4-8-8-1
BWS-5	d, a_v/d, M_f/bd^2, f_c, $\rho_w \cdot f_{yw}$	5	5-10-10-1
BWS-6	d, b/d, a_v/d, $M_f/f_c bd^2$, ρ_w, f_{yw}	6	6-12-12-1
BWS-7	d, b/d, a_v/d, $M_f/f_c bd^2$, f_c, ρ_w, f_{yw}	7	7-14-14-1
BWS-8	d, b/d, a_v/d, $M_f/f_c bd^2$, f_c, $\rho_w \cdot f_{yw}$	6	6-12-12-1

Table 2: Summary of the eight developed ANN models (BWS-1 to BWS-8), showing the input parameters considered, the number of parameters used, and the corresponding network architecture for each model.

The performance results of the eight ANN models (BWS-1 to BWS-8) are illustrated in Figure 5 and Figure 6. Figure 5 presents scatter plots showing the correlation between predicted and experimental values of V_u for each model, providing a visual assessment of prediction accuracy. Figure 6 quantitatively evaluates each model using three key statistical metrics: mean squared error (MSE), mean absolute error (MAE), and Pearson's correlation coefficient (R).

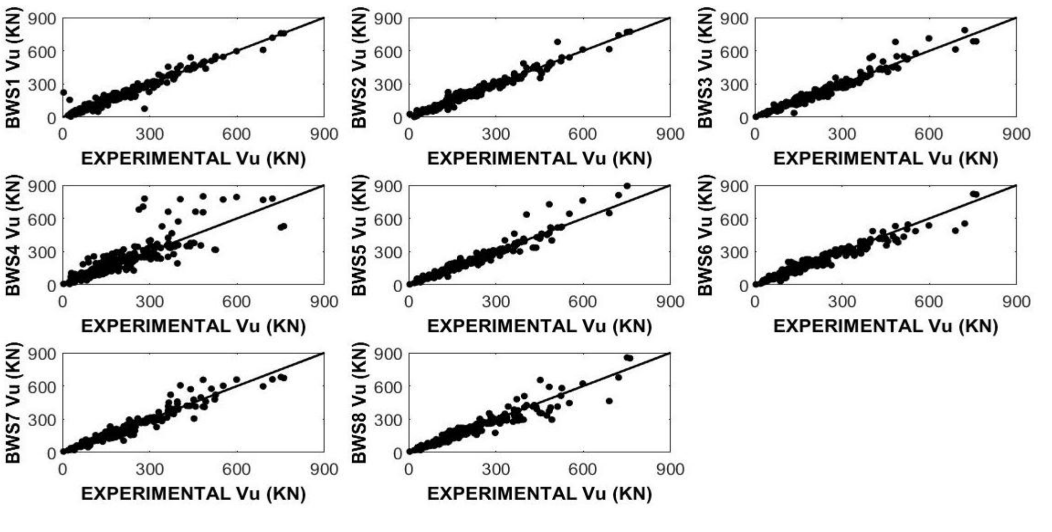


Figure 5: Comparison of predicted shear capacity (V_u) vs. experimental values for the eight ANN models (BWS-1 to BWS-8).

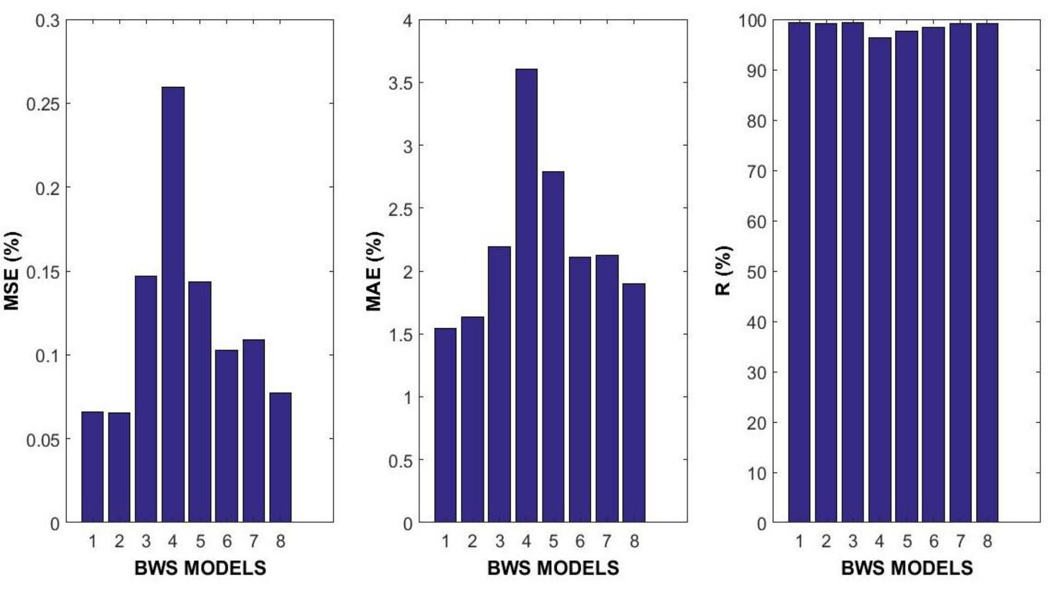


Figure 6: Statistical performance metrics for the eight ANN models (BWS-1 to BWS-8).

These metrics offer insight into each model's accuracy and generalization capability, following the evaluation framework outlined in previous studies [27, 32, 34, 35, 38, 39]. Among the tested models, BWS-7 achieves the best overall performance, exhibiting the lowest error values and the highest correlation coefficient. This model utilizes a well-balanced set of seven input parameters: beam depth (d), width-to-depth ratio (b/d), shear span-to-depth ratio (a_v/d), normalized moment capacity parameter ($M_f/f_c bd^2$), concrete compressive strength (f_c), transverse reinforcement ratio (ρ_w), and yield strength of web reinforcement (f_{yw}). The BWS-7 configuration effectively captures the structural behavior and delivers the most reliable predictions among the models tested.

4 COMPARATIVE STUDY OF THE ANN MODEL WITH DESIGN CODES

This section presents a comparative evaluation of shear capacity predictions for reinforced concrete beams with stirrups (RC BWS) using three distinct approaches: conventional design codes, the CFP method, and the data-driven ANN model—specifically, BWS-7. The predicted shear capacities from each method are benchmarked against experimental results to assess their accuracy and reliability.

As illustrated in Figure 7, the ANN model (BWS-7) exhibits the strongest correlation with experimental data, outperforming the traditional design codes and other alternative methods. This highlights the potential of ANN-based approaches, which rely on heuristic, data-driven learning, to capture complex structural behavior more effectively than conventional, mechanics-based formulations.

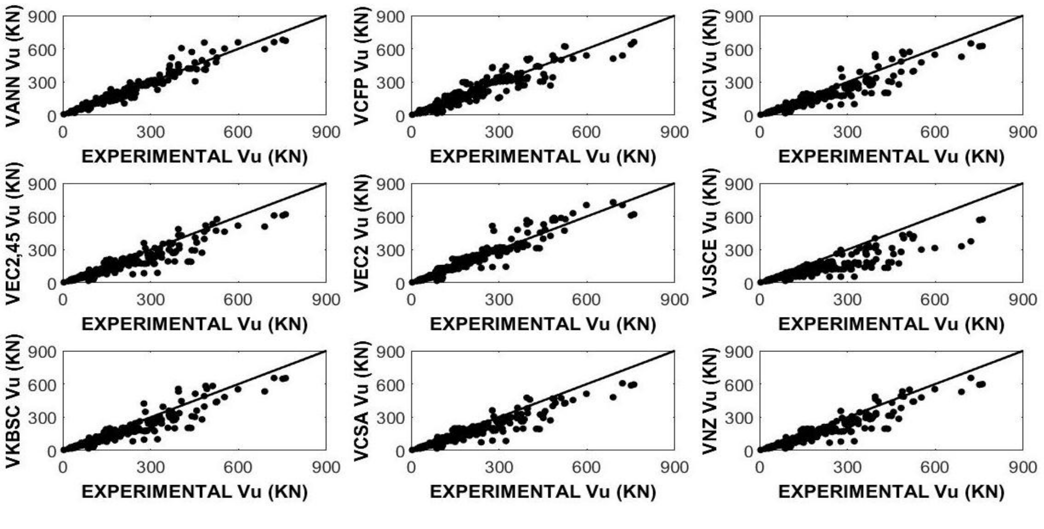


Figure 7: Comparison of predicted vs. experimental shear capacity (V_u) for RC beams with stirrups using the ANN model (BWS-7), the CFP method, and various international design codes.

While methods such as EC2 [7], CFP [12], and other design code-based approaches [8-11] provide reasonable predictions, their accuracy varies across the dataset. Notably, the CFP method, despite relying on non-traditional physical assumptions, delivers predictions that closely align with experimental results. However, the ANN model consistently shows superior agreement with experimental results across the full range of tested values, demonstrating its robustness and adaptability in modeling RC beam behavior beyond the limitations of code-based approximations.

Figure 8 illustrates the distribution of prediction accuracy for all methods, represented as the ratio of experimental to predicted shear capacity (V_{EXP}/V_{PRE}). The results reveal that traditional RC design codes—such as ACI-318 [6], EC2 [7], JSCE [8], NZ [9], KBSC [10], and CSA [11], as well as the CFP method [12], tend to underestimate shear strength. This tendency is evident from the larger number of predictions falling outside the acceptable range of 0.76–1.25.

In comparison, the ANN model (BWS-7) demonstrates superior predictive consistency, with the majority of its results concentrated within the desired accuracy interval. Conversely, the CFP method and most code-based approaches show significantly higher frequencies in the underestimation zones (1.26–2.00 and 2.01–12.00), reinforcing their conservative nature. These findings underscore the variability in prediction performance across methods and highlight the ANN's advantage in delivering more balanced and accurate shear strength predictions for RC beams with stirrups.

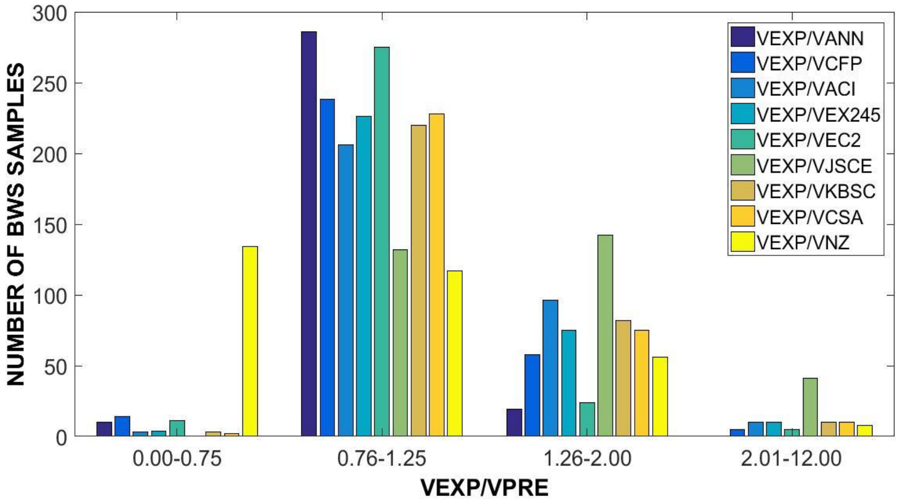


Figure 8: Distribution of prediction-to-experiment ratios (V_{Exp}/V_{PRE}) for RC beams with stirrups (BWS) across different methods.

5 CASE STUDY: ANALYSIS OF INDETERMINATE RC BEAM SPECIMENS

In this study, the proposed ANN–FEA methodology is applied to analyze indeterminate reinforced concrete beams with stirrups (RC-BWS) and conventional cross-sections [32]. The case involves beams subjected to a combination of axial compression (N) and a mid-span transverse load (P) applied to the longer span. The loading and support configuration are shown in Figure 9, which represents a continuous beam tested under realistic loading conditions as reported in [12].

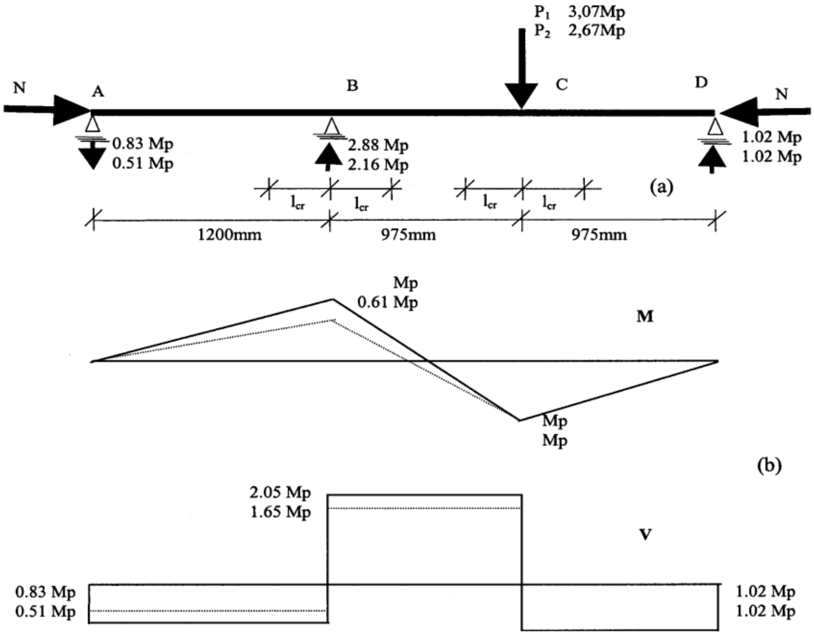


Figure 9: Experimental setup, loading scheme, and internal force diagrams for the indeterminate RC beam specimens [12].

5.1 Specimens with CN=0 and CN=180 kN

To evaluate the structural behavior of statically indeterminate RC beams, three analytical approaches were employed: the proposed ANN-FEA model [32], ABAQUS [13], and SAP2000 [14]. The numerical results obtained from these methods were systematically compared with corresponding experimental data. The experimental study [12] focused on two beam specimens subjected to different axial compression levels: CN = 0 kN and CN = 180 kN. The geometric and reinforcement details of these specimens are presented in Figure 10, which provides a complete overview of the design configuration and loading conditions used in the tests.

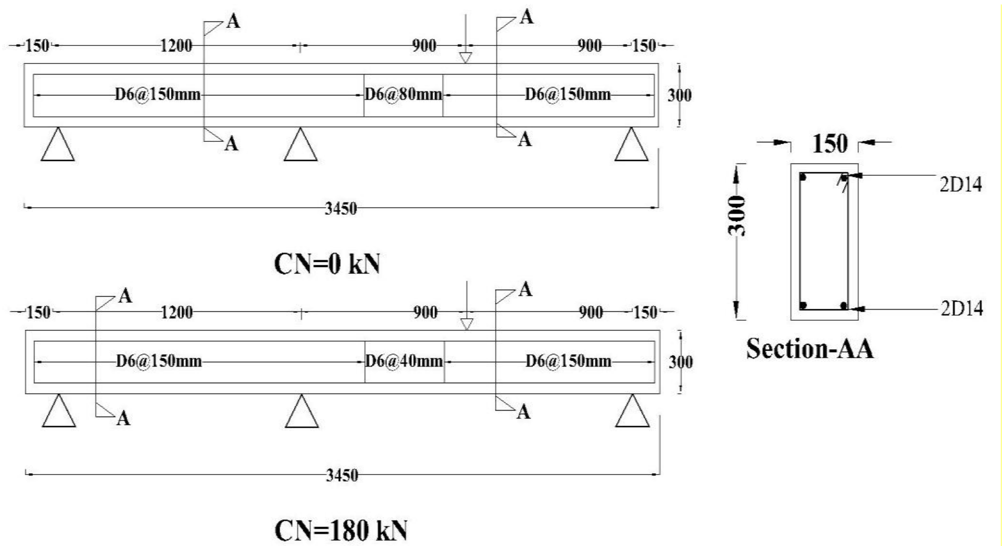


Figure 10: Geometric and reinforcement details of the indeterminate RC beam specimens subjected to axial compression levels of CN = 0 kN and CN = 180 kN [12].

Figure 11 presents a comparative assessment of experimental observations and numerical predictions for indeterminate RC beams subjected to axial loads of (a) CN=0, and (b) CN=180 kN. The results are obtained from three analytical approaches: the ANN–FEA model [32], ABAQUS [13], and SAP2000 [14]. The first row (Experiment) displays the observed cracking patterns at the ULS. The second row (SAP2000) highlights the formation and location of plastic hinges, indicating flexural failure zones as identified through SAP2000 analysis. The third row (ABAQUS) illustrates the distribution and intensity of concrete damage predicted by finite element simulations in ABAQUS as the beam approaches failure. The fourth row (ANN-FE) shows the failure mode predicted by the ANN–FEA methodology.

This visual comparison demonstrates the capacity of the ANN–FEA model to replicate experimental outcomes with high fidelity, while also highlighting the distinct representation of damage and failure in each numerical approach.

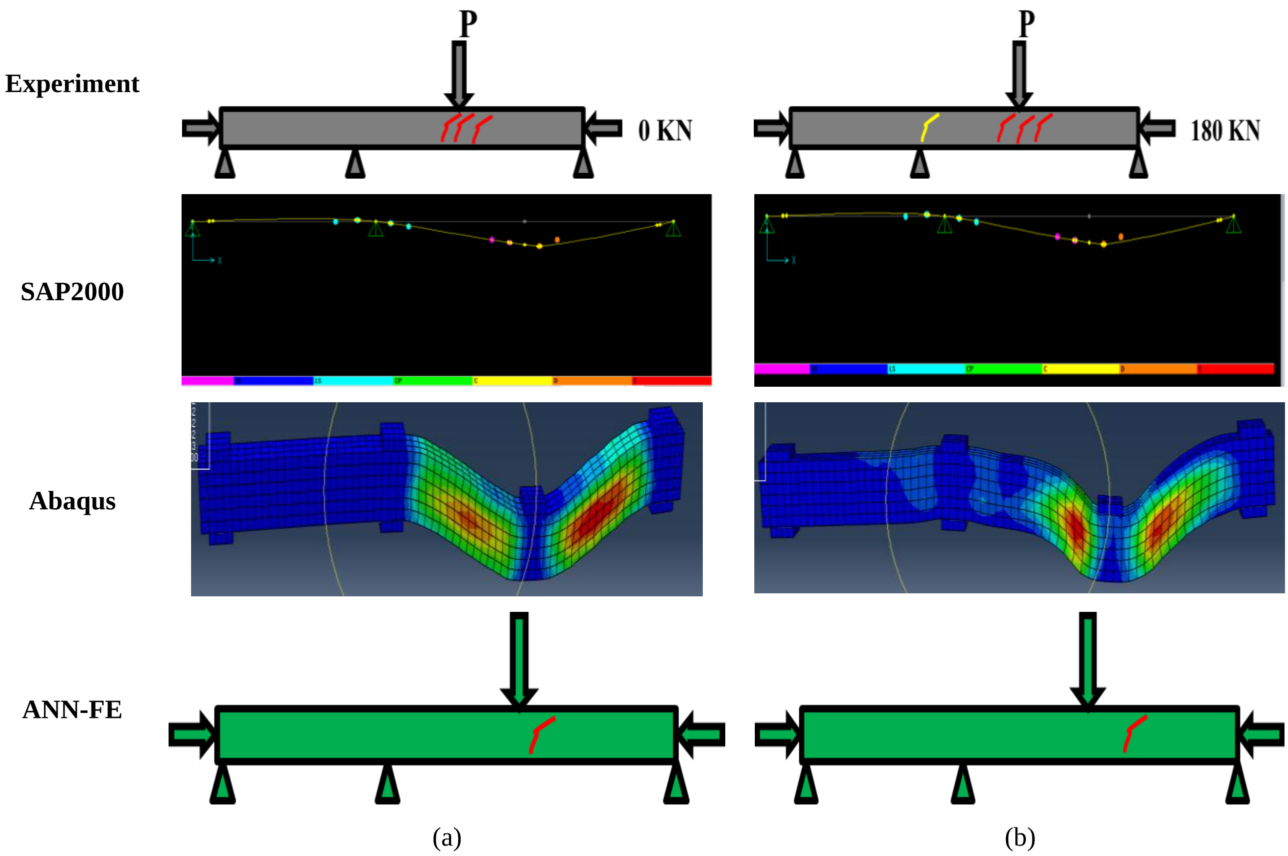


Figure 11: Comparison of experimental and numerical results for indeterminate RC beam specimens under axial loads: (a) CN = 0 kN; (b) CN = 180 kN [12].

Figure 12 presents a comparative analysis of the load–deflection behavior for RC beam specimens under axial loads of (a) CN=0, and (b) CN=180 kN. The curves capture the full loading response up to the ULS, as observed experimentally and predicted by SAP2000, ABAQUS, and the ANN–FEA model [32].

The results show that the ANN–FEA model accurately replicates the experimentally observed failure behavior, including crack initiation and progression, especially in the post-peak region. ABAQUS also exhibits strong alignment with the experimental curves, capturing both stiffness and ultimate capacity effectively. In contrast, SAP2000 tends to overestimate the load-carrying capacity, reflecting its limitations in modeling nonlinear behavior and brittle failure modes.

These findings underscore the enhanced predictive accuracy of both the ABAQUS and ANN–FEA approaches, particularly in capturing complex structural responses under combined axial and transverse loading. Their reliable simulation of load–deflection behavior reinforces their suitability for advanced structural analysis and design of RC elements.

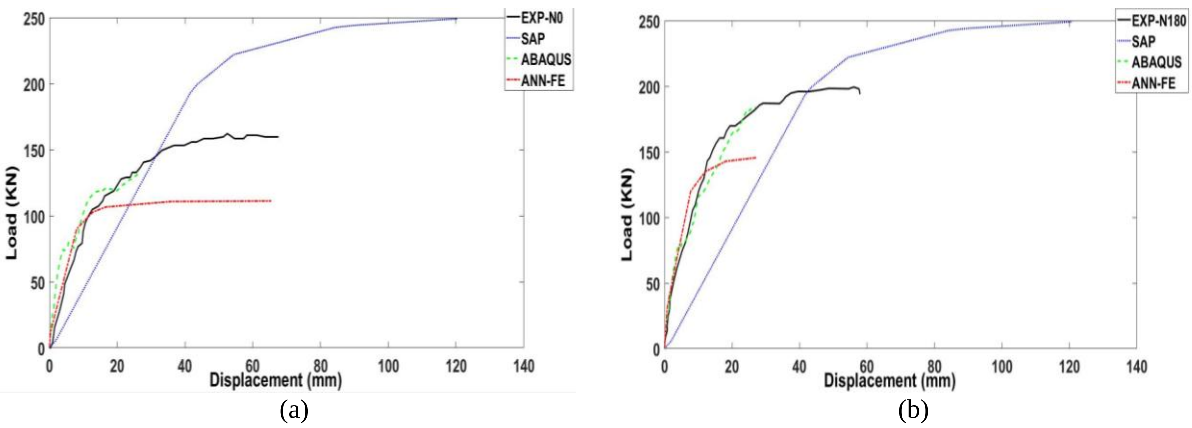


Figure 12: Comparison of load–deflection curves for indeterminate RC beam specimens under axial loads at ULS: (a) CN = 0 kN; (b) CN = 180 kN.

6 DISCUSSION AND CONCLUSIONS

The proposed ANN–FEA methodology [32] has been specifically developed for the nonlinear static analysis of RC frame structures under pushover loading. Based on the results of the four investigated cases, the method has demonstrated strong capability in accurately predicting the structural response of shear-critical RC elements. Its predictive performance is particularly notable in complex scenarios, such as indeterminate RC beams, where conventional tools often fall short.

The following key conclusions can be drawn from the study:

- **Importance of Shear Effects**: Accurately evaluating the strength and ductility of RC frames requires explicit consideration of shear effects. Neglecting these effects can lead to unsafe or overly optimistic assessments—particularly relevant given the continued use of shear-critical frames in real-world applications.

- **Limitations of Common Professional Tools**: Widely used structural analysis programs like SAP2000 [14] tend to oversimplify or ignore shear effects. As a result, they often overestimate both the strength and ductility of RC structures in shear-critical conditions, potentially compromising the accuracy and safety of structural designs.

- **Strengths and Constraints of Research-Grade Tools**: High-fidelity platforms such as ABAQUS [13] provide more accurate simulations that align closely with experimental data. However, their use is hindered by significant computational demands and longer analysis times, which can limit their practicality for routine engineering tasks.

- **Advantages of the ANN–FEA Model**: The proposed ANN–FEA approach offers an efficient, accessible, and accurate alternative for nonlinear analysis. It successfully replicates key aspects of experimental behavior—such as crack initiation, load-bearing capacity, and post-peak response—making it a powerful tool for assessing shear-critical RC frames with high precision.

In conclusion, the ANN–FEA methodology represents a meaningful advancement in the nonlinear analysis of RC structures. By addressing the limitations of existing professional and research tools, it provides a practical and reliable framework for structural assessment. Its ability to simulate complex behaviors under combined loading with minimal computational effort makes it a promising solution for safer, more efficient, and realistic RC design and evaluation practices.

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