

UNIVERSITY OF BAHRAIN

College of Engineering



Department of Civil Engineering

Strength Prediction of Reinforced Concrete Beam-Column Joints through Machine Learning

A Thesis Submitted in Partial Fulfilment of the Requirements for the
M.Sc.Degree in Civil Engineering

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February 2024

بسم الله الرحمن الرحيم

Defense Committee's Approval

University of Bahrain
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☐ Without making any changes to the thesis.

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Modified by University Council Decision No. 2043/2013 dated 20/11/2013.

Abstract

Recent destructive earthquakes like the Indian Ocean earthquake and tsunami (2004) in Indonesia, the earthquake and tsunami Sichuan (2008) in China, the Tōhoku earthquake and tsunami in Japan (2011), the Gorkha earthquake and tsunami in Nepal (2015), and the Turkey–Syria earthquakes (2023) in Turkey and Syria have demonstrated structural deficiencies that have caused significant loss of life and economic damage. Most of these buildings were lacked in seismic reinforcement and had poor seismic designs. Inadequate seismic reinforcement in beam-column joints, load-bearing walls, and columns are the major source of damage in reinforced concrete structures during seismic event.

Most reinforced concrete (RC) buildings built in the 1980s were not seismically detailed; instead, they were designed for gravity loads. In seismically active areas, these kinds of structures are widely accessible worldwide. Beam column joints play an essential role in integrating structural systems in reinforced concrete structures. Beam-column joints (BCJs) are critical components in reinforced concrete (RC) structures, which undergo high stress under seismic events. The shear strength of these joints needs to be predicted to ensure the overall safety of structures during an earthquake event.

One of the greatest motivations for this study is to predict the shear strength of such joints that have no seismic reinforcement. The use of machine learning (ML) approaches in conjunction with finite element analysis (FEA) approaches has recently seen a lot of interest from the research community. In this study, ML-ANN has been utilized to predict the strength of RC-BCJs with a lack of seismic detailing. Developing ANN model needs data for training, validation and testing the ANN model. Thus, data is crucial for ANN models to perform better. In this study, data sets needed for the ANN model have been generated using FEA software ABAQUS. Different BCJs were simulated in ABAQUS, considering seven influential design parameters as inputs for the ANN model. The input parameters used for the collection of data sets were column depth, beam depth, concrete compressive strength, beam tension reinforcement total area, beam tension reinforcement yield strength, axial column load as a ratio of its capacity, and the joint area. The total number of 6480 BCJs were simulated in ABAQUS and analyzed. After reviewing the results of FEM analysis flexure failure samples were discarded and the samples with joint shear failure were considered only.

The total number of samples with joint failure was 4320, which has been used to develop the proposed model. The data set of FEA samples was divided into three sets: 1) training set 70% (3024 samples), 2) testing set 15% (648 samples), and 3) validation set 15% (648 samples). These sets were utilized to develop an ANN model to predict the shear strength of RC-BCJ as an output variable. The performance of the proposed ANN model was validated using the testing data set of 648. The proposed model showed 95.6% accuracy in predicting the shear strength of the BCJ samples data. In addition, the testing data was also compared to the ACI code equation along with the ANN proposed model. It has been found that the proposed model accurately predicts the shear strength of the exterior RC-BCJs as compared to the ACI equation. Moreover, the shear strength of 80 BCJs collected from the literature was predicted through the ANN model. It has been observed that the proposed ANN model accurately predicts the shear strength of BCJs with an average accuracy of 91.5%.

Participations

Strength Prediction of Reinforced Concrete Beam-Column Joints through Machine Learning

The Annual Postgraduate Student's Forum 2023, Venue: University of Bahrain, Sakhir Campus, Date: 4th May 2023, Organizer: Deanship of Graduate Studies and Scientific Research.

Status: Abstract accepted and presented.

Dedication

To my children, husband, mom, and family

Acknowledgments

First and foremost, I would like to praise Allah the Almighty, the most gracious, and the most merciful for his blessing given to me along my master's study and thesis.

I would like to sincerely thank and express my gratitude to Dr. Muhammad Ajmal, my supervisor, for his time and effort while providing me with the guidance and support needed through my master's thesis journey.

I would also like to express my deep thanks to Ibrahim, my husband, for his continuous encouragement and support throughout this journey. This would not have been possible without his help and belief in me.

To my children, Farah and Yahya, you are my inspiration to achieve greatness.

Many thanks to my parents and family for their love, support, and prayers along this journey.

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Abbreviations

ACI	American Concrete Institute
ADaBOOST	Adaptive Boosting Algorithm
AI	Artificial Intelligence
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
ASCE	American Society of Civil Engineers
BCJ	Beam-Column Joint
BNN	Backpropagation Neural Network
BR	Bayesian Regularization Algorithm
CDP	Concrete Damage Plasticity
CFRP	Carbon Fiber-Reinforced Plastic
CPU	Central Processing Unit
DL	Deep Learning
EC	Eurocode
ELM	Extreme Learning Machine
FEA	Finite Element Analysis
FEM	Finite Element Method
FFBPN	Feed Forward Back Propagation Network
FFNN	Feed Forward Neural Network
GRNN	General Regression Neural Network
KNN	K-Nearest Neighbor Regression
LM	Levenberg-Marquardt Algorithm
LR	Linear Regression
MARS	Multivariate Adaptive Regression Splines
ML	Machine Learning
MLR	Multiple Linear Regression
MSE	Mean Square Error
OLS	Ordinary Least Squares

R	Coefficient of Correlation
R^2	Coefficient of Determination
RAC	Recycled Aggregate Concrete
RBFNN	Radial Base Function Neural Network
RC	Reinforced Concrete
RMSE	Root Mean Square Error
SI	Scatter Index
SR	Symbolic Regression
SSE	Sum of Squared Errors
SVM	Support Vector Machines
3D	Three-Dimensional

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Chapter One

Introduction

Chapter 1 Introduction

1.1 General

RC structures are available extensively around the world, and they are the most used type of construction. Many RC structures are constructed prior to the seismic design development in the code provisions. Most of these structures are vulnerable to high lateral loads -like seismic loads- due to little or lack of transverse reinforcement in beam-column joint regions as given in Figure 1.1. Beam-column joints are the most critical component in RC structures that is a key part in integrating the structure's overall stability. If BCJ regions experience shear failure, that could cause structural collapse, as shown in Figure 1.2.

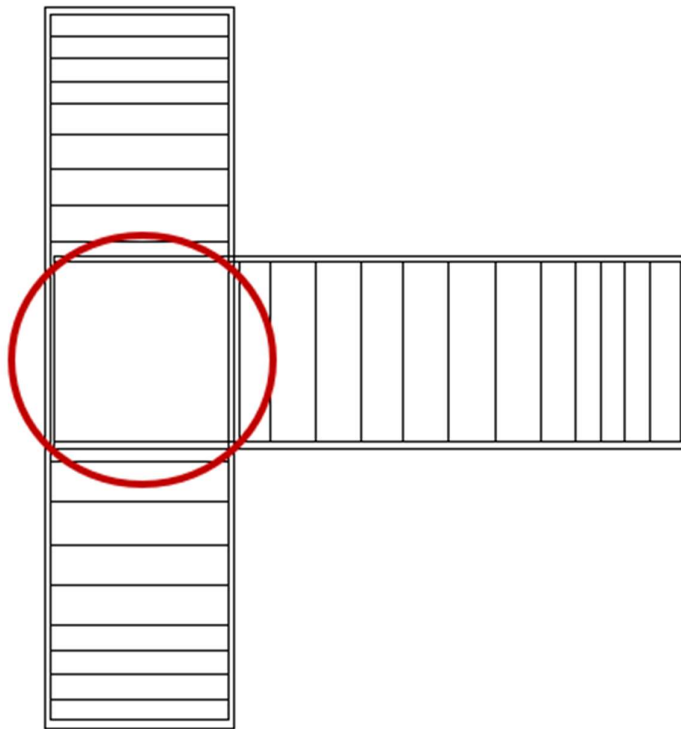


Figure 1.1 Unreinforced Beam-Column Joint



Figure 1.2 Typical BCJs during earthquake in Turkey (1999) and Algeria (2003) (Ajmal, 2016)

Beam-column joints contribute significantly to the loss of vertical load-carrying capacity of gravity-load-designed structures during earthquake events (Ajmal, 2016). Serious danger could occur if beam-column joint region design is neglected or improperly designed.

Connections are classified as exterior, interior, and corner connections depending on their location in the structure. Figure 1.3 presents different connection classifications. In exterior connection, the joint has a higher potentiality of failing when compared to other types of joints because they are less confined, have less axial loads, and due to torsional effect that happens for exterior joints because they are far away from center of rigidity. There are two major failure mechanisms of BCJs: shear failure and end anchorage failure. Shear failure is mostly observed failure mechanism and is caused by shear stress at the joint which developed from resultant moment and shear force at the member end. Most of the old structures that were constructed prior to the seismic designed codes do not have any shear reinforcement in the joint area. Poor or lack of joint detailing, weak-column strong beam design, and inappropriate beam longitudinal bar anchorage are the reasons for joint failure and

general loss of sufficient strength and ductility required by the design code (K. Marimuthu & Kothandaraman, 2019).

Many design parameters contribute to the strength and ductility of beam-column joint. Researchers have reported that the compressive strength of concrete and the rate of transverse reinforcement at the joints are the main influential parameters on joint behavior. Other parameters include beam tension steel detailing, presence of ties within the joint, position of tie within the joint, joint aspect ratio, and column axial force. The behavior of beam-column joints under seismic loading is still not well understood due to their critical location in structure and the contribution of many parameters to their strength (Alva, Eldebs, & Eldebs, 2007).

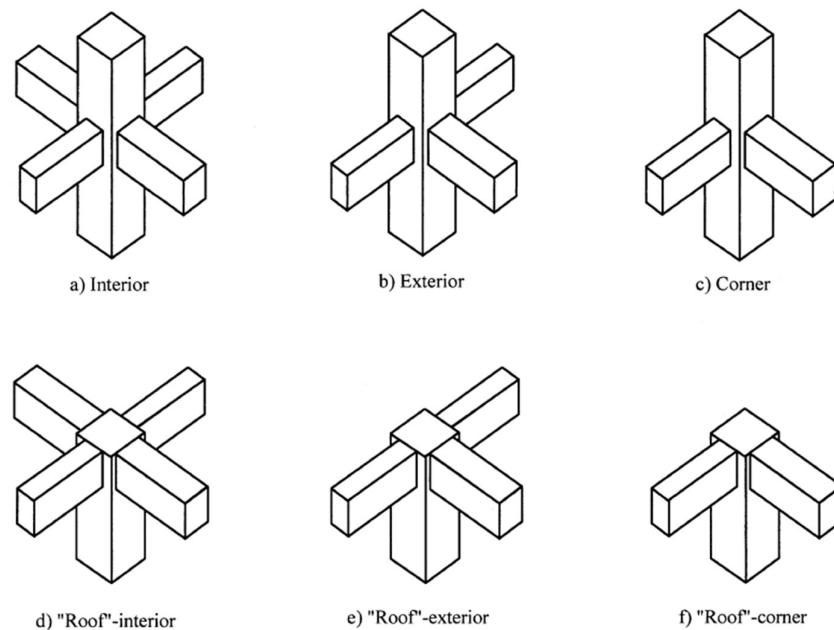


Figure 1.3 Typical types of beam-column connections (ACI-ASCE Committee 352, 2002)

ML is one type of artificial intelligence (AI) and it can be defined as a science in which a machine can be able to perform a task without being explicitly programmed by the actions and steps required for performing a task. The capability of machines of reasoning, learning, planning, and

creativity simulates how humans can do so on (What is artificial intelligence and how is it used?, 2020). One type of ML technique is ANN. ANN is a computational system with inspiration from biological neural cells in the brain for its architecture and operation. ANN is an adaptive system that learns from data examples by using interconnected nodes or neurons in a layered structure that mimics a human brain. ANN can find the relation between inputs and outputs for the complicated relationship. It can be used for complicated regression and classification too. It is a powerful tool in regression, where it maps the inputs to the output using a nonlinear relationship.

In the last two decades, machine learning has become an important tool in the engineering field to find the solution to many engineering problems. Many structural engineering problems have been solved using different machine learning techniques, and these techniques showed promising results in predicting the solution. ANN algorithms are very powerful predictive tools, but due to their complexity, they generally do not provide analytical relationships between the input and output data and are often referred to as “black boxes” as the user loses insight into the underlying physics.

The use of ML approaches in conjunction with Finite Element Method (FEM) has recently seen a lot of interest from the research community. Advancing computational techniques and the capability of computers have led to a better performance of different machine learning techniques. In addition, the data needed for different machine learning techniques is not a problem anymore since that data can be produced using reliable simulation software that depends on the FEM, such as ABAQUS.

This research is about prediction of exterior beam-column joint strength that is without joint reinforcement using machine learning

technique: ANN. Feed Forward Back Propagation Network (FFBPN) was used to develop the prediction model depending on the data produced from Finite Element non-linear analysis software called ABAQUS.

1.2 Research Problem

How to predict the shear strength for exterior reinforced concrete beam-column joints. Moreover, how to predict that shear strength using simple parameters from the connection and avoiding the long simulation or experimental work. That was selected as the research problem in this study.

1.3 Research Questions

- What is the shear strength of an exterior reinforced concrete beam-column joint that is without joint transverse reinforcement (unconfined joint)?
- What is the performance of the machine learning technique that is used in the BCJ strength prediction in terms of accuracy when compared to literature and testing data.

1.4 Research Objectives

- To develop a model for strength prediction of reinforced concrete beam-column joint using machine learning technique.
- To compare the performance of machine learning model in the prediction of the reinforced concrete beam-column joint strength with the literature.

1.5 Research Significant

The main significance of this research is predicting the strength of the exterior beam-column joint, which can be used in the design of the

reinforced concrete structure to prevent the failure of the joints and ensure the structure stability that affects people's safety.

Also, this research provides a prediction model for RC-BCJ's strength that can be utilized for old RC structures. It is necessary to check the strength of these buildings' joints in order to examine them and ensure the overall safety of the structures. It will be beneficial to show whether the structures' beam-column joints require strengthening and retrofitting. This way, human lives and safety will be maintained.

Another benefit is to save the structural engineer's time and effort required to calculate the strength of beam-column joint, where the engineer can easily check how much the strength of beam-column joint shear capacity before deciding the final dimension of the connection and other design parameters that are contributing to the strength of beam-column joint.

Moreover, the final model in this research will have a shortcut to show how effective is each design parameter on the joint strength and can give an idea to the engineer on how the capacity of the joint can be increased using different parameters, not just the main one. This can be effective for reducing the cost of building a reinforced concrete structure while following the design code requirement for safety under the designed loads.

Furthermore, this research provides a conclusion on the machine learning technique applicability for solving structural problems while it uses finite element analysis results rather than experimental data to provide the data required for training, validating, and testing. Hence, the required data can provide the artificial neural network with the examples needed for learning without affecting the economy with the high cost of experiments

and without affecting the environments with high carbon dioxide emissions due to testing.

1.6 Research Scope

The scope of this research is to develop a machine learning model that can predict the strength of exterior reinforced concrete beam-column joints that are without joint reinforcement. The size and quality of training data for machine learning techniques are very important factors affecting the accuracy and performance of the prediction model. Therefore, to collect a wide range value of data for unreinforced beam-column joints (weak joints), a finite element software ABAQUS was used to produce the required data in this research which is not available in the literature by varying sizes of beam-column joints. Seven input parameters were decided depending on their importance on the strength of the BCJ, as investigated in many previous studies. The design variables that are mentioned previously in section 1.1 are varied in a wide range to provide various data values for the machine learning to perform better. The seven input parameters are column depth (h_c) in mm, beam depth (h_b) in mm, concrete compressive strength (f_c') in MPa, beam tension reinforcement total area (A_{st}) in mm^2 , beam tension reinforcement yield strength (f_y) in MPa, axial column load as a ratio of its capacity (P_y), and the joint area (A_j) in mm^2 . The Concrete compressive strength range started at 17 MPa and ended at 60 MPa with approximately 5 MPa intervals. Column and beam depth vary from 150 mm to 600 mm with approximately 100 mm intervals. Beam tension reinforcement rebars are varied using 16, 20, and 25mm diameters, allowing three different values of reinforcement area (A_{st}). The beam tension reinforcement yield varies too as 460 and 660 MPa. Axial force on column is provided by using three different values as a ratio from column capacity with 5%, 10%, and 15% percentage of column axial capacity,

where column load carrying capacity is being affected by the lateral loading and that is why different percentage of column capacity was considered as one parameter. Moreover, the joint area was used as an input parameter, which gave the model faster convergence when added as input parameters while developing the machine learning model. The mentioned range of parameters provided the research study with 6480 possible samples for exterior connection beam-column joints. The samples were simulated using the nonlinear finite element analysis software ABAQUS. The non-linear behavior of concrete was defined numerically using concrete damage plasticity (CDP), which was calibrated with one experimental test. That was essential for capturing the behavior of concrete failure behavior during beam-column simulations. The simulation of such a number of configurations was taking a lot of time, so a 12-CPU desktop was bought to run the simulation faster with the same required accuracy. The configurations results were filtered, and only the shear failure samples were considered in the study. Required data for ANN was extracted using Python scripts, MATLAB, and directly through ABAQUS.

After the collection of data, ANN (nonlinear regression) was deployed using MATLAB nftool to fit an artificial neural network. The hyperparameters of the ANN model were optimized after many trial models, and the most accurate model was picked as the final ANN model for this research. The model was checked for performance using mean square error (MSE), root mean square error (RMSE), and coefficient of correlation (R). Furthermore, the proposed ANN model was verified with experimental results collected from the literature for exterior connections. Finally, a comparison with the American Concrete Institute (ACI 318R-19) code provision was done to check the capability and performance of the proposed ANN model.

1.7 Research Outline

The thesis includes six chapters and is organized as follows. Chapter 1 outlines the introduction to the study. Chapter 2 discusses the theoretical framework and provides a literature review of beam-column joints and machine learning techniques - ANN. Chapter 3 describes the configurations details and data collection work. Chapter 4 explains the ANN prediction model development. The result, comparison and discussion are illustrated in Chapter 5. Finally, the conclusions are provided in Chapter 6.

Chapter Two

Theoretical Framework and Literature Review

Chapter 2 Theoretical Framework and Literature Review

2.1 Introduction

According to ACI 318-19 (2019), a joint is the intersection of members' portion of a structure, whereas the portion of adjoining members and a joint together is called a connection. The location of the reinforced concrete Beam-Column joint is very critical because it undergoes high stress under lateral loads like seismic and high wind loads.

Beam-column joint is a very important component in reinforced concrete structures, which affects the overall stability and integration of the structure. It is the responsible component for load transfer between beams and columns and enables these structure's components to reach their ultimate capacity. The behavior of RC structures under different loads is affected by the ductility, stiffness, and strength of beam-column joints (Abdelwahed, 2020).

Before the 1970s, reinforced concrete frames were constructed to withstand gravity loads without considering the seismic detailing in their design, and therefore, beam-column joints of such structures are with little or no transverse reinforcement. As a result, these structures are vulnerable to seismic loads, and shear failure of beam-column joints of such structures could cause structure collapse. On the other hand, modern reinforced concrete frames are designed using the seismic detailing provided in code provision [(ACI 318-19 Committee, 2019), (ACI-ASCE Committee 352, 2002), (ASCE/SEI 41-13, 2014)]. The proper design of beam-column joint is done by satisfying both strength and ductility requirements. To ensure the structure's safety, it is required to avoid any type of failure in column part and hence, move it to beam region. That is because if plastic hinge

formed in beam-column joint at column region may cause global failure of structure (Paulay & Priestley, 1992).

Joints that are built without transverse reinforcement could cause a brittle failure of the structure during seismic events. Brittle behavior in the joint compromises the ductility of the structure, which is an important aspect of design to save human lives and the economy. If beam-column joints in the reinforced concrete structures are not designed well, then the overall safety of structure is at risk of partial or full collapse.

The exterior beam-column joint consists of a framed column by a single beam where this joint type can face higher shear stress on the joint region. On the other hand, the interior joint consists of a column framed by two or more beams, and in this joint type, the shear force at the joint is small because of detracting the opposite side of the joint shear force from the opposite beams (Hamil, 2000).

This study focuses on the unreinforced exterior beam-column joint that is under monotonic loading. The shear capacity of these joints is predicted using machine learning techniques and validated with literature experimental specimens.

2.2 Exterior Beam-Column Connections Mechanism

Beam-column connections can undergo high stress under high lateral forces like seismic events. Many researchers have shown that beam-column joint is weak under shear stress if it is not reinforced at the joint area. According to Kiran and Genesio (2014), the most popular deficiencies of pre-1970s reinforced concrete frame structures are four: absence of transverse reinforcement at beam-column joint (unconfined joints), provision of plain bars for longitudinal reinforcement, insufficient anchorage detailing, and low concrete strength.

To design a beam-column joint for shear stress, its shear strength capacity has to be evaluated. Due to the complexity of joint location, many forces are being transmitted to the joint from the adjacent structural elements. Axial forces, moments, and shear forces affect joint strength and performance. Figure 2.1 shows the forces equilibrium within an exterior monotonic beam-column joint, where (P) is the applied load on beam's tip and (N) is the axial load on the top of column. Joint shear strength is mainly controlled by horizontal tension force from beam longitudinal reinforcement (T_b) and column horizontal shear force (V_c) (Paulay & Priestley, 1992).

The evaluation of joint horizontal shear force (V_{jh}) across joint region of exterior connection (see Figure 2.2) is defined as follows in equation (2-1) (Paulay & Priestley, 1992):

From the horizontal equilibrium equation, joint horizontal shear force (V_{jh}) can be evaluated as in equation (2-1).

$$V_{jh} = T_b - V_c \quad (2-1)$$

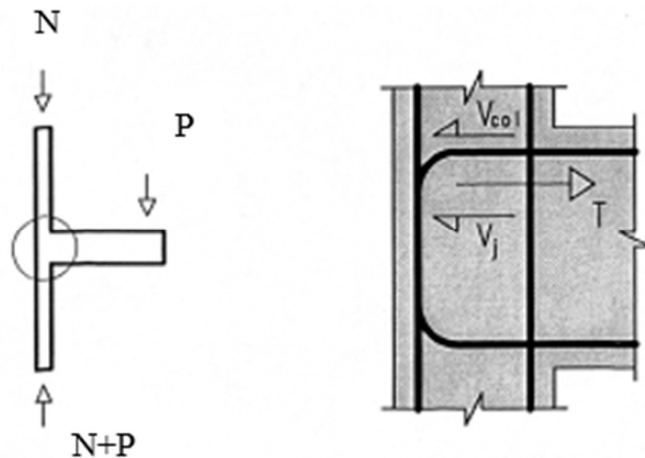


Figure 2.1 Forces equilibrium within an exterior monotonic beam-column joint (Hamil, 2000)

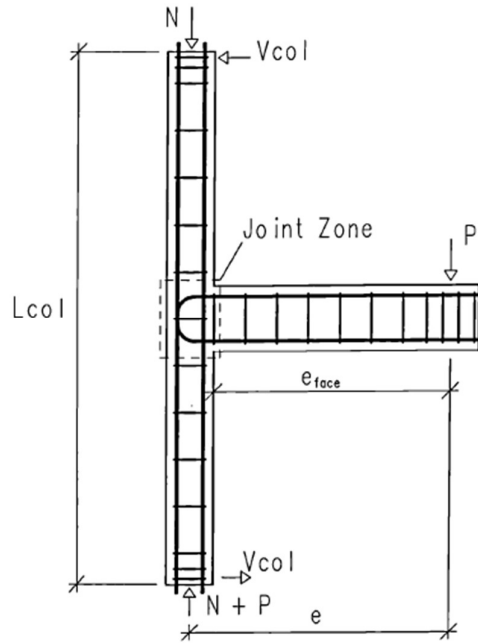


Figure 2.2 Exterior Connection Forces (Hamil, 2000)

Note that e_{face} in Figure 2.2 is the distance from the point load P to the face of the joint, while L_{col} is column length.

To calculate V_c , beam and column loading in the connection has to be understood first. Referring to Figure 2.3, Beam loading effect on joint is represented by the moment reaction at the interface of the joint (M_n). In equation (2-2)(2-2) the calculation of M_n depends on the point load (P) and the distance from P to interface of joint, (L_B). The moment within column is assumed to be the same as the moment at end of beam (M_n), where the inflection points in column have zero bending moment at the midpoint between the floors. Therefore, column horizontal shear force (V_c) can be calculated as follows in equation (2-3), where the distance between the inflection points is the length of column (L_C).

$$M_n = P \times L_B \quad (2-2)$$

$$V_c = \frac{M_n}{L_C} \quad (2-3)$$

Where:

L_C : is the length of column

L_B : is the distance from the face of the joint to the applied point load point

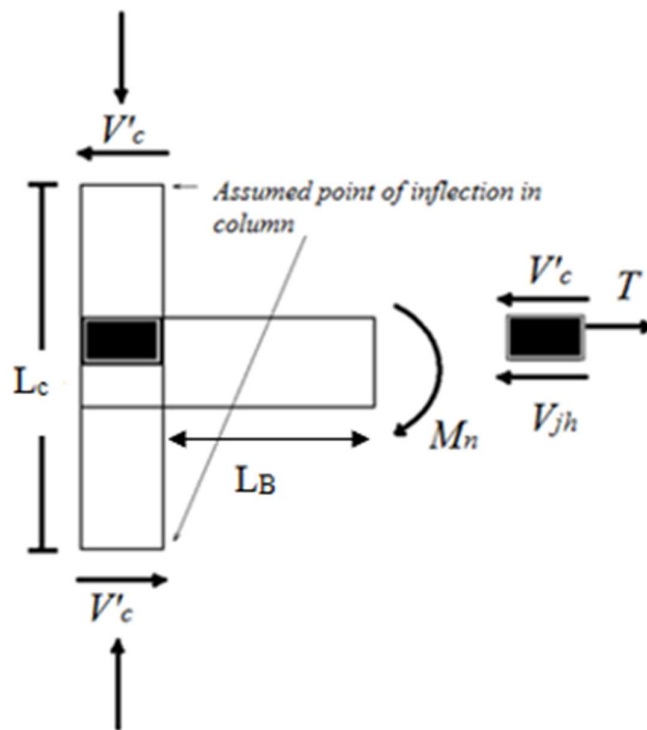


Figure 2.3 Schematic diagram for exterior BCJ Forces (Ajmal, 2016)

2.3 Nominal Joint Horizontal Shear Strength by ACI Code

Nominal joint horizontal shear strength (V_n) can be calculated according to the ACI 318-19 and ACI-352R-02 using equation (2-4). Using equation (2-5), the area of the joint A_j can be calculated, while the effective width of the joint can be calculated using equation (2-6). Figure 2.4 shows the schematic diagram for the depth and effective width of the joint according to ACI 318-19 committee.

$$v_n = \sqrt{f'_c} \times A_j \quad (2-4)$$

$$A_j = b_{effective} \times h \quad (2-5)$$

$$b_{effective} = \text{minimum} ((b + h), (b + 2X)) \quad (2-6)$$

Where:

b: beam width

h: joint depth (column depth)

x: half of the difference between column and beam width

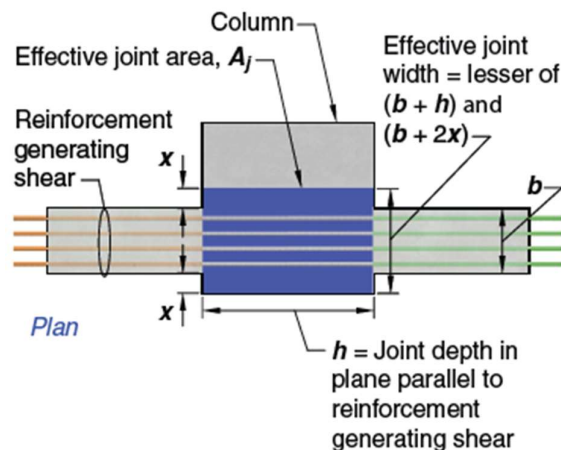


Figure 2.4 The schematic diagram for the depth and effective width of the joint according to ACI 318-19 committee

2.4 Monotonically Loaded Beam-Column Connection Failure Modes

Previous researchers have tested beam-column connections, and the method was as follows: first column is loaded with constant axial load during the testing. Then, beam is loaded with a series of downward increments until failure occurs. Different types of failure modes can occur in monotonically loaded beam-column connections and can be categorized as follows (Hamil, 2000).

2.4.1 Flexural Failure

When the joint has more strength than the intersecting members at the connection, these adjacent members flexural strength will govern the failure of the connection. It is important to have the required number of stirrups in beam to avoid shear failure in beam and let the flexural failure governed to ensure the yielding of beam rebars. Moreover, it is desirable to make the column stronger than beam to avoid column failure (Hamil, 2000). Figure 2.5 shows the flexural failure of beam which it is characterized by large cracks in beam near to column face where there is the point of the yielded reinforcement of beam.

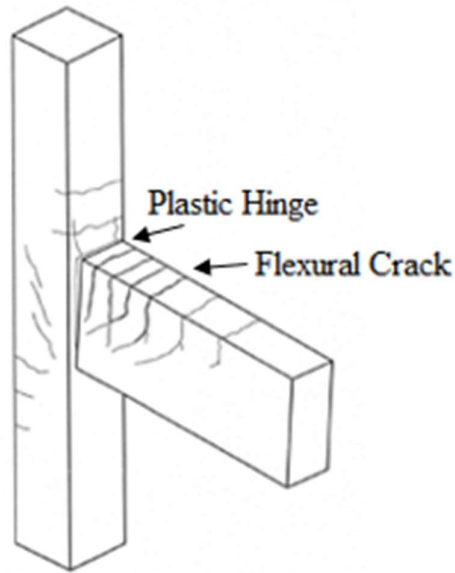


Figure 2.5 Diagrammatic representation of a beam flexural failure
(Hamil, 2000)

2.4.2 Joint Failure

When the shear strength of beam is higher than the strength of joint then joint failure will occur at that lower force. Figure 2.6 shows the joint failure that is characterized by extensive diagonal shear cracks in the joint region. Initial shear cracks start appearing in the joint region even before the ultimate shear strength of the joint and researchers reported that the joint even can withstand higher loading after the initial shear cracking has occurred.

This type of failure is usually accompanied by unconfined joints. A pure shear failure can occur in the joint region without developing any plastic hinge in beams or columns, which gives evidence that the flexural capacity of beams and columns is resisting loading without yielding. In addition, joint shear failure is a brittle failure, and by the effects of relatively small rotation, joint shear failure can happen (Murad, 2016). Therefore, the brittle behavior in this failure type has to be prevented and

well-designed. A good design can be possible with the precise prediction of the shear capacity of the joint and its behavior under loading.

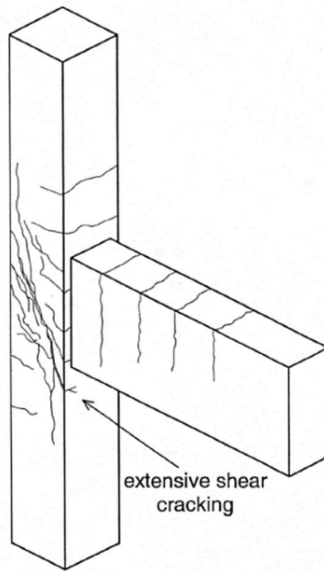


Figure 2.6 Diagrammatic representation of a joint failure (Hamil, 2000)

2.4.3 Anchorage Failure

Anchorage failure may occur when beam tension rebars are not sufficiently anchored within the joint. When beam tension rebars are being pulled out from the joint causing anchorage failure of the connection, the loading of beam at that failure is significantly lower than the loading required to reach the flexural strength of beam or the shear strength of the joint.

2.5 Exterior Beam-Column Joint Relevant Experimental and Numerical Investigations Literature Review

In the last few decades many researchers have studied the behavior of exterior beam-column connections under different loading types. Moreover, many experiments have been done to introduce the shear strength of the joint and its effect on the structure stability.

This section gives a brief review of the exterior beam-column joints experimental and numerical investigations. The review is carried out according to the date of the study, from the oldest to the latest. All the reviewed studies involve exterior reinforced concrete beam-column joints.

Ajmal (2016), studied the response of reinforced concrete exterior beam-column joints without seismic detailing (unreinforced joints) under cyclic loading. The study examines the joints experimentally and numerically using ABAQUS Finite Element method software for numerical analysis. The experimental work includes seven full-scale specimens where three of them were control specimens and the other were retrofitted connections. The geometry and reinforcement detailing of beam-column joints are shown on Figure 2.7. The specimens were tested under monotonic, cyclic and reverse cyclic loading. Figure 2.8 shows the testing setup. In Table 2.1 the description for control specimens and type of loading are described.

In Table 2.2 a comparison for the control specimens shear capacity is done between the test and FE analysis results. It has been noticed that the FE analysis prediction is performing very well in the prediction of the shear capacity for exterior BCJ when compared to the experimental results for

the same specimens. The load deflection curves of the three control specimens are shown in (Figure 2.9, Figure 2.10, Figure 2.11).

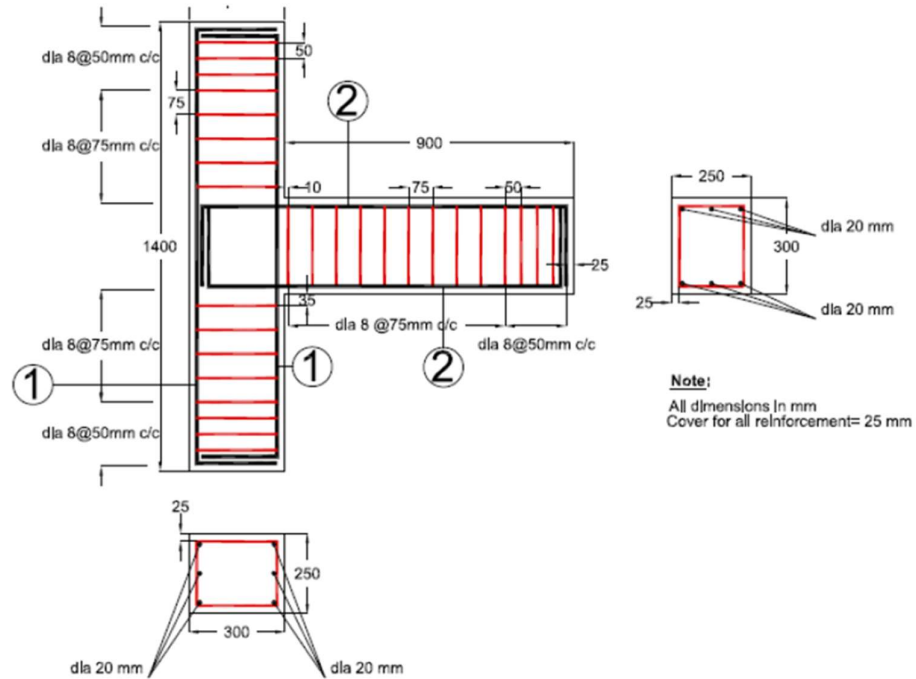


Figure 2.7 Geometry and reinforcement detailing of tested exterior beam-column joints (Ajmal, 2016)

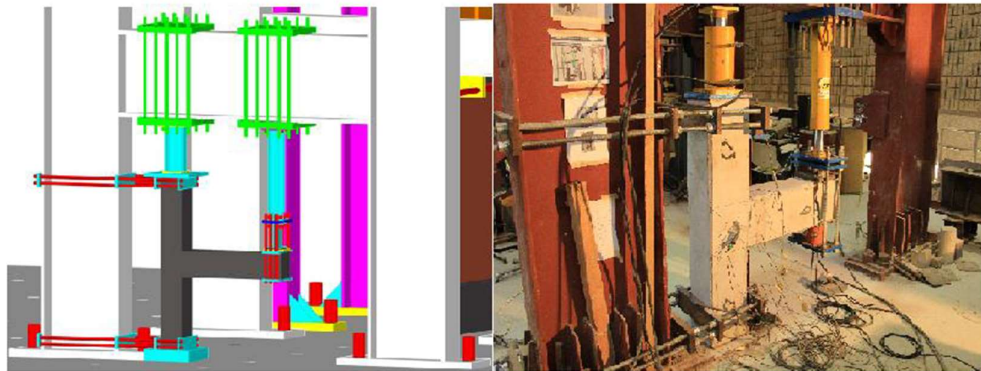


Figure 2.8 Testing setup (Ajmal, 2016)

Table 2.1 Specimens description and loading protocol (Ajmal, 2016)

Serial#	Specimen	Description	Loading
1	BCJ-M	Control specimen	Monotonic
2	BCJ-CL	Control Specimen	Cyclic
3	BCJ-RC	Control Specimen	Reverse Cyclic

Table 2.2 Comparison of joint shear capacity for control specimens obtained from experiment, and FEM simulations (Ajmal, 2016)

Specimens	V _{test}	V _{Mechanistic}	V _{FEM}	V _{test}	V _{predicted}	V _{FEM}	$\frac{V_{predicted}}{V_{test}}$	$\frac{V_{FEM}}{V_{test}}$
	kN	kN	kN	MPa	MPa	MPa		
BCJ-M	379.3	392.3	383.2	4.21	4.36	4.26	1.0	1.0
BCJ-RC	317.9	392.3	357.2	3.53	4.36	3.96	1.2	1.1
BCJ-CL	296.6	392.3	360.3	3.29	4.36	4.0	1.3	1.2

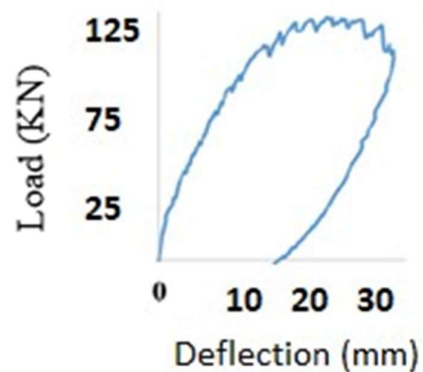


Figure 2.9 Load-Displacement response of monotonic control specimen (BCJ-M) (Ajmal, 2016)

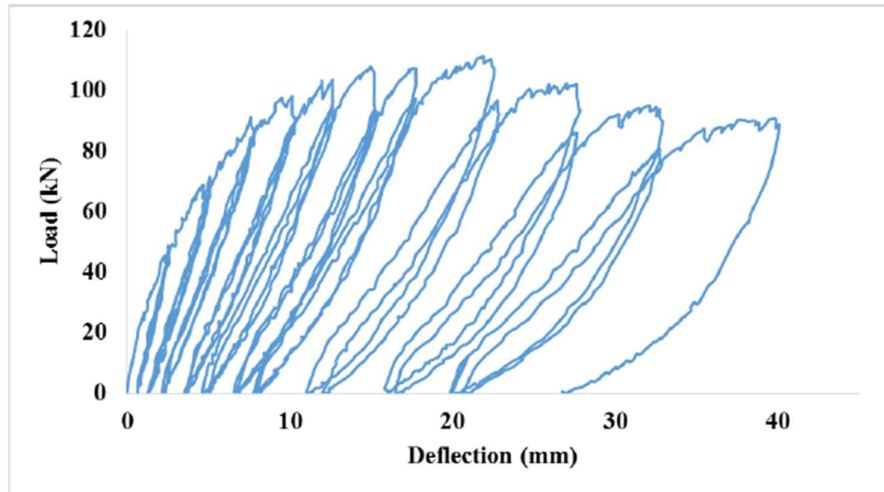


Figure 2.10 Load-Displacement response of cyclic control specimen (BCJ-CL) (Ajmal, 2016)

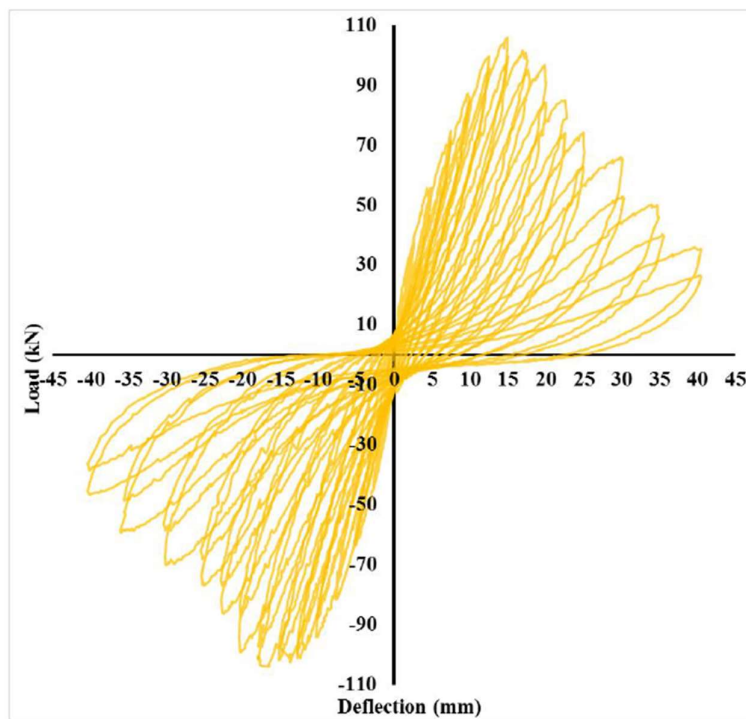


Figure 2.11 Load-Displacement response of reverse cyclic control specimen (BCJ-RC) (Ajmal, 2016)

Risi, Ricci, Verderame, & Manfredi, (2017), tested exterior beam-column joints without transverse reinforcement to improve the understanding of its seismic performance. The assessment of four full-scale

exterior unreinforced beam-column joints was done under cyclic loading. The specimens were different in type of reinforcement bars for beam (plain or deformed bars) and ratio of longitudinal beam reinforcement. Moreover, the specimens tested were splitting into two groups of design perspective: gravity load designed, and second group were designed for old/obsolete seismic code. Figure 2.12 shows the geometry and reinforcement details of beams and columns for the specimens while Table 2.3 shows the used material properties. Test setup is shown in Figure 2.13. The failure mode expected in this research were two types of failure: joint shear failure prior to beam yielding (J-Failure) or following the beam yielding (B-J – Failure). Specimens 1P and 1D are designed to old seismic design code with higher longitudinal reinforcement ratio than other specimens while 2P and 2D are the second group of specimens with less longitudinal reinforcement ratio in the beam and designed for gravity load only without seismic load consideration. Specimens 1P and 2P are reinforced with plain bars at beam while 1D and 2D are reinforced with deformed bars at beam. After the analysis of results, it was found that with higher longitudinal reinforcement ratio (1P & 1D) the maximum strength of the connection was controlled by the joint shear failure (J-Failure) without beam flexural yielding while with less beam longitudinal reinforcement (2P & 2D) the beams were yielded before and followed by joint failure (B-J – Failure). Moreover, at the interface of joint-beam the rotation was high in the specimens with plain reinforcement bars when compared to rotation of deformed bars specimens. The experimental responses of the specimens in terms of lateral load-displacement are shown in Figure 2.14 and the experimental final damage state is shown in Figure 2.15.



Steel properties				Concrete properties	
Diameter [mm]	Yield strength (f_y) [MPa]	Ultimate strength (f_u) [MPa]	Hardening ratio (f_u/f_y) [-]	Cubic sample	Cylindrical compressive strength (f_c) [MPa]
20 D	487	596	1.22	CS1	27.2
12 D	459	560	1.22	CS2	29.2
8 D	492	607	1.23	CS3	31.2
20 P	344	465	1.35	CS4	27.4
14 P	316	489	1.55	mean	28.8



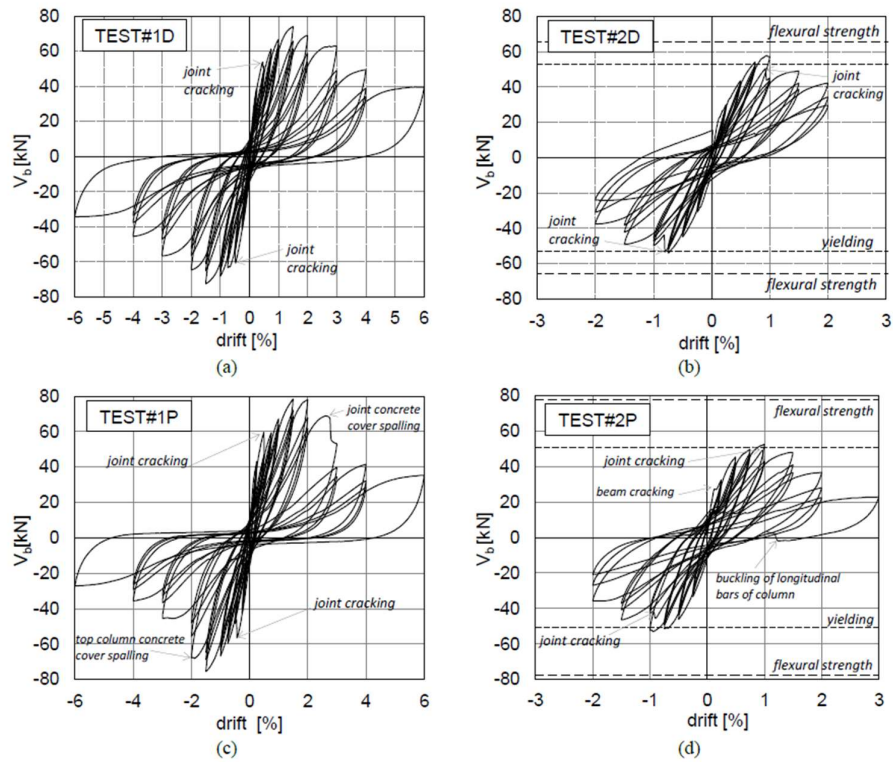


Figure 2.14 Lateral load-displacement cyclic response (Risi et al., 2017)

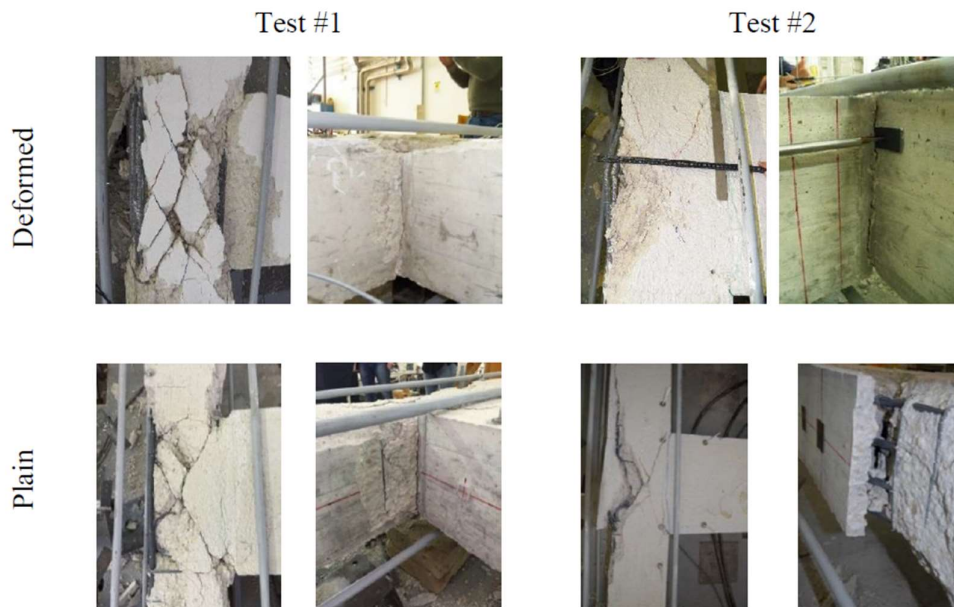


Figure 2.15 Experimental final damage state (Risi et al., 2017)

Allam, Elbakry, & Arab, (2018) performed numerical study for the behavior of exterior reinforced concrete beam-column joint under monotonic loading. Aiming to evaluate the effect of concrete compression strength, column axial load, joint stirrups, and the shape of the beam top reinforcement on the joint ultimate strength and deformation capacity. Thirty numerical exterior connections were analyzed using nonlinear finite element software ABAQUS. All the specimens failed due to shear diagonal tension of joint. The results show that with the increase of concrete strength, column axial load, and joint stirrup the joint ultimate load capacity increase significantly. While for the L-shaped and U-shaped beam tension reinforcement the performance is similar, the straight bars shape of beam reinforcement had reduced the beam tip load capacity. Table 2.4 shows the numerical results of the loading and deformation capacity of the beam tip for the thirty specimens. Figure 2.16 shows the effect of concrete compression strength on the ultimate loading capacity of beam's tip using the load-displacement curves of the specimens for the comparison between the varied concrete strength specimens.

Table 2.4 Numerical results of the loading and deformation capacity of the beam tip (Allam et al., 2018)

Joint No.	Strength capacity (kN)	Deformation capacity (mm)	Joint No.	Strength capacity (kN)	Deformation capacity (mm)
S1	19.90	23.15	S16	19.03	25.02
S2	21.75	21.23	S17	19.27	23.37
S3	24.82	22.58	S18	19.41	23.57
S4	16.27	28.45	S19	19.42	26.88
S5	16.62	24.51	S20	19.64	24.64
S6	17.37	26.15	S21	20.51	24.79
S7	17.61	26.93	S22	19.21	22.11
S8	18.02	25.23	S23	19.981	22.15
S9	18.16	26.05	S24	19.983	22.21
S10	17.87	26.13	S25	19.95	24.20
S11	18.58	25.47	S26	20.73	22.94
S12	18.64	25.86	S27	20.74	23.05
S13	18.28	24.87	S28	20.60	24.38
S14	18.46	22.63	S29	21.43	23.51
S15	18.58	23.89	S30	21.47	23.56

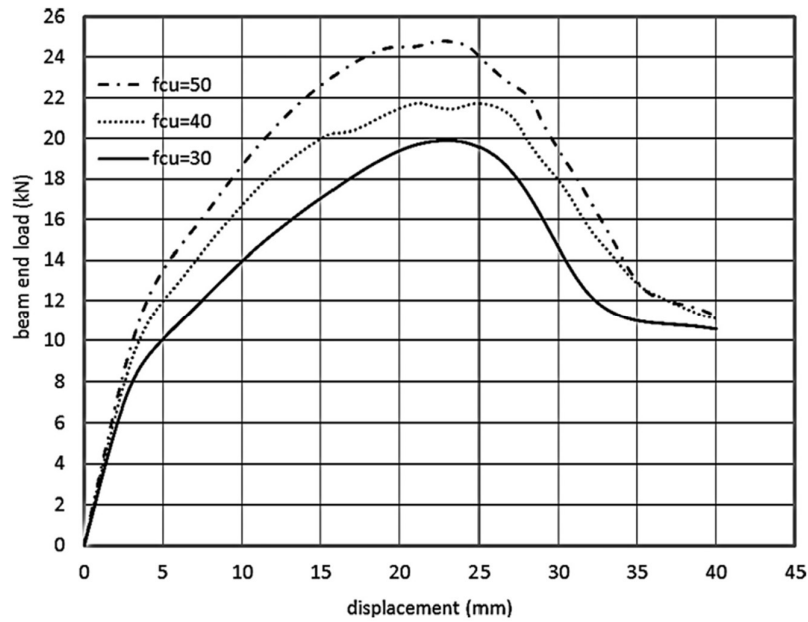


Figure 2.16 The effect of concrete compression strength on the ultimate loading capacity of beam's tip (Allam et al., 2018)

Ercan, Arisoy, & Ertem, (2019), studied different strengthening techniques for the beam-column joints using carbon fiber-reinforced plastic (CFRP). Five exterior beam-column joint samples were tested including the control sample (no reinforcement in the joint). Figure 2.17 shows the reinforcement details of the control sample and Figure 2.18 shows the control sample failure. The control sample joint failed at load of 71.1 kN at 22.38 mm displacement which is considered as brittle failure of joint (failure mode). It can be revealed that the BCJ is weak in shear without examining its shear capacity to provide sufficient transverse reinforcement. The control sample load-displacement curve under cyclic load is shown in Figure 2.19.

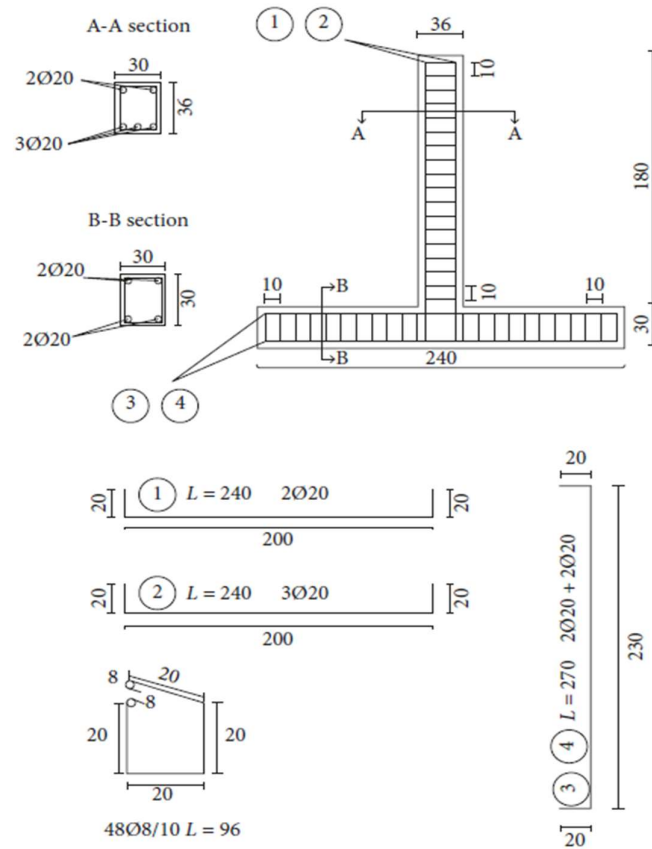


Figure 2.17 Geometry and reinforcement detailing of the control sample (Ercan et al., 2019)



Figure 2.18 Failure of the control sample (Ercan et al., 2019)

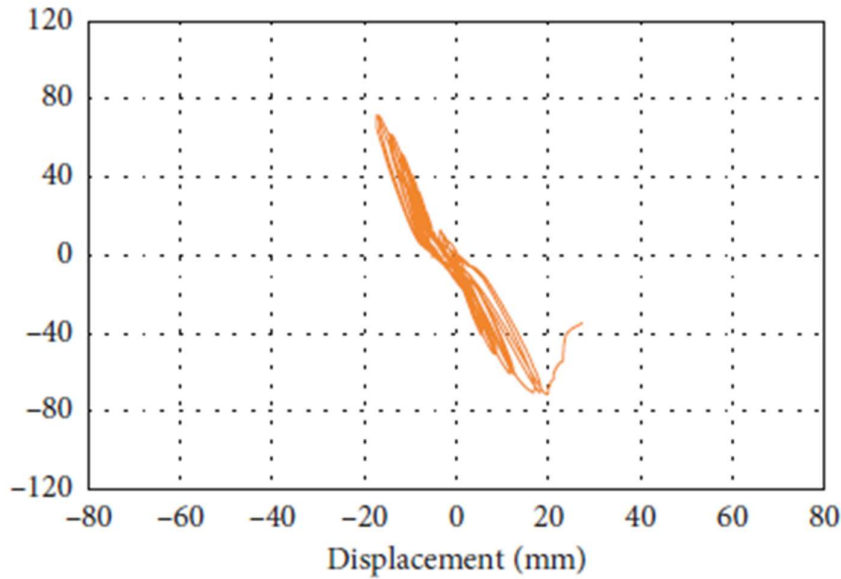


Figure 2.19 Load-Displacement response of the cyclic control specimen (Ercan et al., 2019)

El-Naqeeb, Abdelwahed, & El-Metwally, (2022) investigated two sets of beam-column exterior connections (namely Jo and SP-6) numerically using nonlinear finite element software ABAQUS. Different beam-column connections with different joint reinforcement location and layout were simulated. The main object in this author's research was to investigate the effect of joint stirrup presence in joint with different options in joint performance in terms of joint strength and deformation capacity. As reference for different configurations effect, two validated experimental specimens were used as control specimens. One of these specimens where unreinforced in the joint area as shown in Figure 2.20 which shows the geometry and reinforcement details of the reference specimens. Table 2.5 shows the reference specimens details and in Figure 2.21 the numerical simulation for reference specimens is presented. The reference specimens were tested under monotonic load and started with column loading and then with beam loading where the load-displacement curves for both

specimens presented in Figure 2.22 and compared with the numerical result too. The shear strength of the specimens is shown in Table 2.6. The study concluded that the evaluated shear strength of unreinforced joint SP-6 using ACI 352R-02 is overestimated since the ACI 352R-02 requirement is not satisfied with minimum joint reinforcement (it is unreinforced).

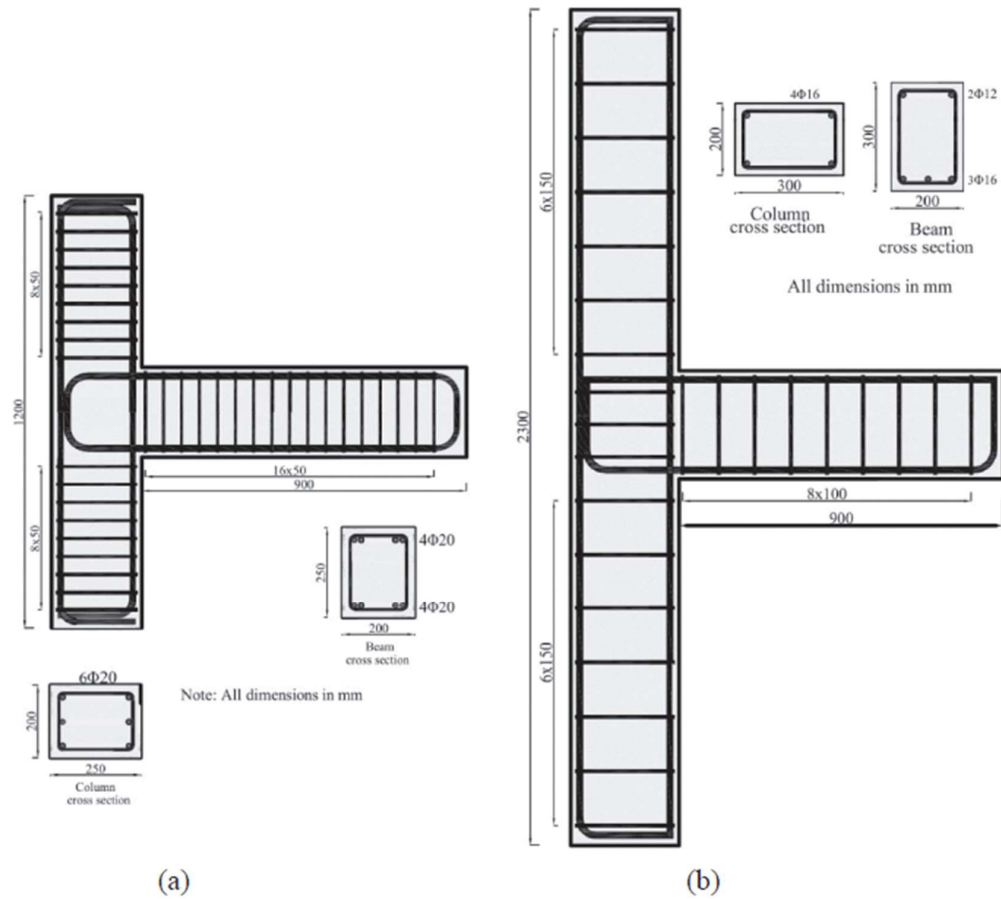


Figure 2.20 Specimens details (a) Specimen SP-6; and (b) Specimen Jo (El-Naqeeb et al., 2022)

Table 2.5 Specimens details (El-Naqeeb et al., 2022)

Specimen	f_c (MPa)	f_y (MPa)		Column Reinforcement		Beam Reinforcement		
		Main	Transverse	Longitudinal	Stirrups	Tension	Compression	Stirrups
SP-6	30	605	500	6Φ20	1Φ9@50 mm	4Φ20	4Φ20	1Φ9@50 mm
Jo	20.3	400	240	4Φ16	1Φ9@150 mm	4Φ16	2Φ12	1Φ9@100 mm

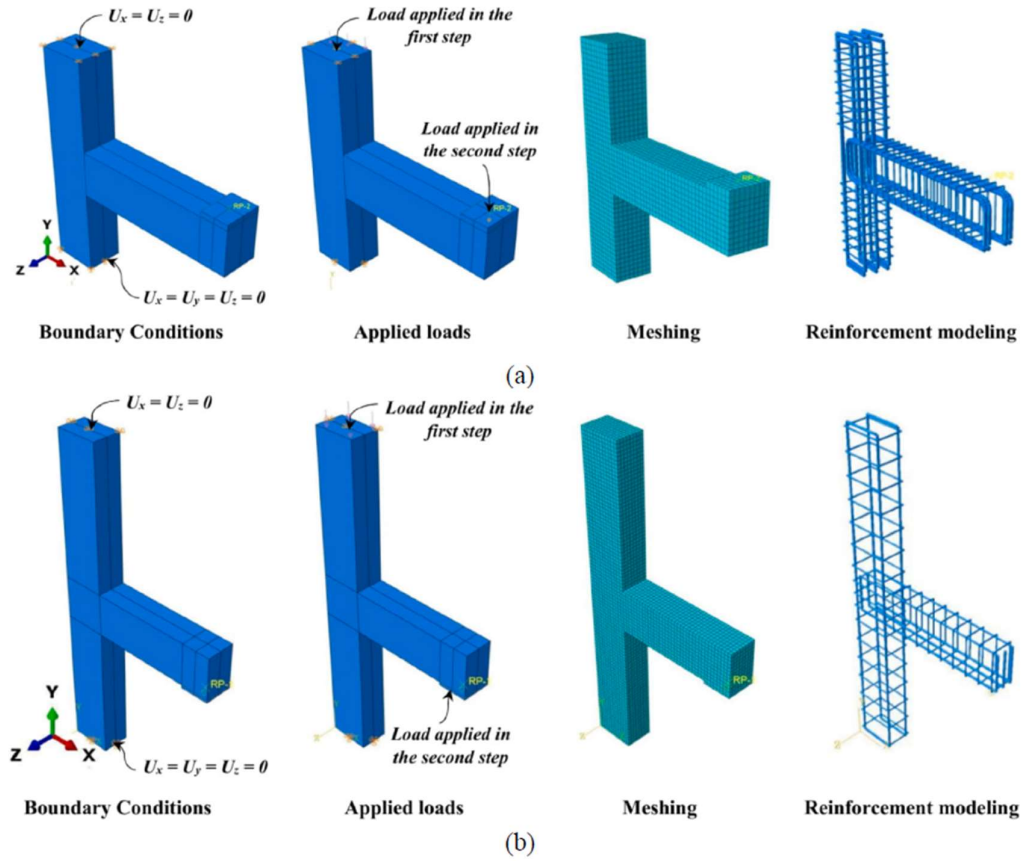


Figure 2.21 Numerical models (a) specimen SP-6; and (b) specimen Jo (El-Naqeeb et al., 2022)

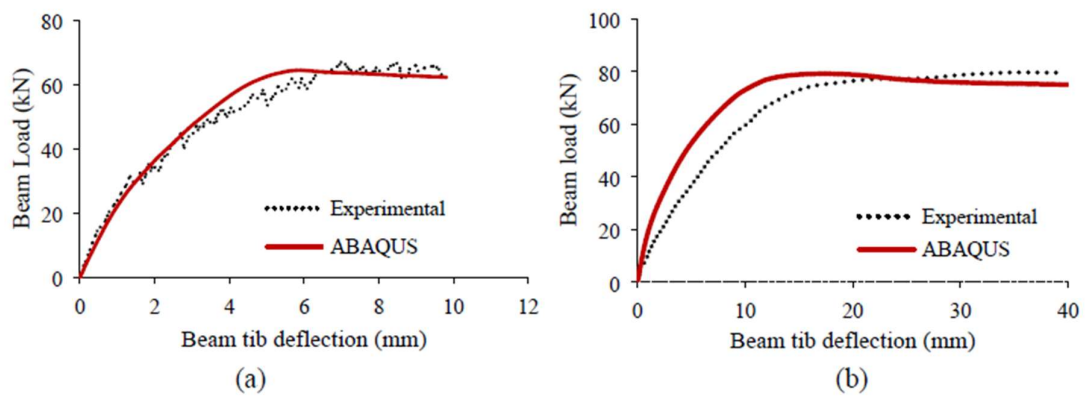


Figure 2.22 Load-deflection curve of the tested specimens (a) specimen SP-6; and (b) specimen Jo (El-Naqeeb et al., 2022)

Table 2.6 Joint shear strength for final models according to ACI-352-02 and using numerical result (El-Naqeeb et al., 2022)

Model	Joint shear stress v_j (N/mm ²)	
	Numerical	ACI 352-02R
SP-6	4.62	5.44*
R1	6.24	5.44

Melo, Varum, & Rossetto, (2022) studied the behavior of monotonically and cyclic loaded exterior reinforced concrete beam-column joints. A total of six full-scale specimens were tested where five specimens were built using plain reinforcing bars and one specimen was built with deformed reinforcing bars to assess the effect of reinforcing bar surface on the exterior joint behavior. All the tested specimens were non-seismically designed -without or with inadequate transverse reinforcement of joint- to represent the existing old reinforced concrete structures that were designed for gravity load only. Figure 2.23 shows the specimens geometry and reinforcement details and Table 2.7 shows the testing materials properties. Melo et al., 2022, study focused on the investigation of bond properties, lapping of the longitudinal bars, anchorage of the beam reinforcing bars and loading on the beam-column joints (monotonic or cyclic) effect on the behavior of exterior beam-column joint. The final damage of the tested connections is presented in Figure 2.24, and the maximum shear force for each specimen is shown in Table 2.8. It has been noticed that the poor anchorage detailing caused compromising in the strength of the beam-column exterior joint. Moreover, the results show that the specimens with deformed reinforcing bars performed better than those with plain reinforcing bars. Figure 2.25 shows the experimental force-drift envelopes.

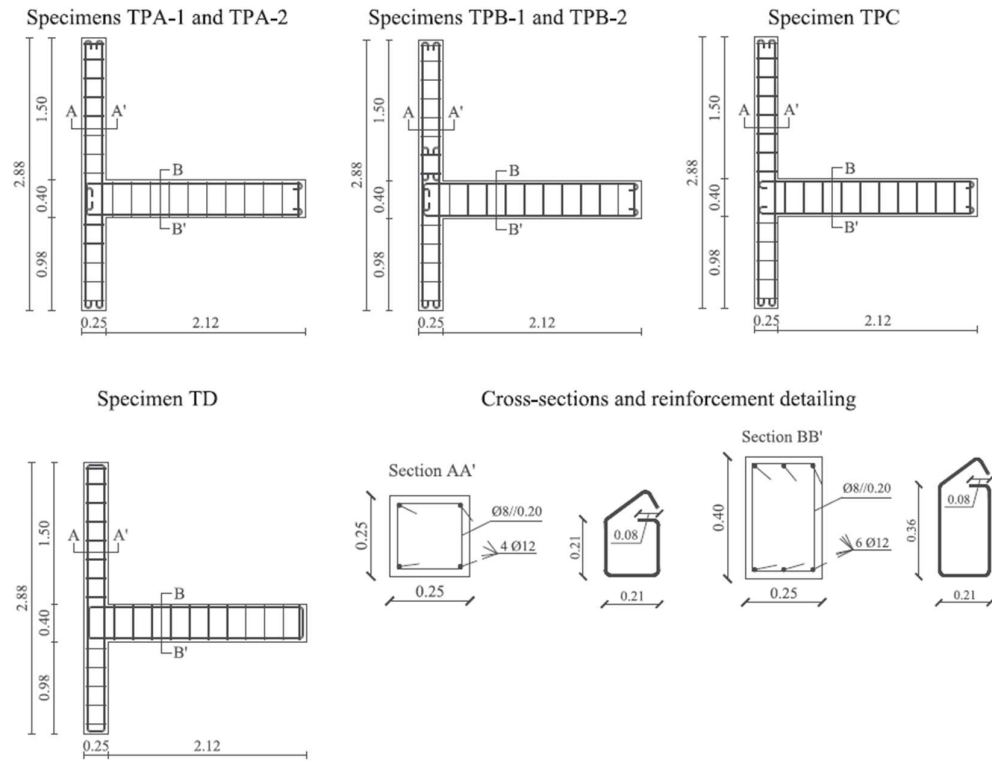


Figure 2.23 Geometry and reinforcement details of the specimens (Melo et al., 2022)

Table 2.7 Testing materials properties (Melo et al., 2022)

Specimen	Concrete		Steel						
			Bar surface	Ø6 mm			Ø12 mm		
	MPa (ksi)			MPa		GPa	MPa		GPa
				(ksi)		(ksi)	(ksi)		(ksi)
				f_{cm}	f_{cm}	f_{ym}	f_{um}	E_{ym}	f_{ym}
TPA-1	24.5 (3.55)	2.3 (0.33)	Plain	410	495	190	405	470	199
TPA-2	25.0 (3.74)	2.5 (0.36)							
TPB-1	15.0 (2.29)	2.0 (0.29)		(59.5)	(71.0)	(20717)	(50.7)	(60.2)	(20863)
TPB-2	27.3 (3.95)	2.9 (0.42)							
TPC	23.0 (3.45)	2.6 (0.30)	Deformed	470	605	190	465	505	199
TD	21.5 (3.12)	2.4 (0.35)		(60.2)	(87.7)	(20717)	(67.4)	(84.0)	(20863)

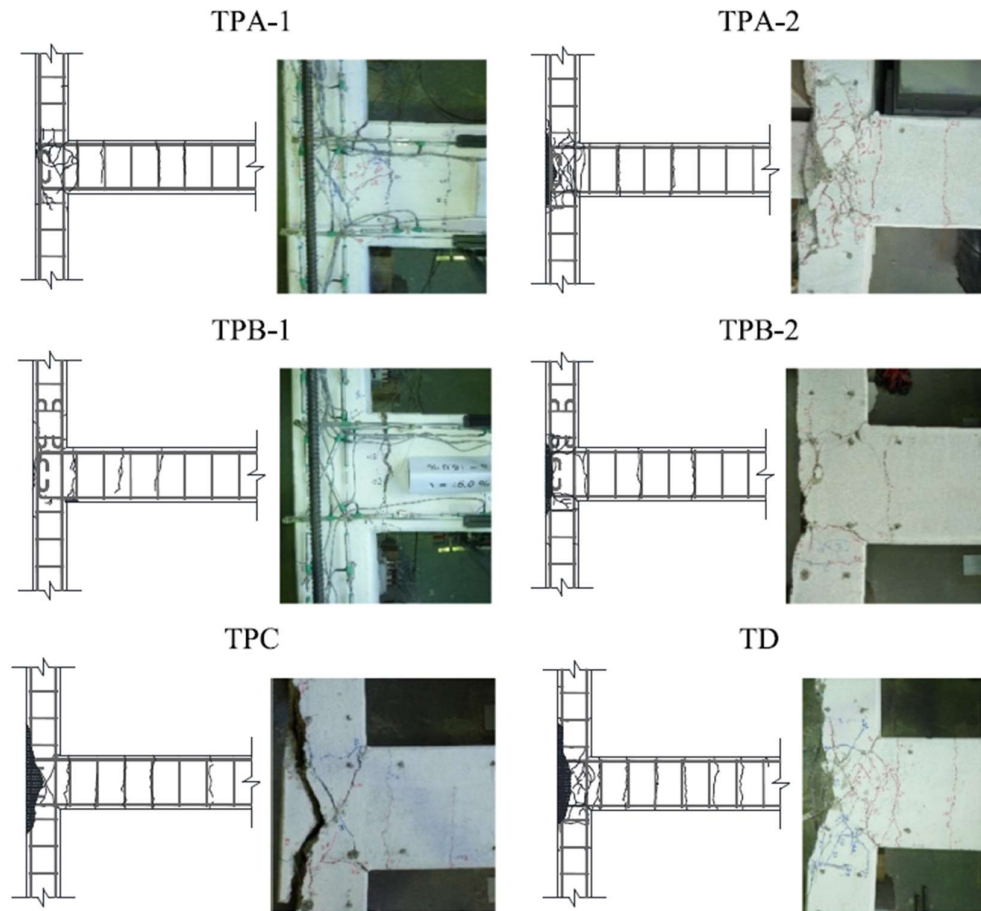


Figure 2.24 The final damage state of the top face of the tested connections (Melo et al., 2022)

Table 2.8 The maximum shear force for each specimen (Melo et al., 2022)

Specimen	$\Delta v_{jh, \max}$ %	$V_{jh, \max}$ kN
TPA-1	-1.2	-131.7
TPA-2	1.5	137.5
TPB-1	-2.4	-130.3
TPB-2	1.5	137.7
TPC	1.0	126.6
Mean value		
CoV		
TD	1.3	145.4

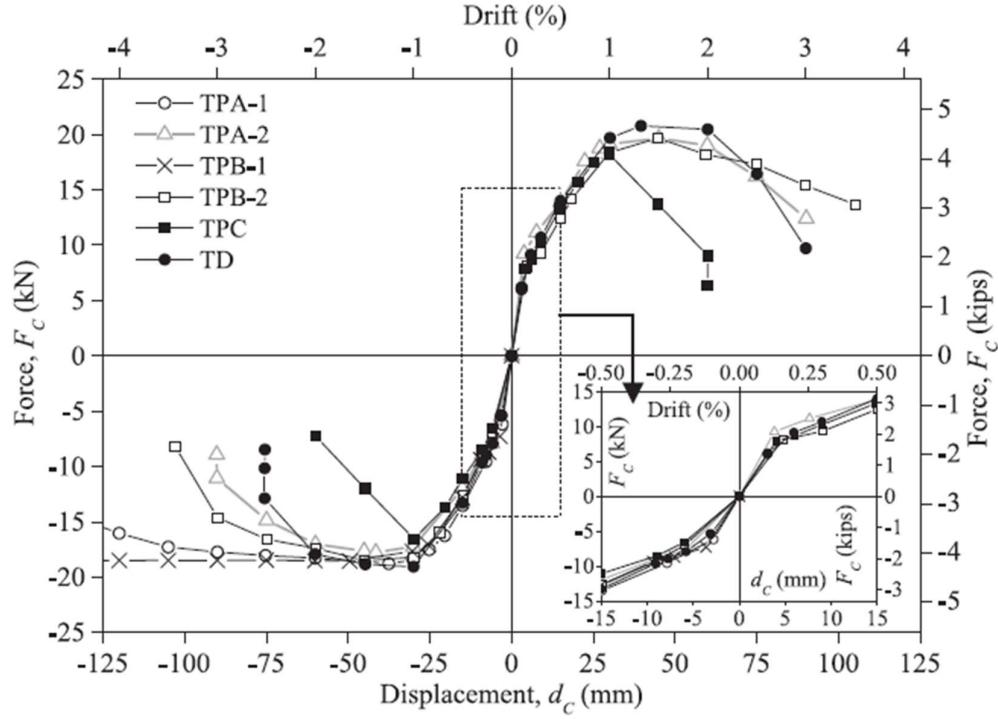


Figure 2.25 Experimental force-drift envelopes (Melo et al., 2022)

Algassem & Vollum, (2023) experimentally studied the influence of beam reinforcement anchorage detailing, joint shear reinforcement, and column axial load on the strength of exterior reinforced concrete beam-column joint. A total number of twelve specimens were tested under monotonic load and divided into three groups for the purpose of investigating each mentioned variable individually. Figure 2.26 shows the geometric and reinforcement details of the beam-column joint specimens and Figure 2.27 shows the joint shear reinforcement detailing for the specimens. Table 2.9 presents the column axial loading and material properties of the specimens. The testing setup schematic diagram is shown in Figure 2.28. It has been noticed that in group 1 specimens the L-shaped anchorage of beam had higher shear strength of joint when compared with U-shaped specimens. Moreover, the column axial load effects on joint shear strength found to be insensitive in the comparable specimens that had

axial column stress ranged between $0.1 f_c'$ to $0.6 f_c'$. However, the joint shear reinforcement variable enhanced the shear strength of joint and provided it with greater value. Table 2.10 summarizes the experimental results including the maximum beam loading of specimens.

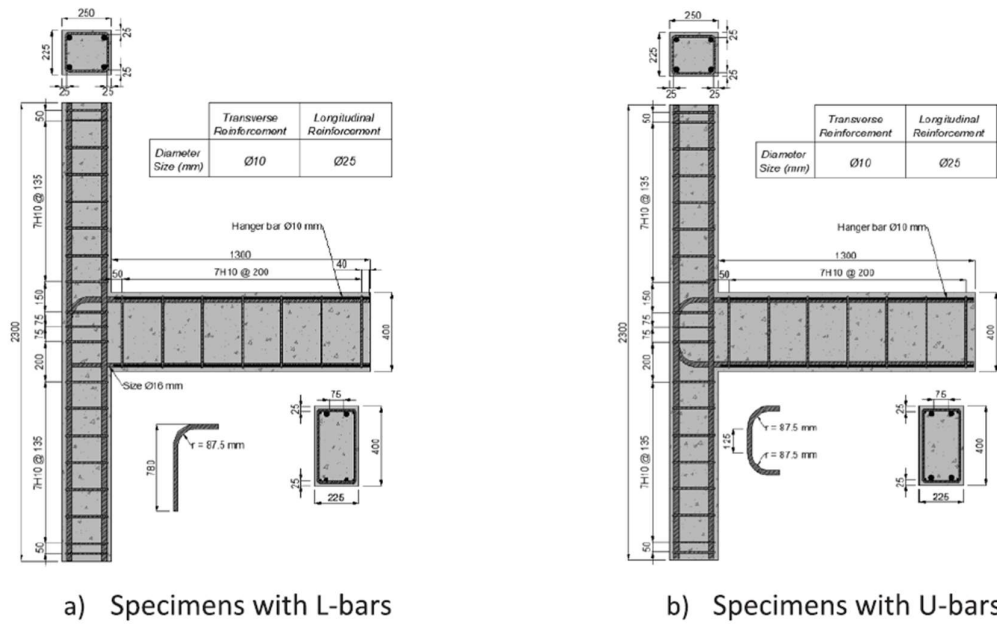


Figure 2.26 The geometric and reinforcement details of the beam-column joint specimens (Algassem & Vollum, 2023)

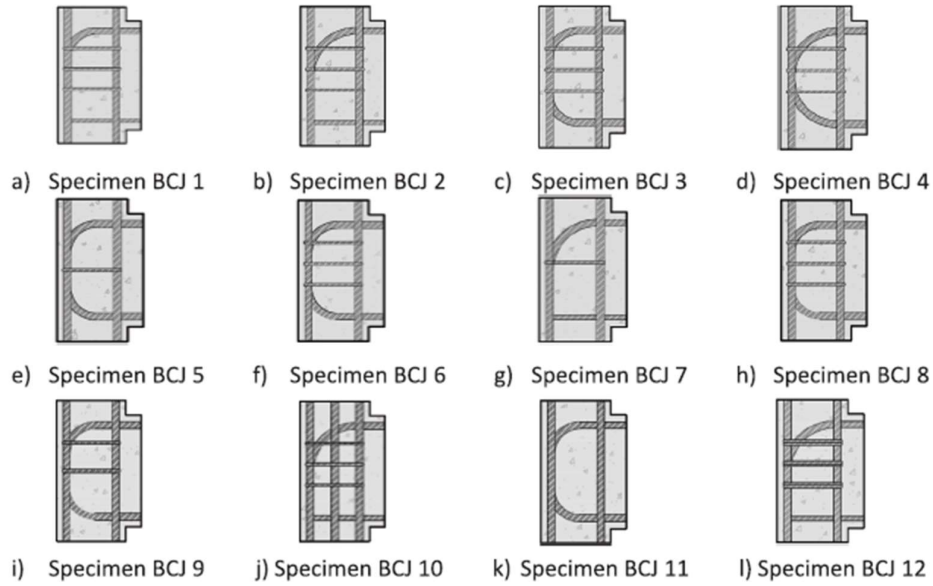


Figure 2.27 Joint shear reinforcement detailing for the specimens (Algassem & Vollum, 2023)

Table 2.9 Column axial loading and material properties of the specimens (Algassem & Vollum, 2023)

Specimen	Detail	No. of bars & diameter			r^* (mm)	N (kN)	f_c (MPa)	f_t (MPa)	f_y (MPa)		
		Col.	Beam	stirrups					B10	B16	B25
BCJ 1	L	4B25	2B25	3B10	87.5	300	33.7	3.9	515	534	550
BCJ 2	L	4B25	2B25	3B10	150	300	33.4	4.1	515	534	550
BCJ 3	U	4B25	2B25	3B10	87.5	300	33.2	4.1	515	–	550
BCJ 4	U	4B25	2B25	3B10	150	300	32.9	4.3	515	–	550
BCJ 5	U	4B25	2B25	1B10	87.5	300	27.0	3.8	515	–	550
BCJ 6	U	4B25	2B25	3B10	87.5	600	26.9	3.9	515	–	550
BCJ 7	L	4B25	2B25	1B10	150	300	39.9	5.3	515	534	550
BCJ 8	U	4B25	2B25	3B10	87.5	900	26.8	4.1	515	–	550
BCJ 9	U	4B25	2B25	2B10	87.5	300	51.3	5.5	515	–	550
BCJ 10	L	6B25	2B25	3B10	150	300	51.1	5.4	515	534	550
BCJ 11	U	4B25	2B25	NO	87.5	300	48.9	5.5	515	–	550
BCJ 12	L	4B25	2B25	6B10	150	300	49.9	5.4	515	534	550

Note: * r depicts the bend radius of beam anchorage bar.

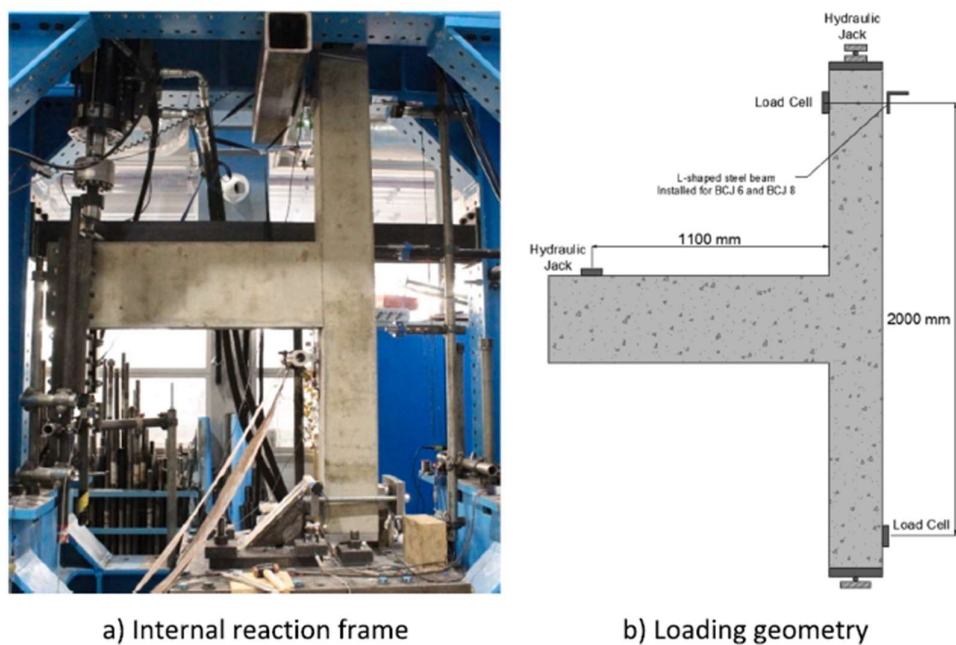


Figure 2.28 The testing setup schematic diagram (Algassem & Vollum, 2023)

Table 2.10 The experimental results including the maximum beam loading of specimens (Algassem & Vollum, 2023)

Specimen	No. B10 joint stirrups	Column load N (kN)	Column axial stress/ f_c	Horizontal reaction (kN)		Beam load (kN)	
				Top	Bottom	1st crack P_{cr}	Maximum P
BCJ 1	3	300	0.16	92	74	63	132.8
BCJ 2	3	300	0.16	96	74	58	139.7
BCJ 3	3	300	0.16	78	62	60	120.8
BCJ 4	3	300	0.16	77	58	55	118.8
BCJ 5	1	300	0.20	53	42	45	81.1
BCJ 6	3	600	0.40	75	54	65	111.5
BCJ 7	1	300	0.13	86	68	60	127.6
BCJ 8	3	900	0.60	80	39	85	107.9
BCJ 9	2	300	0.10	94	67	70	139.7
BCJ 10 [#]	3	300	0.10	125	97	90	181.2
BCJ 11	0	300	0.11	67	52	65	101.9
BCJ 12	6	300	0.11	124	93	80	184.6

Notes: [#] Intermediate column bars provided.

2.6 Application of Machine Learning Techniques in Civil Engineering Field

The machine learning approach proved efficiency and reliability in solving real life engineering problems that require fast solutions and cost effective (Chatterjee, et al., 2017). Several ML techniques have been employed in the civil engineering field for the purpose of regression models or classification problems. Among various ML techniques used in real life problems, Artificial Neural Network (ANN) has shown promising accuracy in solving the issues when compared to other ML techniques (Chatterjee, et al., 2017).

ANN showed a promising solution for many Civil Engineering applications such as performance based seismic design of bridge's pier (Todorov & Muntasir Billah, 2022), prediction of concrete strength (Nguyen, Vu, Vo & Thai, 2020), seismic performance of corroded reinforced concrete buildings (Xu, Hong, Zhang, Hou, & Wu, 2022, crack detection (Ali, et al., 2021), labor productivity (Golnaraghi, Zangenehmadar, Moselhi, & Alkass, 2019) , ultimate shear strength of reinforced concrete deep beams (Sanad & Saka, 2001), classification of reinforced concrete building structural failure (Chatterjee, et al., 2017).

2.6.1 Artificial Neural Network

Artificial Neural Network (ANN) is one type of supervised machine learning technique and recently has been extensively used in Civil Engineering applications which showed a highly competitive level regarding effectiveness when compared to other conventional regression and statistical models (Abiodun, et al., 2018). Due to excellent behavior in self-learning, adaptivity, fault tolerance, nonlinearity, and advancement of

mapping the input to output capability, ANN is being used highly in numerical generalization function approximation (Abiodun, et al., 2018).

ANN is a computational model that manages information in similar structure and function of biological nervous system of the human brain; and that is why it is called artificial neural network. ANN depends on examples for learning, like humans. As human brain processes capability of information, ANN works through complex interconnected neurons to form a task or solve a problem. Figure 2.29 shows the typical architecture of neural networks and the processing element.

Neural networks consist of layers that are dependent on one another. Each layer can have an arbitrary number of nodes which is called bias node and always set as equal one (Abiodun, et al., 2018). The main function of these bias nodes is providing the node with trainable constant value additionally with the inputs value provided by the network node. Moreover, a bias value plays a part in the ANN training success, which allows the node activation function to move to left or right in its graphical representation. In addition to the bias, each layer consists of several processing elements that are called neurons or nodes. The interconnection between each layer nodes to another presents the network of ANN architecture.

ANN can be used for classification and regression problems. For function approximation (regression) problems, the architecture of the model consists of an input layer containing the features, hidden layers (one or more), and an output layer containing the observations. Depending on the problem's characteristics and complexity, the number of nodes in each layer will differ. The greater the number of hidden layers and nodes, the more complex the model will be.

There are two main classifications in artificial neural networks models as shown in Figure 2.30. Multi-layer feed forward neural network (ML-FFNN) is the most used network due to its generalization capability (Sanad & Saka, 2001). More details about the machine learning algorithm selected for this research are explained later, in Chapter 4.

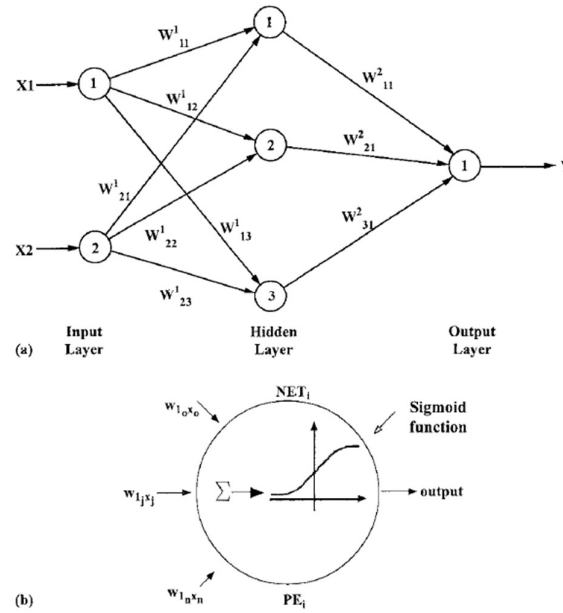


Figure 2.29 (a) Artificial Neural Network Typical Architecture
(b) Processing element (Sanad & Saka, 2001).

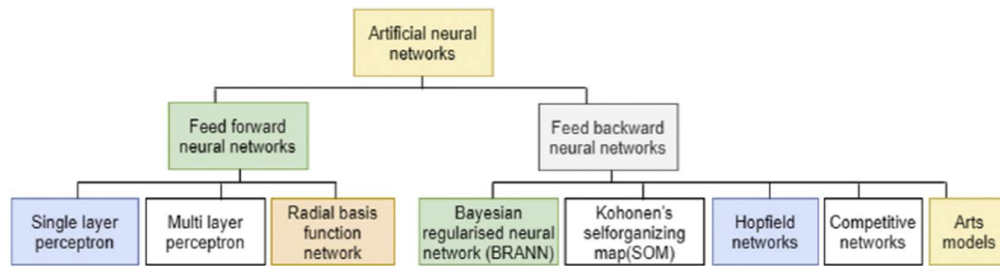


Figure 2.30 Classification of Neural Networks (Abiodun, et al., 2018)

Machine learning different techniques are being used for solving many complicated civil engineering problems. Many researchers have applied these different ML techniques in their study and checked their capability of solving the issues.

Khademia, Jamal, Deshpande, & Londhe, (2016) have developed three different models to predict the 28 days compressive strength of recycled aggregate concrete (RAC) using different ML techniques Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS), and Multiple Linear Regression (MLR). The required data sets were collected from literature for experimentally performed specimens of a total of 257 data sets. For the ANN model, one output parameter and 14 different input parameters were used in the development of the model. Table 2.11 shows the characteristics of input and output parameters. The data for ANN model was divided into 70% (179 specimens), 15 % (39 specimens), 15% (39 specimens), for training, validation, and testing sets, respectively. The sigmoidal tangent function was used for the hidden layer and 29 nodes in the hidden layer were chosen as final proposed model. The best training algorithm for this study was the Levenberg–Marquardt (LM) algorithm, which was used to develop the ANN model using MATLAB software. Figure 2.31 shows the architecture

of the developed ANN model. The ANN model performance was checked using the coefficient of determination (R^2), mean squared error (MSE), and sum of squared errors (SSE). Figure 2.32 presents the relationship between the measured and predicted compressive strength of the training set of the ANN model while Figure 2.33 presents the same for validation set. The relationship between the measured and predicted compressive strength of the testing set of the ANN model is presented in Figure 2.34. It has been found that ANN and ANFIS models can predict the 28 days compressive strength of concrete with good accuracy. However, ANN performed better than ANFIS in the prediction. Table 2.12 presents the performance evaluation for the developed three models.

Table 2.11 The characteristics of input and output parameters
(Khademia et al., 2016)

Parameter	Unit	Minimum	Maximum
Cement (C)	(kg/m ³)	235	645
Natural fine aggregate (NFA)	(kg/m ³)	0	1050
Recycled fine aggregate (RFA)	(kg/m ³)	0	1050
Natural coarse aggregate 20 mm (NCA20)	(kg/m ³)	0	1508.64
Natural coarse aggregate 10 mm (NCA10)	(kg/m ³)	0	553
Recycled coarse aggregate 20 mm (RCA20)	(kg/m ³)	0	1508.64
Recycled coarse aggregate 10 mm (RCA10)	(kg/m ³)	0	840
Water (W)	(kg/m ³)	120	358
Admixture (AD)	(kg/m ³)	0	10.4
Aggregate to cement ratio (A/C)	–	2.279	9.327
Water to cement ratio (W/C)	–	0.299	1.028
Sand to aggregate ratio (S/A)	–	0.149	1.566
Replacement ratio (RR) (%)	–	0	100
Water to total materials (W/T)	–	11.287	11.553
28 days compressive strength of concrete	(N/mm ²)	10.319	100.5

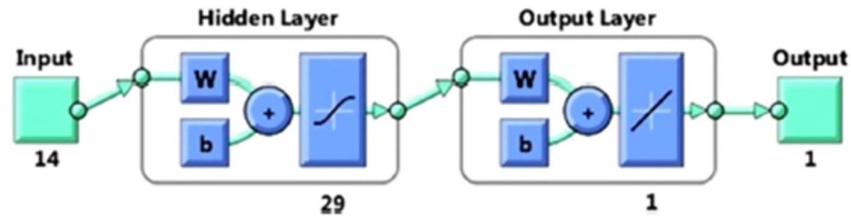


Figure 2.31 The architecture of the developed ANN model (Khademia et al., 2016)

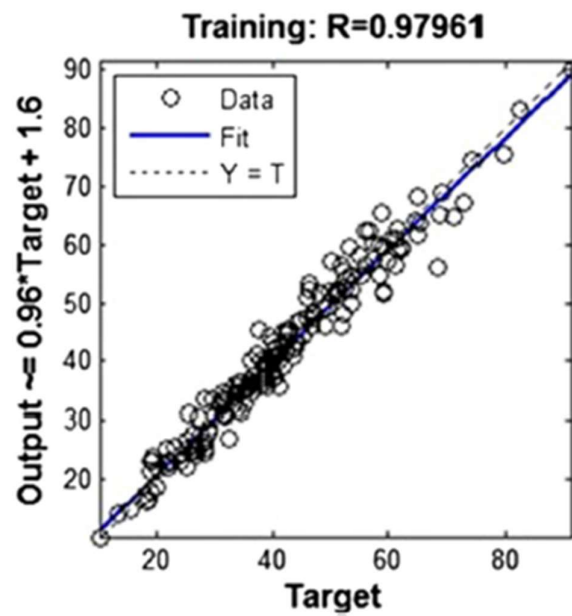


Figure 2.32 The relationship between the measured and predicted compressive strength of the training set of the ANN model (Khademia et al., 2016)

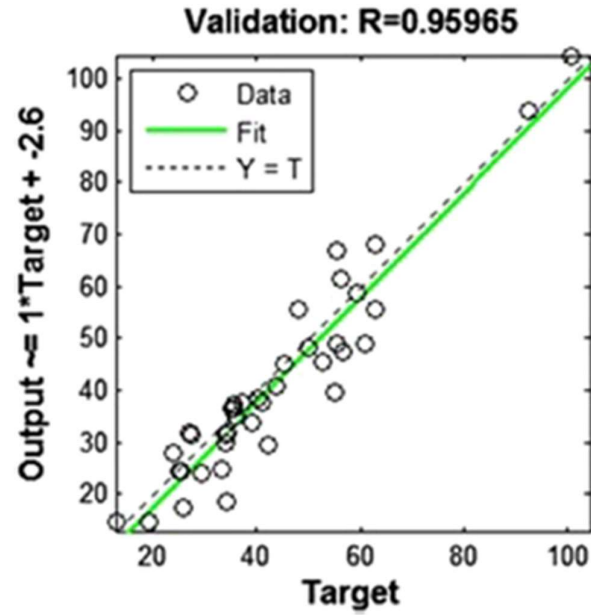


Figure 2.33 The relationship between the measured and predicted compressive strength of the validation set of the ANN model (Khademia et al., 2016)

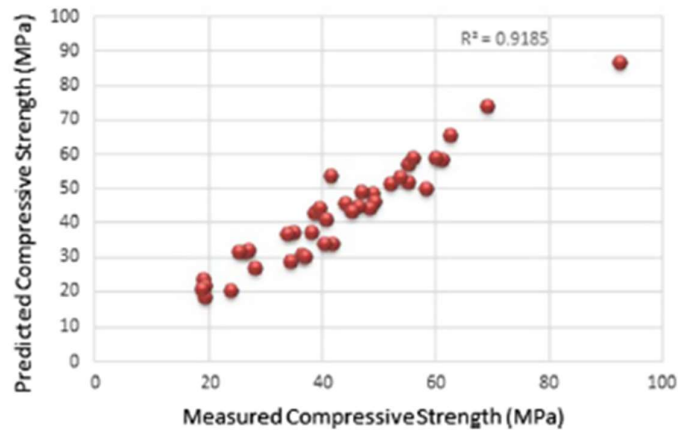


Figure 2.34 The relationship between the measured and predicted compressive strength of the testing set of the ANN model (Khademia et al., 2016)

Table 2.12 The performance evaluation for the developed three models (Khademia et al., 2016)

Data-driven model	Coefficient of determination (R^2)	Sum of squared errors (SSE)	Mean squared error (MSE)
MLR	0.6085	3880.67	99.5043
ANN	0.9185	770.94	19.7676
ANFIS	0.9075	992.67	25.4530

Mangalathu, Heo, & Jeon, (2018) proposed a multi-parameter fragility methodology to generate bridge-specific seismic fragility curves using ANN, which avoids the challenge in the traditional regional seismic risk assessment procedure. One million samples were used in the process of proposing the ANN model, where those samples were divided into 70% training set, 15% validation set, and 15% testing set. The architecture of the proposed ANN is presented in Figure 2.35, which shows the input, hidden, and output layers. The input parameters consisted of categorical variables, numerical variables, and continuous variables related to different details of skewed concrete box-girder bridges. The seismic demand of bridge components was the outputs of the ANN proposed model. The hidden layer was one layer containing 10 hidden nodes that gave better performance for the model. It has been found that the proposed ANN model has good performance and is capable of predicting with less complexity than the traditional seismic risk assessment.

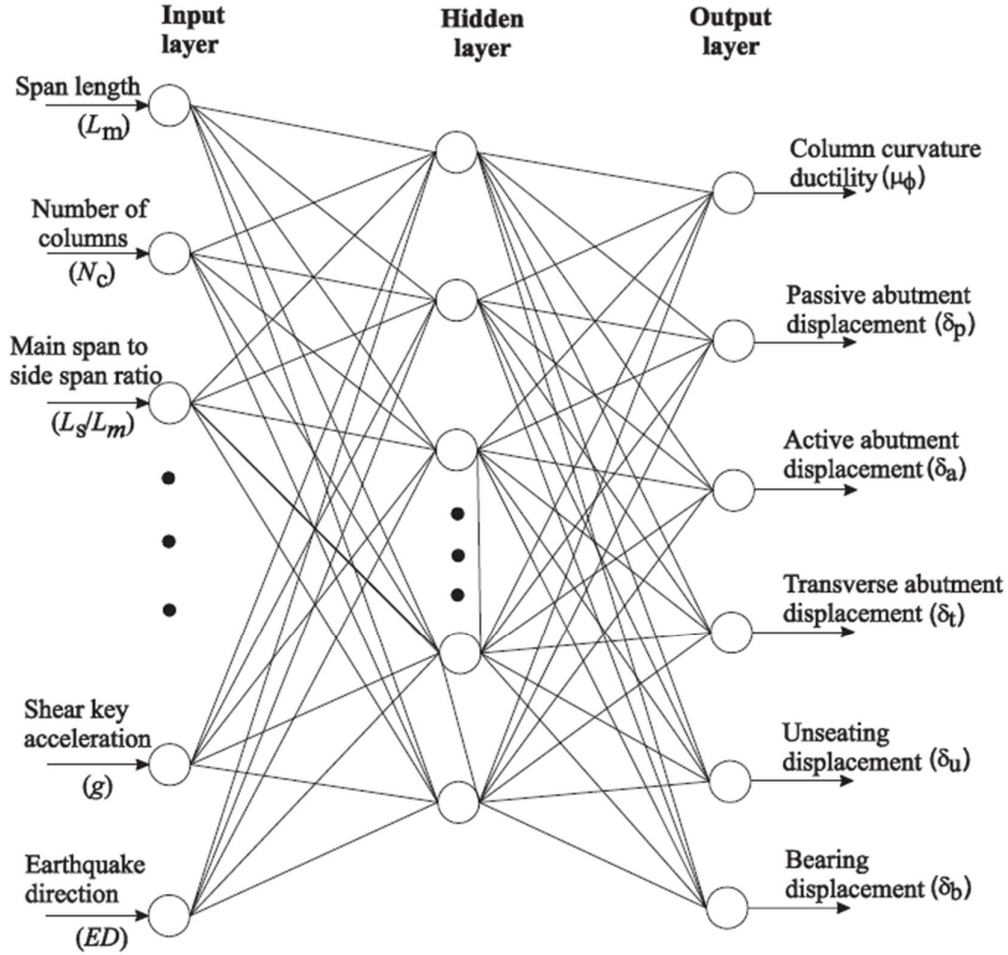


Figure 2.35 Architecture of the proposed ANN (Mangalathu et al., 2018)

Golnaraghi, Zangenehmadar, Moselhi, & Alkass, (2019) deployed different machine learning techniques to develop models to predict the productivity of labor in formwork installation operation. Various environmental and operational variables were considered in the models. Many ML techniques were used to develop different models and compare their capability in predicting the productivity of labor. The used ML techniques are General Regression Neural Network (GRNN), Backpropagation Neural Network (BNN), Radial Base Function Neural Network (RBFNN), and Adaptive Neuro-Fuzzy Inference System (ANFIS). The dataset used in the modeling was collected from field

observations of two high-rise buildings in Canada for a period of eighteen months. A total of 221 data points were collected, which were randomly divided into 80% training set, and 20% testing set. In BNN model, MATLAB software was used to develop the proposed model that contains nine input parameters in the input layer, two hidden layers with twenty hidden nodes for each layer, and the output parameter in the output layer. The BNN model was trained using Bayesian Regularization (BR) algorithm which is more suitable for noisy and small data sets problem. Table 2.13 presents the performance check comparison between the techniques used in the prediction of the productivity of labor. It has been found that BNN proposed model has the best accuracy when compared to other ML techniques used in the study, which had MSE and R^2 evaluation check values of 0.0054 and 0.949, respectively.

Table 2.13 Performance check comparison between the used techniques in the prediction of the productivity of labor (Golnaraghi et al., 2019)

	R^2 train	R^2 test	MSE train	MSE test
BNN	0.98	0.83	0.0023	0.020
RBF	0.91	0.85	0.0096	0.018
GRNN	0.88	0.75	0.0103	0.047
ANFIS	0.89	0.66	0.0100	0.020

Feng, Liu, Wang, Jiang, & Liang, (2020) used ensemble learning technique, adaptive boosting algorithm (AdaBoost) for classifying the failure mode of the reinforced concrete column and predicting its bearing capacity. AdaBoost is one of ML techniques that can be used for both classification and regression problems. A total of 254 RC columns tested under cyclic loading were collected from website, which have been used for training and testing the models. From the results, it has been found that

the proposed models are very accurate in both classification and prediction problems. The classification of failure mode for RC columns model had accuracy of 0.96 and the bearing capacity prediction model had 0.98 as coefficient of determination value (R^2), where 1 is the best possible value for matching the expected and predicted values while evaluating the ML model. The study revealed that ML techniques can be an alternative to the conventional method models.

Muliauwan, Prayogo, Gaby, & Harsono, (2020) utilized three different machine learning techniques to propose models that can predict the compressive strength of concrete. The ML techniques used are ANN, SVM, and linear regression (LR). A total number of 1030 concrete samples were collected from tests obtained from the University of California, Irvine, to be used in developing the models. Different input variables were decided as can be shown in Table 2.14. Performance evaluation using different accuracy indicators was done for the three models, it can be seen in Table 2.15 that the coefficient of correlation (R) is the best in ANN model with value of 0.909 for the testing data. The proposed ANN model had showed very good accuracy and revealed that ML techniques (ANN especially) can be good alternative for the conventional statistical models in the prediction of concrete compressive strength.

Table 2.14 Input variables that affect the compressive strength of concrete (Muliauwan et al., 2020)

Variables	Unit	Min	Mean	Max	Standard deviation
X ₁ : Cement	kg/m ³	102.0	281.17	540.0	104.51
X ₂ : Blast-furnace slag	kg/m ³	11.0	107.28	359.4	61.88
X ₃ : Fly ash	kg/m ³	24.5	83.86	200.1	39.99
X ₄ : Water	kg/m ³	121.8	181.57	247.0	24.35
X ₅ : Superplasticizer	kg/m ³	1.7	8.49	32.2	4.04
X ₆ : Coarse aggregate	kg/m ³	801.0	972.92	1,145.0	77.75
X ₇ : Fine aggregate	kg/m ³	594.0	773.58	992.6	80.18
X ₈ : Age of testing	Day	1.0	45.66	365.0	63.17
Y: HPC compressive strength	MPa	2.3	35.82	82.6	16.71

Table 2.15 Performance evaluation for the prediction models using testing data (Muliauwan et al., 2020)

Methods	Testing Result			
	R	RMSE (MPa)	MAPE (%)	MAE (MPa)
ANN	0.909	7.176	19.93	5.550
SVM	0.779	10.914	32.59	8.687
LR	0.768	10.975	31.69	8.634

Ganasan et al., (2021), developed artificial neural network (ANN) models using Rapidminer software to predict the crack width of beam-column joint under cyclic loading. Seven exterior beam-column joints were experienced and used as performance index for the developed models. Four types of artificial neural network were used: deep learning (DL) max-out, deep learning (DL) rectifier, support vector machine (SVM) dot and support vector machine (SVM) neural (see Table 2.16). The best performance between the four models were selected and optimized using split data ratios, number of inputs, and indices of performance. The inputs for the ANN models were the design parameters of the RC beam-column joints and the cyclic loading as drifts ratio. The four models were compared, and it found that the support vector SVM-dot kernel prediction

model for the crack widths had less difference between the measured and predicted crack width when compared to the other developed models. Regarding the input variables number, this research found that with more input variables the error was less than 20% and with optimization by using root mean square error (RMSE) performance index, the error became 5% between the predicted and measured crack width. Table 2.17 presents the different performance indices for examine the prediction models.

Table 2.16 The details of four prediction models (Ganasan, et al., 2021)

No	Model	Prediction Method
1.	Deep learning (DL)	Max-out: Based on the maximum coordinate of the input vector.
2.	Deep learning (DL)	Rectifier: Rectifier Linear Unit (RLU), which chooses the maximum of $(0, x)$ where x is the input value.
3.	Support Vector Machine (SVM)	Dot: The dot kernel is defined by $k(x,y) = x \times y$, i.e., it is the inner product of x and y .
4.	Support Vector Machine (SVM)	Neural: The neural kernel is defined by a two-layered neural net $\tanh(ax \times y + b)$, where a is alpha and b is the intercept constant. These parameters can be adjusted using the kernel a and kernel b parameters. A common value for alpha is $1/N$, where N is the data dimension.

Table 2.17 Types of performance index (regression) used for SVM—dot model (Ganasan, et al., 2021)

No	Parameter	Description
1.	Absolute error (AE)	AE is determined by adding the variance of all expected values from the label attribute's actual values and dividing the amount by the total number of predictions.
2.	Prediction average (PA)	PA is determined by adding all the real label values and dividing the total number of examples by this figure.
3.	Root mean square error (RMSE)	RMSE is a quadratic scoring method calculating the error's average magnitude. It is the cumulative square root of variations between predictive and real observation.

Recently, different machine learning techniques were deployed to develop prediction models for shear strength of the RC beam-column joints, and some include the failure mode of BCJ too. Therefore, the recent studies that ML techniques are used in reinforced concrete beam-column joints are presented below.

Jeon, Shafieezadeh, & DesRoches, (2014) have proposed three probabilistic shear strength models for reinforced concrete beam-column joint using conventional multiple linear regression method (MLR) and advanced machine learning technique of multivariate adaptive regression splines (MARS) and symbolic regression (SR). They mentioned that advanced machine learning methods are capable of capturing the complex and nonlinear relationship between the variables. Therefore, machine learning techniques can provide powerful tools for high-dimensional problems. Laboratory sub-assembly tests were collected from literature with (516) reinforced joints specimens and (204) unreinforced joints specimens, where the specimens were exterior and interior connections. The independent variables that affect the shear strength of the joint depending on the previous experimental and analytical research have been used in this study for the prediction models. These variables include compressive strength of concrete, ratio of joint transverse reinforcement (for the reinforced joint specimens), design shear stress of joint, geometry factors, and aspect ratio of joint. The accuracy of the regression models was evaluated, and it has been noticed that MARS mean squared error (MSE) is the lowest and the coefficient of determination (R^2) is the highest between the other models (see Table 2.18). An additional evaluation of the MARS model was conducted by comparing the reinforced and unreinforced joint specimens shear strength between the experimental and model prediction results. The comparison showed that the prediction MARS model for beam-column joint shear strength can predict the joint capacity with high accuracy and therefore can be applied for future inputs.

Table 2.18 Comparison of results for three regression methods (Jeon et al., 2014)

Database	Method	Number of variables	Regression (logarithmic)	
			MSE	R^2
Reinforced joint	MLR	8	0.0196	0.894
	MARS	8	0.0139	0.923
	SR	7	0.0181	0.901
Unreinforced joint	MLR	7	0.0254	0.858
	MARS	8	0.0155	0.910
	SR	6	0.0180	0.898

Kotsovou, Cotsovos, & Lagaros, (2017) developed ANN prediction model for the load carrying capacity and mode of failure of the exterior reinforced concrete beam-column joint. The data set used for training and validation was collected from the literature with a total number of 153 test results. The input parameters include the geometrical and reinforcement details of the beam, column, and beam-column joint area. In addition, the yield strength of rebars and column axial load are considered as input parameters too. The load carrying capacity was converted to the horizontal shear capacity of the exterior joint and compared with the available code [ACI 318 and EC2-EC8] (see Table 2.19). The comparison result had shown that there are shortcomings in the method in the current code and provides evidence that ANN prediction model can be an alternative for it.

Table 2.19 Mean values and standard deviation of the shear capacities calculated by ANNs, ACI 318, and EC2-EC8 methods (Kotsovou et al., 2017)

Methods:	ANNs	ACI 318	EC2-EC8
Normalised shear capacity:	V_{ANNI}/V_{EXP}	V_{ACI}/V_{EXP}	V_{EQ}/V_{EXP}
Number of predictions:	101	5	23
Mean values:	0.99	1.262	1.487
Standard deviations:	0.064	0.328	0.365

The research of Mangalathu & Jeon, (2018) introduces the uses of machine learning techniques in the prediction of shear strength of reinforced concrete beam-column joint and the classification of its failure mode. Different machine learning techniques have been used for the shear strength prediction of BCJ, including Linear regression, Stepwise, Ridge, Lasso regression, Elastic net, and Random Forest. The required data sets for training and testing were collected from the literature tests done by other researchers of a total of 536 sub-assemblages specimens of BCJ exterior, interior and knee joints. The input parameters include 12 different variables from the beam, column, and joint details and geometry. The collected data had mixed failure modes of joint failure and beam-joint failure. A prediction model for each failure mode was developed after identifying the failure type. Figure 2.36 shows comparison result between the predicted and experimental strength results for the testing data of 30% (160 specimens). The results revealed that Lasso regression is a simple and accurate model for the strength prediction of RC-BCJ due to its performance and ability to disregard the insignificant variables from the regression model.

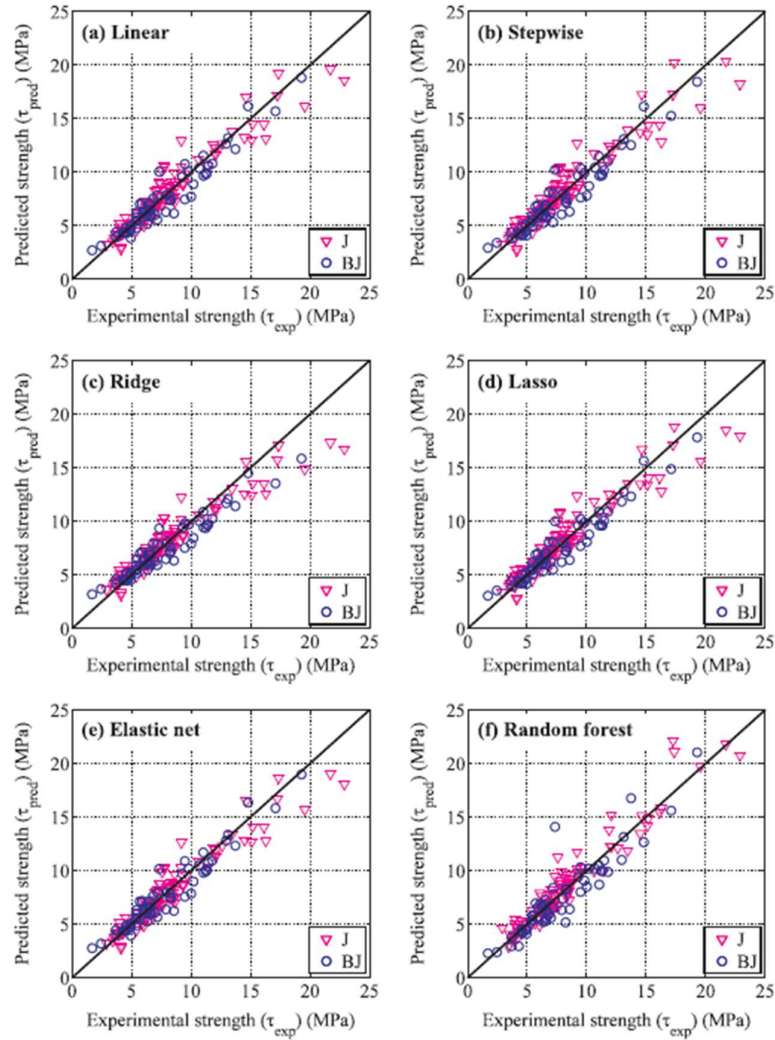


Figure 2.36 Comparison of experimental and predictive strength for the test set (160 specimens) (Mangalathu & Jeon, 2018)

Alwanas et al. (2019) proposed a model for predicting the load carrying capacity and failure mode of exterior reinforced concrete beam-column joint using extreme learning machine (ELM). The training and testing data set required for the predictive model were collected from the literature with a total number of 153 experimental testing results. The input variables were a multiple of beam-column joint details. In addition, concrete and reinforcement specifications affecting the loading capacity of

the exterior RC beam-column joint have been considered as input parameters too. The proposed prediction model was compared with another known regression model called multivariate adaptive regression spline (MARS). Figure 2.37 shows the architecture of ELM model. The statistical evaluation results were as follows: RMSE in load carrying capacity for ELM and MARS models equal to (14.44, 18.63 kN), respectively. The comparison between ELM and MARS results indicated that ELM prediction model could provide better performance than MARS model and therefore can be used for pre-design structural problems as alternative of empirical codes.

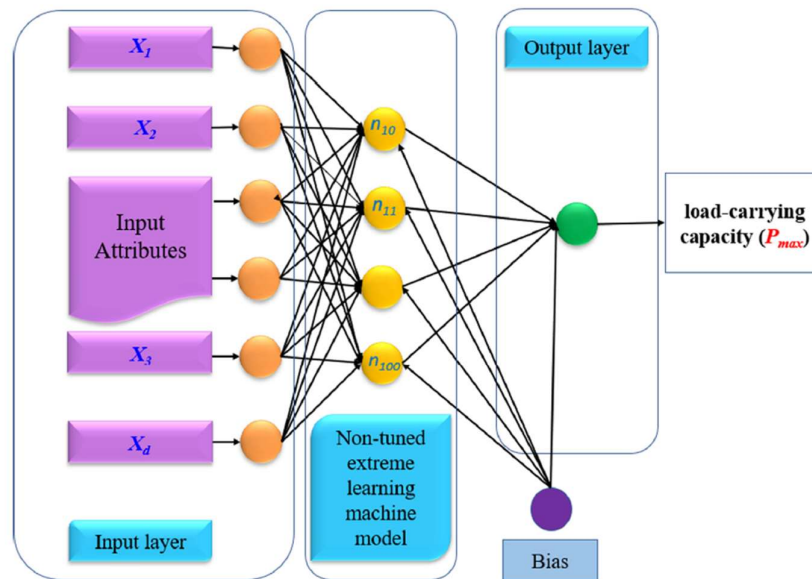


Figure 2.37 The architecture of ELM model (Alwanas, et al., 2019)

Marie, El-Hassan, Almetwally, & El-Mandouh, (2022) developed prediction models for the shear strength of cyclic loaded reinforced concrete beam-column joint using different machine learning techniques. The used ML prediction techniques were six: Ordinary Least Squares (OLS), Support Vector Machines (SVM), K-Nearest neighbor regression

(KNN), Multivariate Adaptive Regression Splines (MARS), Artificial Neural Networks (ANN), and kernel regression with mixed data types (Kernel regression). Research's flow diagram is presented in Figure 2.38. Different types of joints were considered in this research's data, where a total of 98 dataset results were collected from literature and provided for the training and testing of ML prediction models. The influencing parameters on the shear strength of RC beam-column joint were selected depending on previous experimental research. The prediction models result for shear strength were compared with the experimental shear strength of beam-column joint. The performance evaluation of the previously mentioned models is presented in Table 2.20. It can be seen from performance check results that the Kernel regression showed highest accuracy while ANN was the second highest accuracy. Figure 2.39 shows the coefficient of determination R^2 value for different developed ML prediction models. This research had shown a greater ANN prediction model accuracy when compared to previous ANN models. The predicted joint shear strength using different ML prediction models is shown in Figure 2.40.

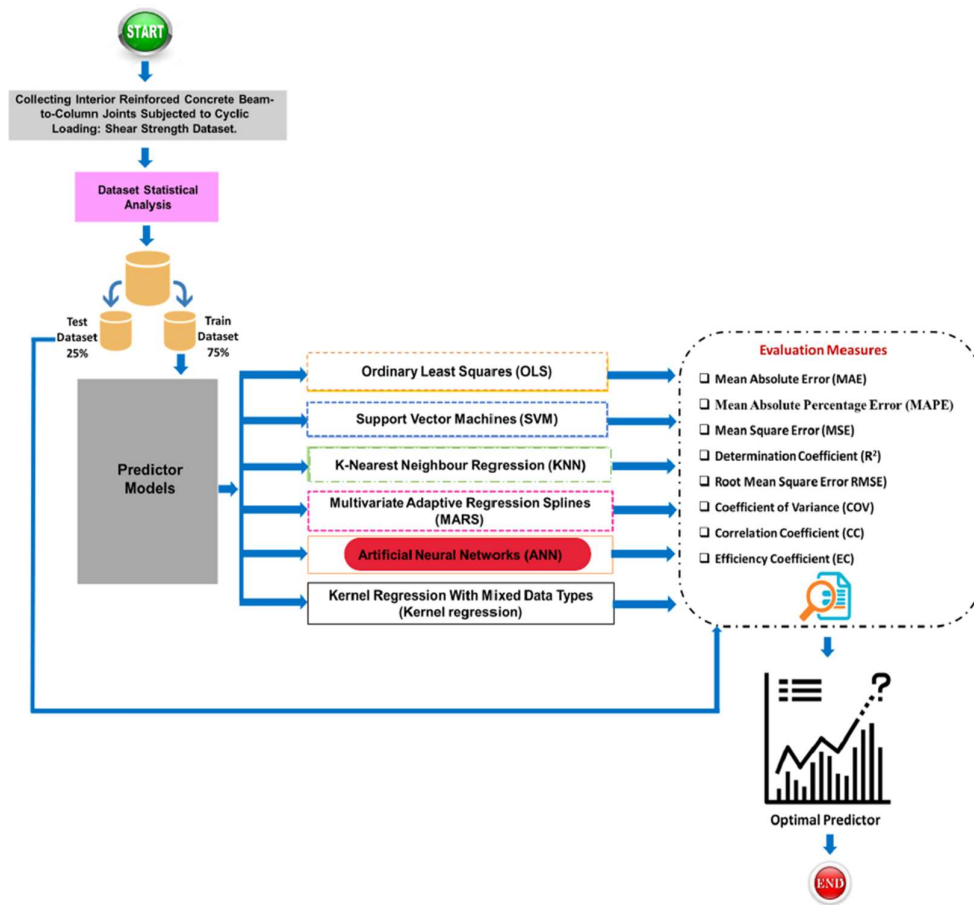


Figure 2.38 Research's flow diagram (Marie et al., 2022)

Table 2.20 Performance evaluation for the developed models in predicting the joint shear strength (Marie et al., 2022)

	OLS	SVM	k-NN	Adaptive regression splines	NNs	Kernel
MSE	4.5785	2.6009	1.7011	1.3370	1.0579	0.1620
MAE	1.5924	0.9112	0.7829	0.9138	0.7004	0.1951
MAPE	26.1770	12.5659	12.8322	15.2819	11.5139	3.1069
RMSE	2.1397	1.6127	1.3042	1.1563	1.0285	0.4025
COV	0.3179	0.2551	0.1919	0.1718	0.1507	0.0598
CC	0.5479	0.8584	0.8608	0.8920	0.9164	0.9875
EC	2.3315	1.4248	0.3672	0.2568	0.1992	0.0255

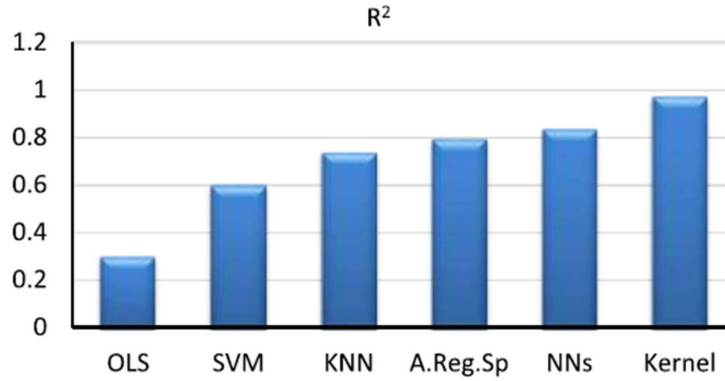


Figure 2.39 The coefficient of determination R^2 -value for different developed ML prediction models (Marie et al., 2022)

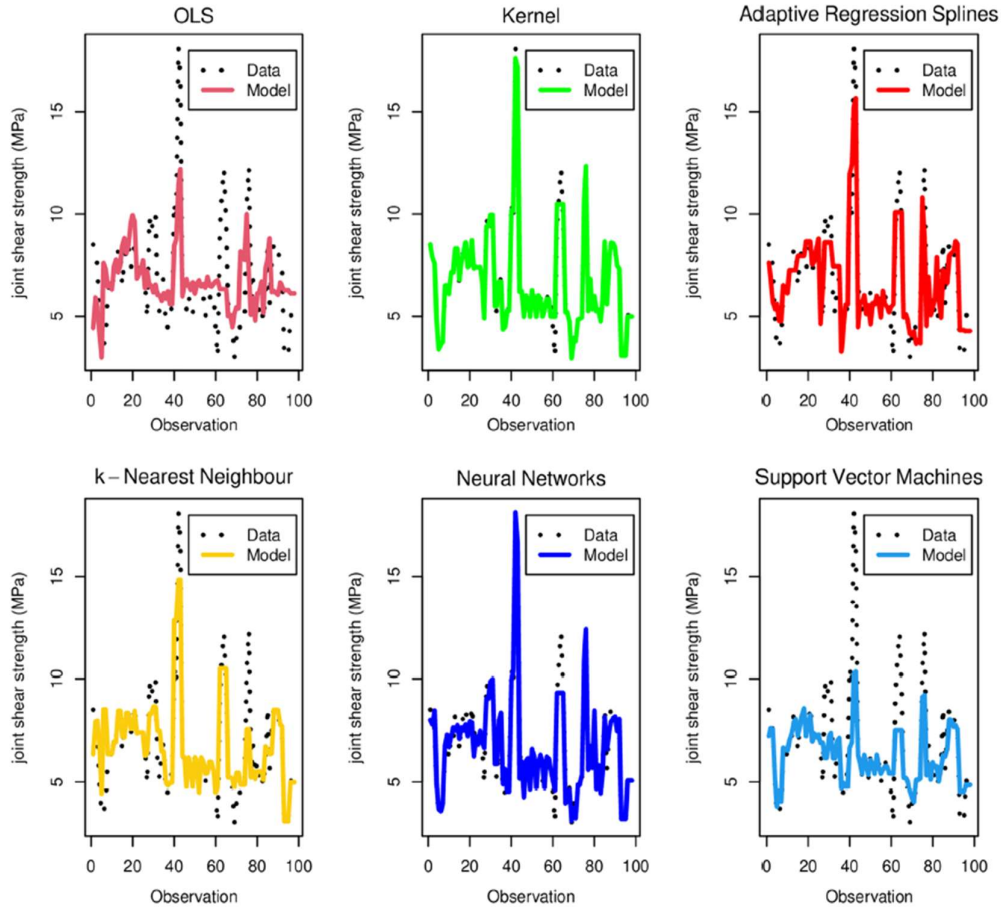


Figure 2.40 The predicted joint shear strength using different ML prediction models (Marie et al., 2022)

The research of Alagundi & Palanisamy, (2022) developed a prediction model for the shear capacity of exterior reinforced concrete beam-column joint using Artificial Neural Network (ANN). The data needed for training, testing, and validation of the model was collected from previous experimental works from the literature. A total number of 76 data sets were used as 60% for training, 20% for validation, and 20% for testing purposes. The model was developed depending on eleven input parameters that are proposed depending on their possible contribution in the shear capacity of the joint. Figure 2.41 shows the architecture of the author's finalized model which presents 11 input nodes in the input layer. The chosen input parameters in their research were as follows: joint's width and depth, compressive strength of concrete, beam's length, top and bottom longitudinal beam reinforcement, yield strength of beam longitudinal reinforcement, beam to column depth ratio, index of joint shear reinforcement, beam bar index, and index of column load. The developed ANN model was evaluated using statistical relation like coefficient of correlation (R), root mean square error (RMSE), and scatter index (SI). The RMSE value for training, testing, and validation were 3.7122, 5.4864 and 4.8515, respectively. Moreover, the developed ANN model results compared with the design codes such as the ACI code. The predicted and actual values of shear strength of exterior beam columns are shown in Figure 2.42. The results indicated that the developed ANN prediction model efficiently predicted the shear strength of reinforced concrete exterior beam-column joint.

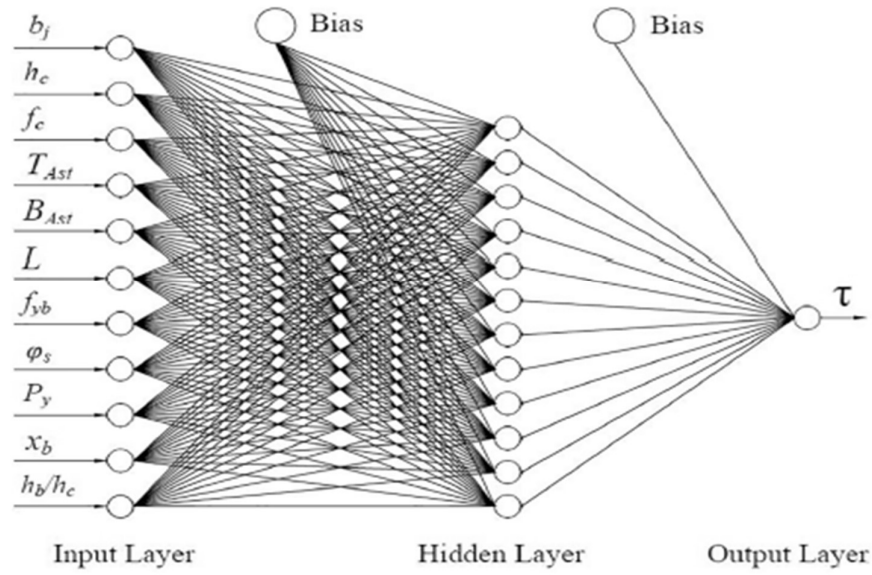


Figure 2.41 The architecture of the author's finalized model (Alagundi & Palanisamy, 2022)

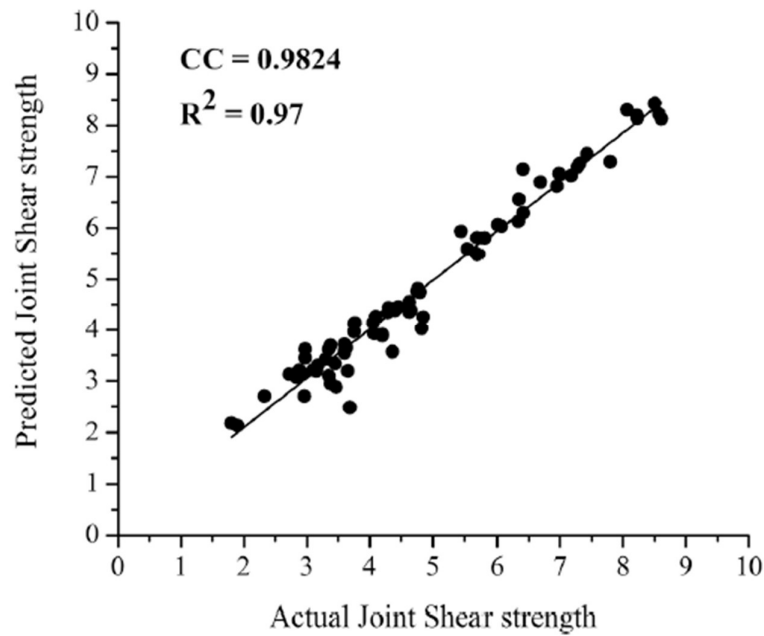


Figure 2.42 The predicted and actual values of shear strength of exterior beam column (Alagundi & Palanisamy, 2022)

Haido (2022) employed Artificial Neural Network (ANN) to propose a model for shear strength prediction and failure mode estimation of exterior and interior reinforced concrete beam-column joint using experimental data sets. Over 200 experimental specimen results were collected from literature and used for training, validation, and testing for the ANN models, where the data was mixed between exterior, and interior, reinforced, and unreinforced beam-column joint. The final formulation of ANN models depended on 22 independent variables as input parameters, where at the end, only four were chosen for the final models, which were the most influential variable on shear strength prediction of RC joint. The independent variables include joint loading, joint geometry, and material properties of the samples. Figure 2.43 shows the ANN models architecture for shear strength prediction of both exterior and interior RC beam-column joints. The performance of the ANN models had been evaluated and compared with the ACI code as shown in Figure 2.44. The evaluation revealed that the proposed ANN models are reliable in the shear capacity prediction of RC beam-column joints.

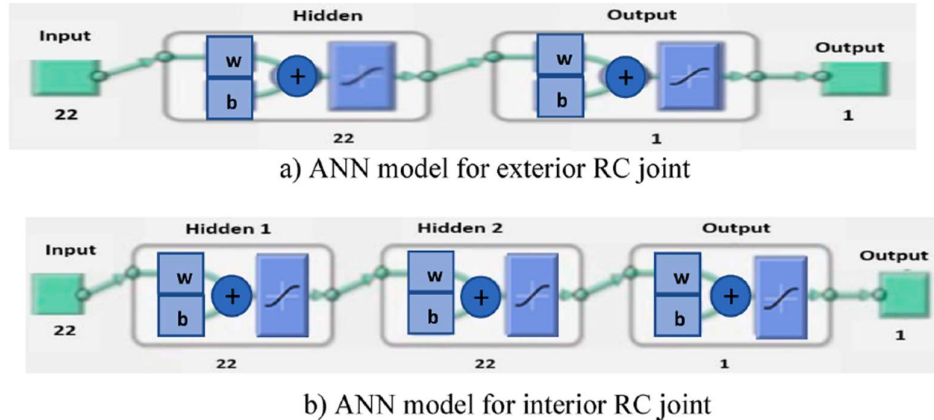


Figure 2.43 The ANN models architecture for shear strength prediction of both exterior and interior RC beam-column joints (Haido, 2022)

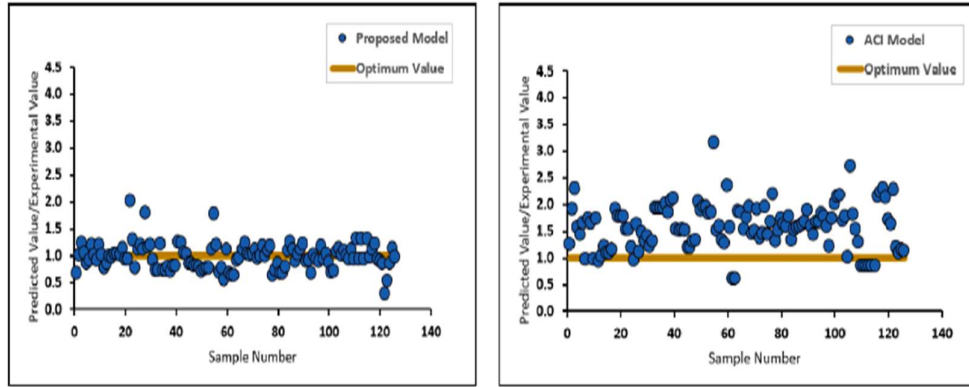


Figure 2.44 Comparison between the proposed ANN model performance and ACI model in the prediction of shear strength of Exterior BCJ (Haido, 2022)

After going through the previous studies, it has been shown that different machine learning techniques can solve engineering problems, especially, the ANN. ANN showed better performance than other techniques in the same field of civil engineering applications. Therefore, this study has used the ANN technique to develop the prediction model for the shear strength of the reinforced concrete beam-column joints that are without joints reinforcement, which has not been used before for the unreinforced beam-column joint using ANN with extensive data of training, validation, and testing (4320 samples).

2.7 Summary

From the above literature review, it can be clearly observed that the number of studies concerning the prediction of shear strength for the reinforced concrete beam-column joint has developed and takes huge concentration due to their critical role in the structure overall stability. The studies encompassed different loading and types of joints such as monotonic, cyclic, and reverse cyclic loading; moreover, the joints were interior or exterior type.

Many researchers developed different analytical and empirical models for shear strength of beam-column joint determination but few of them were focused on the unreinforced joints strength.

Many studies focus on predicting the shear strength of the RC-BCJ using the experimental method. Most prediction models for that purpose depend on the available data from experiments for producing analytical and statistical models. Recently, machine learning techniques took place in developing prediction models for beam-column joint strength prediction.

It can also be observed from the above literature review that there are fewer papers on the prediction of RC-BCJ strength using ML techniques, because ML is relatively new approach. In addition, BCJ regions are critical and under non-linear behavior which makes the ML techniques a potential alternative for the traditional numerical and experimental approaches in the prediction for such part in structures.

It has been noticed that the studies for prediction model of RC-BCJ were using the limited number of available experiments in the literature, where it can compromise the performance of some ML techniques that require large number of data as examples to learn from (like ANN). However, with the recent evolution in structural analysis software specially

the non-linear analysis software's, as well as the availability of more powerful computer devices during the last decades, in this research the development of large number of required data is accomplished and has been used for the prediction model development.

This research has benefited from previous studies such that many studies can be helpful references for evaluating the prediction model developed. Moreover, previous studies showed that the variations in the data provided with more range can give better performance for the ANN model, which gave the inspiration for producing the data through finite element analysis software ABAQUS, and those produced data were calibrated with experimental data of one specimen.

The next two chapters explain data generation through finite element analysis software ABAQUS and the machine learning (ANN) model development procedure done through MATLAB software.

Chapter Three

Finite Element Analysis

Modeling Work

Chapter 3 FE Analysis Modeling Work

3.1 Introduction

Numerical modeling has been used highly to simulate the structures damages and failure modes. The non-linear behavior of structures can be analyzed to predict the failure of these structures. There are many finite element analysis softwares for structural analysis which can simulate and study structural behavior. ABAQUS non-linear finite element analysis software was used in this research to simulate the exterior beam-column connections failure under monotonic loading that are without joint transverse reinforcement. The maximum carrying load capacity for the connection was captured depending on the results of the simulation software which was fed with calibrated concrete material properties. The data produced from the simulation process was filtered to consider the connections with joint failure type only. This data was used later for ANN learning stage to develop ANN prediction model for shear strength of unreinforced exterior RC beam-column joints. The use of simulation by ABAQUS non-linear finite element analysis software helped on minimizing the effect of experiments on the environment by eliminating testing waste and avoiding the emission of carbon dioxide while testing. To maintain the accuracy of the results of this study, one beam column joint (tested by Ajmal, 2016) was modeled in Abaqus, and the results of the FEM model were compared with the experimental results.

3.2 Finite Element Analysis for Nonlinear Behavior of BCJ

The Finite element method (FEM) is an important and highly used method in structural numerical simulation. Complex problems can be solved using finite element modeling starting from elastic linear models for linear elements to highly plastic models for nonlinear and solid elements (Nafees, et al., 2021). FEM can simulate all types of structures, such as timber, steel, concrete, and masonry.

In order to apply the FEM in numerical simulation for unreinforced exterior beam-column connection, ABAQUS/CEA software was selected in this research which is capable of solving different analysis problems such as elastic and inelastic problems of static and dynamic response of elements. The ABAQUS/CAE 6.13-1 version was used to model and analyze unreinforced exterior beam-column connections. The results accuracy from numerical FEM simulation depends mainly on the input data of material properties, which makes material properties a critical step in the numerical analysis. Therefore, to achieve better accuracy, calibration of the experimentally tested specimen has been done in this research to match the experimental results.

The RC beam-column joint area is a critical and nonlinear region that requires modeling of concrete damage, which was modeled through concrete damage plasticity (CPD) in the software that will be discussed in section 3.5.2.1. The following sections (3.5, 3.6) will show the procedure of modeling the sub-assemblages in ABAQUS/CAE software and the analysis results.

3.3 Experimentally tested exterior beam-column connection for calibration (Ajmal, 2016)

For the purpose of calibration of the concrete material behavior that will be entered into the material properties of ABAQUS nonlinear finite element analysis software, one tested unreinforced exterior beam-column connection specimen is referred to and used in this study which is taken from the research study of Ajmal, (2016).

A specimen of exterior beam-column connection without joint reinforcement named by BCJ-M, Figure 3.1 , tested by Ajmal, 2016, has been chosen for verification and calibration of the nonlinear behavior of concrete material that will be used to check the CDP model before utilizing it in finite element analysis modeling of exterior beam-column connections. Figure 3.2 shows the testing setup and Figure 3.3 shows the used hydraulic jacks for experimental loading. The specimen was tested under monotonic loading. The test was divided into two stages starting with a column load of 150 kN applied on the top surface of the specimen's column. After the completion of column loading stage, the beam was loaded using a second hydraulic jack. The loading on beam tip was done using quasistatic cyclic loading approach displacement which was pushed and pulled until the failure of the specimen occurred. The sample was pushed up to ultimate load and when the ultimate load started to decrease, it was pulled to the complete failure of the specimen, which failed completely in shear. In push direction, the ultimate load of 122.46 kN was reached at displacement of 20.46 mm. The load-displacement curve of BCJ-M is shown in Figure 3.4. Figure 3.5 shows the formation of cracks during testing of BCJ-M.

The column in specimen BCJ-M (see Figure 3.1) has a length of 1400 mm with a cross-section of 250×300 mm and is reinforced with $6\phi 20$.

The beam clear length is 900 mm with a cross-section of 250 × 300 mm and equal reinforcement at the top and bottom of reinforcement with 3 ϕ 20. Table 3.1 summarizes the details of connection reinforcement and material characteristics.

Table 3.1 Specimen M-BCJ details

Specimen	f_c' (MPa)	f_y (MPa)		Column Reinforcement		Beam Reinforcement		
		Main	Transverse	Longitudinal	ties	Tension	Compression	Stirrups
BCJ-M	45	607.15	480	6 ϕ 20 mm	1 ϕ 8 @50 mm	3 ϕ 20 mm	3 ϕ 20 mm	1 ϕ 8 @50 mm

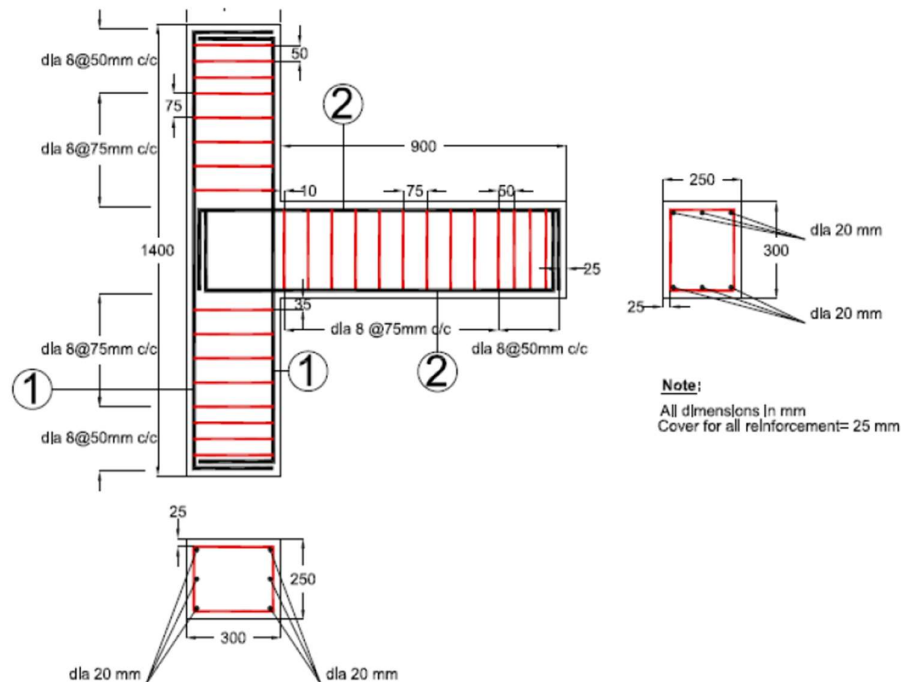


Figure 3.1 Reinforcement and geometry detailing of M-BCJ tested specimen (Ajmal, 2016)



Figure 3.2 Testing setup of M-BCJ Specimen, (Ajmal, 2016)

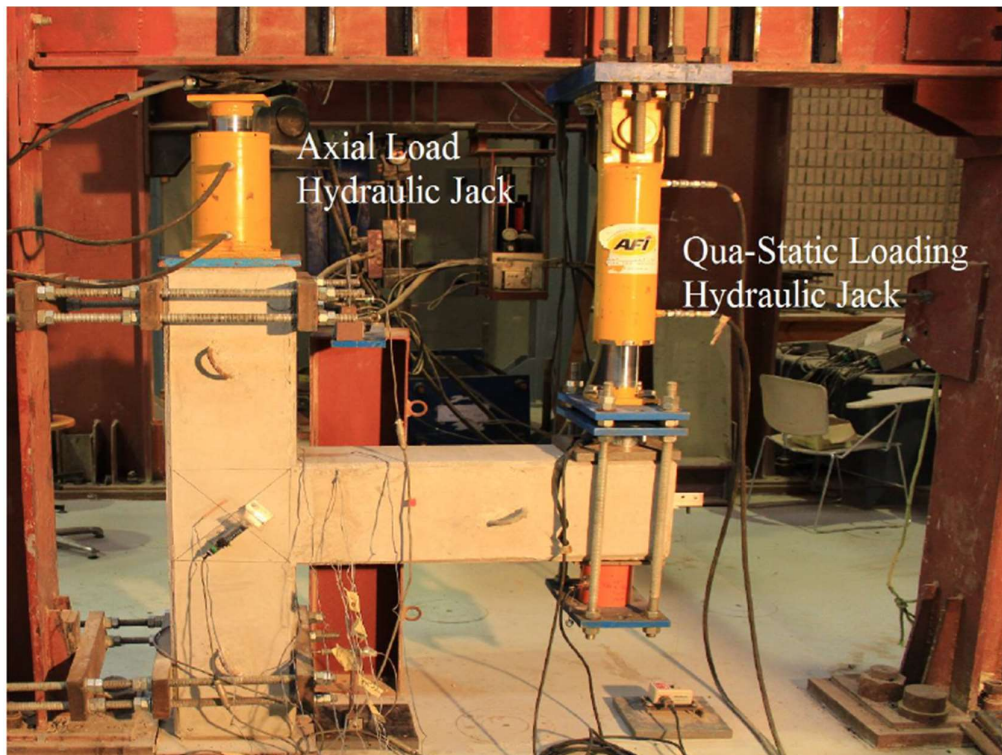


Figure 3.3 Hydraulic jacks for loading of M-BCJ specimen,
(Ajmal, 2016)

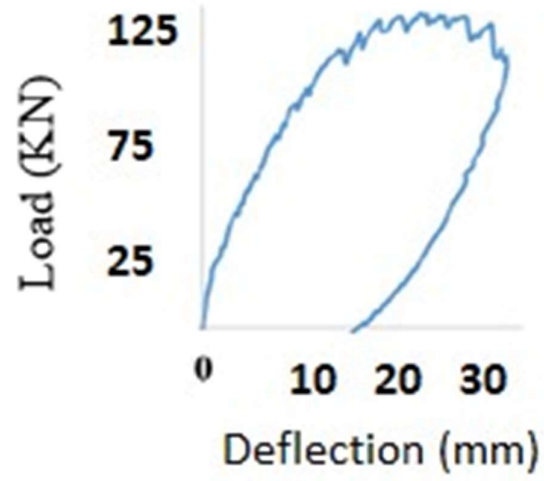


Figure 3.4 The load-displacement curve of BCJ-M specimen (Ajmal, 2016)



Figure 3.5 The formation of different flexural and shear cracks during pushing the beam of BCJ-M (Ajmal, 2016)

3.4 Exterior Connection Different Design Parameters for Data Producing through ABAQUS Software

To provide a wide range of variables value as the required learning examples data for ANN model, different design parameters from the exterior connection were selected and wide range of values were chosen. In addition, the selected parameters were chosen depending on their effectiveness on the shear strength of beam-column joint as mentioned in previous research in literature. The selected design parameters are column depth, beam depth, concrete compressive strength, beam tension reinforcement total area (by changing the rebar diameter), beam tension reinforcement yield strength, axial column load as ratio of its capacity. Table 3.2 presents the design parameters values range. The total number of samples using the varied design parameters were 6480 samples which are numerically modeled through ABAQUS nonlinear finite element analysis software. The results were filtered and the joint shear failure connection samples were selected which were around 4320. The results of these samples were later used in machine learning technique-ANN.

Table 3.2 Design parameters varied values.

Varied values design parameters	Unit	1	2	3	4	5	6	7	8	9	10
Concrete cylinder compressive strength	MPa	17	20	25	30	35	40	45	50	55	60
Column depth	mm	150	200	300	400	500	600				
Beam depth	mm	150	200	300	400	500	600				
axial column load as ratio (as ratio of column's capacity)		0.05	0.10	0.15							

Beam tension reinforcement Area (by changing the rebar diameter)	mm	16	20	25							
Beam tension reinforcement yield strength	MPa	460	660								
Total number of simulated exterior connection samples	$= 10 \times 6 \times 6 \times 3 \times 3 \times 2$ $= \underline{6480} \text{ Samples}$										

3.5 Nonlinear Finite Element Analysis

This section will present the details for numerical simulations of the exterior connection samples analyzed through ABAQUS software to produce the required data for the ML – ANN model.

In ABAQUS software has a large material element library available that is used to simulate the concrete structure precisely, especially these structures modeling is complicated, and their behavior is nonlinear in nature. Numerical modeling steps are presented in the following sections. Appendix (2) provides more details regarding simulation work through ABAQUS.

3.5.1 Geometry

The 6480 samples of exterior beam-column connections were modeled considering the same setup used in tested specimen by Ajmal, (2016), (mentioned in section 3.3) by varying the selected parameters as mentioned in section 3.4, Table 3.2.

As mentioned previously, the wider range of variables values could give a variety of data for machine learning model to train. Some of the parameters were kept constant in all the specimens and their values were taken similar to Ajmal, (2016), tested specimen M-BCJ shown in Figure 3.1. The 6480 samples were modeled in ABAQUS as 3D nonlinear finite element analysis connections.

3.5.2 Material model

Different material properties need to be incorporated in the ABAQUS software to simulate the concrete structure elements precisely. The behavior of concrete material is complicated and brittle. In addition, it is a nonlinear material and nonlinearity of it can be captured in ABAQUS using concrete damage plasticity (CDP).

3.5.2.1 Concrete Damage Plasticity (CDP)

The CDP model is used for defining concrete material behavior in the inelastic range as developed in Mander, (1988), Model (Mander, Priestley, & Park, 1988), due to the ability of that plasticity-based model in taking into account two primary failure modes for concrete elements. These failure modes are concrete compressive crushing and concrete tensile cracking. The stress-strain curves of the response of concrete in tension and compression are shown in Figure 3.6 , where Table 3.3 describes the notations in that figure.

The CDP model has demonstrated its ability in simulating the non-linear behavior of exterior beam-column connections as shown in various research when CDP model has been utilized (Ajmal, 2016; Allam et al., 2018; El-Naqeeb et al., 2022). Many parameters need to be defined as part of the CDP model, such as the plasticity parameters, concrete uniaxial behavior in compression and tension, and the scalar damage parameters in compression and tension. These will be discussed in the next sections.

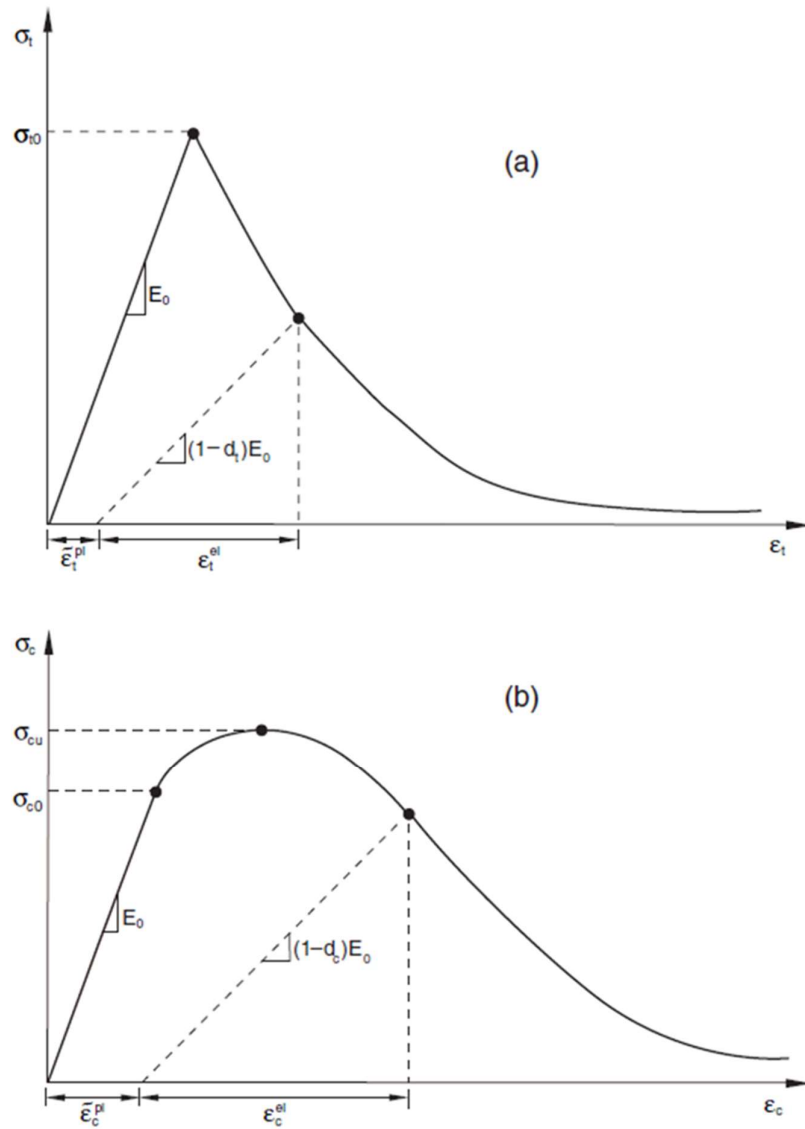


Figure 3.6 Response of concrete: (a) in tension; and (b) in compression (ABAQUS, 2013)

Table 3.3 Notations description related to the response of concrete in compression and tension.

E_0	Tangent modulus of elasticity of the concrete: the initial elastic modulus (MPa)
$\tilde{\epsilon}_t^{pl}$	The equivalent tension plastic strain rate
$\tilde{\epsilon}_c^{pl}$	The equivalent compression plastic strain rate
ϵ_t^{el}	Tension elastic strain
ϵ_c^{el}	Compression elastic strain
d_c	Compression scalar damage parameters
d_t	Tension scalar damage parameters
σ_c	Concrete compressive stress (MPa)
σ_t	Concrete tension stress (MPa)
ϵ_c	Concrete compressive strain
ϵ_t	Concrete tension strain
σ_{cu}	Ultimate concrete cylinder compressive strength (MPa)
σ_{c0}	Concrete compressive stress at the end of elastic region (yield stress) (MPa)
σ_{t0}	Concrete tensile strength (MPa)

3.5.2.1.1 The Plasticity Parameters

Many plasticity parameters need to be defined as part of the CDP model. The main plasticity parameters will be discussed as follows. The dilation angle of concrete, which is taken as 36° , is the angle that causes plastic shearing due to the volumetric strain change. A study carried out by Ajmal, Ahmed, Baluch, Rahman, & Ayadat, (2023), recommended that dilatation angle must be between 30 to 36 for BCJs that fail in shear. Similarly, in reinforced concrete seismic design, it is recommended by the ABAQUS user manual (ABAQUS, 2013) that the dilation angle is to be taken between 35 to 38° . In addition, eccentricity is another plasticity parameter that can be defined as the deviation from the center and its default value is 0.1 which was taken as presented in Table 3.4. Moreover, the ratio of biaxial loading (f_{b0}) to uniaxial loading (f_{c0}) is one of the plasticity parameters and it is normally taken as one or larger; in this research the value of 1.16 was taken as it is a default value. Furthermore, the ratio between the second stress invariant on the tensile meridian to that on the compressive meridian (K) was taken as 0.667 which is the default value. The concrete modulus of elasticity (E_c) is calculated as $E_c = 4700 \sqrt{f'_{c0}}$ MPa according to the ACI code, and the concrete Poisson's ratio = 0.19, while the density of concrete is taken as 24 kN/m^3 .

Table 3.4 Concrete parameters used in plastic damage model.

Mass Density (kN/m^3)	Young's Modulus (MPa)	Poisson's Ratio	Dilation Angle	Eccentricity	$\frac{f_{b0}}{f_{c0}}$	K
24	$4700 \sqrt{f'_{c0}}$	0.19	36°	0.1	1.16	0.667

3.5.2.1.2 Concrete Behavior in Compression

Concrete behavior in compression is defined in this research using Mander, (1988), model and the uniaxial stress-strain curve of concrete through this model is shown in Figure 3.6 (b). The samples considered in this research do not have transverse reinforcement in the beam-column joints and hence considered as unconfined concrete region. The stress-strain model for unconfined concrete subjected to uniaxial compressive loading by Mander, (1988), is shown in Figure 3.7. Equation (3-1) describes this model and it is followed by its notations detail.

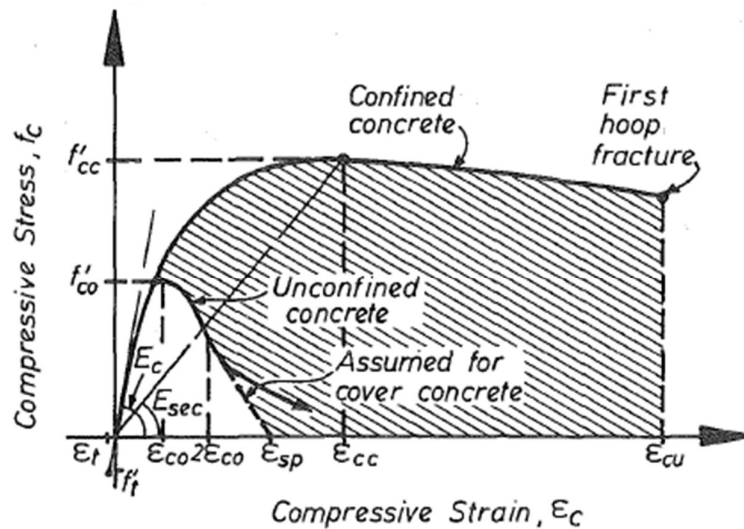


Figure 3.7 Stress-Strain model proposed for monotonic loading of confined and unconfined concrete (Mander, Priestley, & Park, 1988)

Mander, (1988), Model Equation:

$$f_c = \frac{f'_{c0} \times x \times r}{r - 1 + x^r} \quad (3-1)$$

Where:

f_c : Concrete compressive stress (MPa)

f'_{c0} : Unconfined ultimate concrete cylinder compressive strength (MPa)

$$x = \frac{\epsilon_c}{\epsilon_{c0}} \quad (3-2)$$

ϵ_c : Longitudinal compressive concrete strain

ϵ_{c0} : Unconfined concrete strain at the ultimate compressive strength f'_{c0}

$$r = \frac{E_c}{E_c - E_{sec}} \quad (3-3)$$

$$E_{sec} = \frac{f'_{c0}}{\epsilon_{c0}} \quad (3-4)$$

$$E_c = 4700 \sqrt{f'_{c0}} \quad (\text{MPa}) \quad (3-5)$$

According to Mander, (1988), it is generally recommended to take the unconfined concrete strain (ϵ_{c0}) as 0.002 in Equation (3-2), but as per ACI 318, ultimate strain can be taken between 0.003 to 0.004. This research was calibrated with Ajmal study, (2016), and the used strain for concrete at failure (ϵ_{c0}) is equal to 0.0032 which gave better calibration and agreement with the experimental result of Ajmal, (2016).

The compressive behavior of concrete in terms of stress-inelastic strain curve will be defined by many points. The first point will be the starting of inelastic region (end of elastic region), as suggested by previous studies, the stress can be taken as 30% of the ultimate concrete compressive strength ($0.3 \times f'_{c0}$) (Wolanski, 2004). After that point, Mander, (1988),

model will be used to define the points in the inelastic part of curve using equation (3-1).

The ABAQUS software is taking the compressive inelastic behavior of concrete as many points for stress and inelastic strain as shown in Figure 3.8. The inelastic strain (ϵ_c^{in}) is calculated by deducting the elastic strain (ϵ_{oc}^{el}) from the total strain (ϵ_c), as in Equation (3-6). The elastic strain (ϵ_{oc}^{el}) for compression behavior of concrete in Equation (3-7), is equal to $(0.3 \times f'_c / E_c)$ since it is recommended to limit the elastic strain up to 30% of the concrete compressive strength. Poisson's ratio (ν): Poisson's ratio considered to be equal to 0.19 for concrete material.

$$\epsilon_c^{in} = \epsilon_c - \epsilon_{oc}^{el} \quad (3-6)$$

$$\epsilon_{oc}^{el} = \frac{0.3 \times f'_c}{E_c} \quad (3-7)$$

E_c : Tangent modulus of elasticity of the concrete: the initial elastic modulus

Figure 3.8 shows the stress-inelastic strain of concrete in compression for the experimental result of Ajmal, (2016) study which were compared with the stress-inelastic strain curve produced in this research using Mander, (1988), model. From the comparison, it is observed that there is good agreement between the mentioned curves.

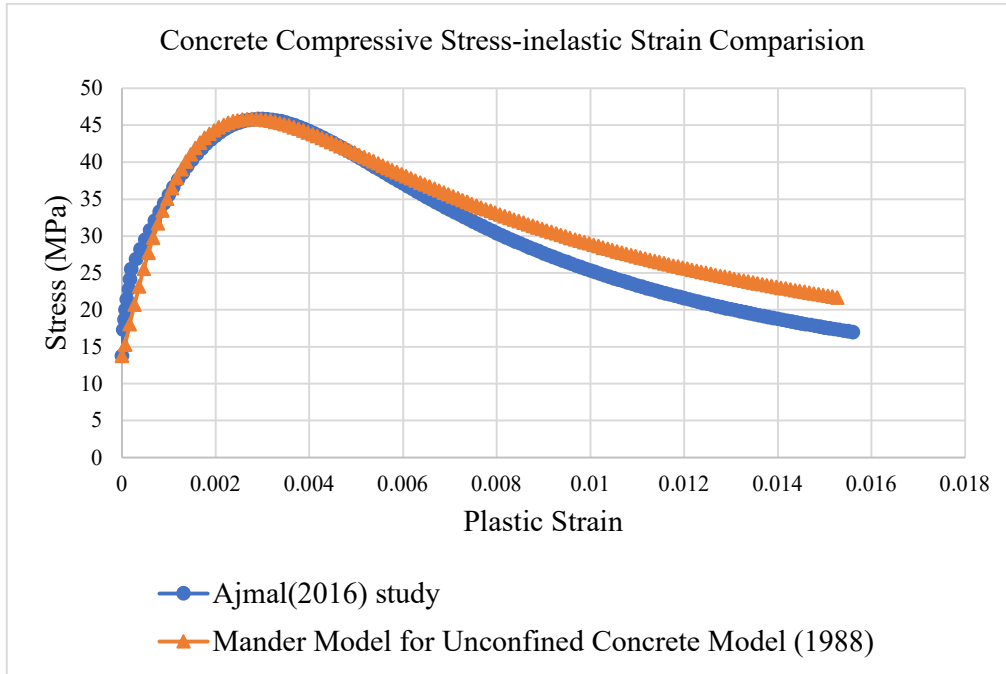


Figure 3.8 Concrete compressive stress-inelastic strain comparison between utilized Mander,1988, model and Ajmal, 2016 experimentally obtained curve.

3.5.2.1.3 Concrete Behavior in Tension

For concrete tension behavior modeling, a linear elastic brittle material with strain softening was used and tension stiffening is allowed by modifying the concrete softening behavior. To simulate the behavior of concrete in tension in post cracking stress-strain relationship, see Figure 3.6 (a), the stress-strain model produced by (Massicotte, Elwi, & MacGregor, 1990) and modified by (Allam, Shoukry, Rashad, & Hassan, 2013), Figure 3.9, was used for the ascending part of the curve after the linear part. The linear relation is stopped at the tensile strength of concrete ($f_{ct\ max}$), where the cracking of concrete is reached. The curve shown in Figure 3.9, was softened to allow the relatively gradual response and consequently prevent the problems that could happen in the convergence (Allam, Shoukry, Rashad, & Hassan, 2013).

According to ACI 318-19 code, concrete cracking strength ($f_{ct\ max}$) is equal to $0.62\sqrt{f'_{c0}}$. The cracking strain (ϵ_{cr}) is the strain value at the tensile strength level ($f_{ct\ max}$). The inelastic tension strain (ϵ_t^{in}) is the total tension strain (ϵ_t) minus the elastic tension strain (ϵ_{ot}^{el}), where the elastic tension strain is equal to the cracking strain (ϵ_{cr}). The inelastic tension strain and its corresponding stress will be obtained for the points as in Figure 3.9. The tensile behavior of concrete will be expressed by stress-inelastic strain curve starting from zero inelastic strain at f_{ct} , and then the modified tension softening curve that initially developed by Massicotte model, Figure 3.9, will be used for the remaining inelastic points in the curve as shown in Figure 3.10. Figure 3.10 shows the concrete tensile stress-inelastic strain for one sample calibrated with M-BCJ specimen tested by Ajmal, (2016), as mentioned in section 3.3.

$$f_{ct\ max} = 0.62\sqrt{f'_{c0}} \quad (3-8)$$

Where:

$f_{ct\ max}$: Tensile strength of concrete (MPa)

f'_{c0} : Compressive strength of concrete (MPa)

$$\epsilon_{cr} = \frac{f_{ct\ max}}{E_c}, \text{ equal to the elastic strain} \quad (3-9)$$

$$\epsilon_t = \frac{f_t}{E_c} \quad (3-10)$$

$$\epsilon_t^{in} = \epsilon_t - \epsilon_{ot}^{el} \quad (3-11)$$

$$\epsilon_{ot}^{el} = \frac{f_{ct\ max}}{E_c} \quad (3-12)$$

f_t : Tensile stress of concrete (MPa)

E_c : Tangent modulus of elasticity of the concrete: the initial elastic modulus

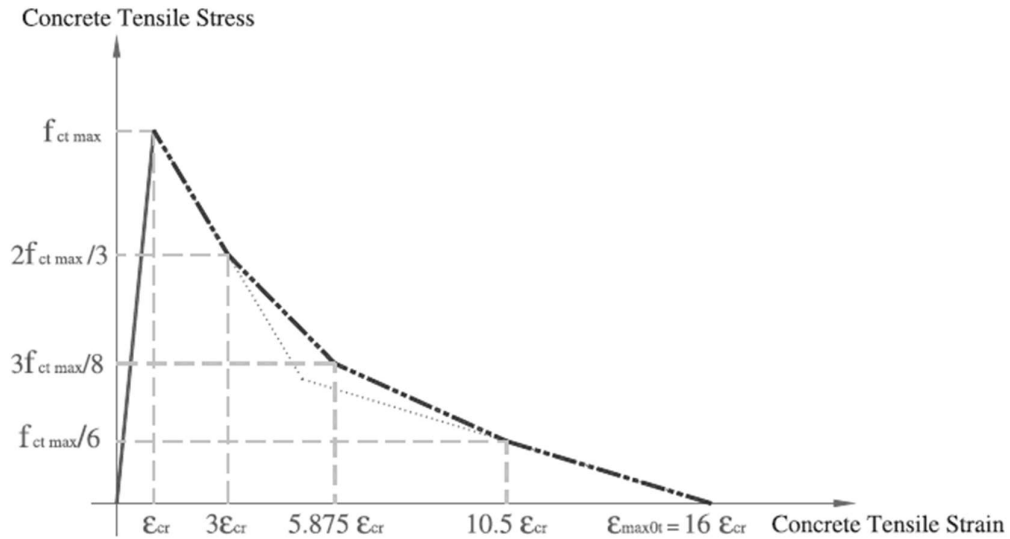


Figure 3.9 Modified tension softening curve (Allam, Shoukry, Rashad, & Hassan, 2013)

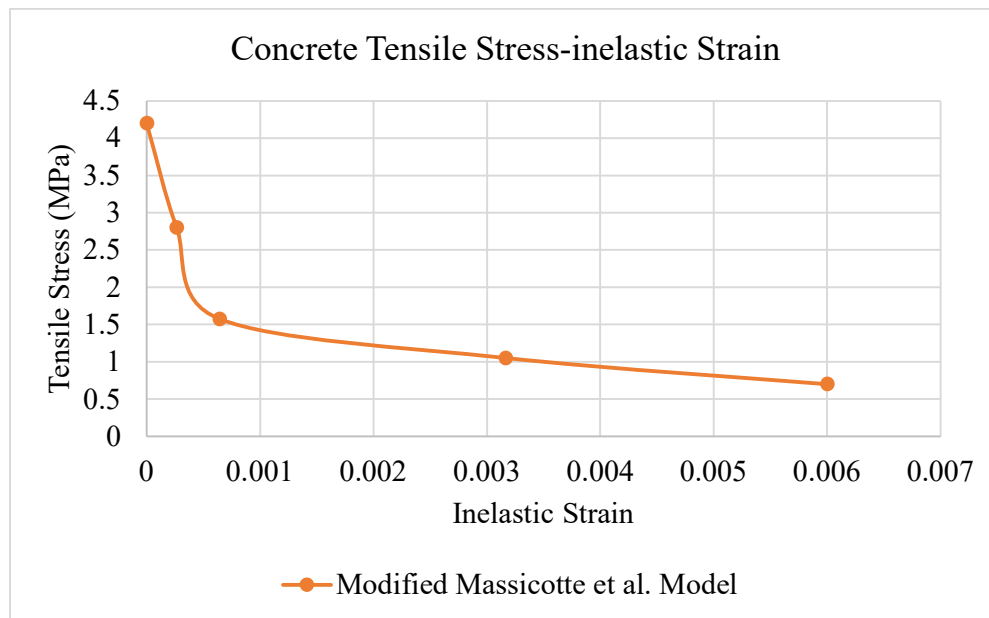


Figure 3.10 Concrete tensile stress-inelastic strain utilized using modified tension softening curve

3.5.2.1.4 Damage Parameters

In ABAQUS user guide, (2013), the scalar damage parameters in compression (d_c) and in tension (d_t) are included in the concrete model after the elastic region has ended as shown in Figure 3.6. The damage will take place in the inelastic region of the stress-strain curve. Equation (3-13) & (3-14) show the scalar damage parameter equations according to ABAQUS software manual (ABAQUS Manual, 2013).

The damage parameters d_c and d_t are linked to the corresponding inelastic compression strain (ϵ_c^{in}) and inelastic tension strain (ϵ_t^{in}). The damage can be determined proportional to the inelastic strain as shown in equation (3-13) & (3-14) using constant factors b_c for the compressive damage parameter and b_t for the tensile damage parameter equation. Both factors b_c and b_t are constant factors with value between 0 to 1. The damage variables can take values from zero, representing the undamaged material, to one, which represents total loss of strength (ABAQUS Manual, 2013). The best values for b_c and b_t which gave better calibration with the tested specimen (M-BCJ) by Ajmal, (2016), were 0.85, 0.98, respectively.

Figure 3.11, and Figure 3.12 show the damage parameters for concrete in compression and tension, respectively, for the calibrated sample that simulated in ABAQUS, which showed good agreement with the experimental result of Ajmal, (2016), M-BCJ specimen.

$$d_c = 1 - \frac{f_c \times E_c^{-1}}{\epsilon_c^{in} \left(\frac{1}{b_c} - 1 \right) + f_c \times E_c^{-1}} \quad (3-13)$$

$$d_t = 1 - \frac{f_t \times E_c^{-1}}{\epsilon_t^{in} \left(\frac{1}{b_t} - 1 \right) + f_t \times E_c^{-1}} \quad (3-14)$$

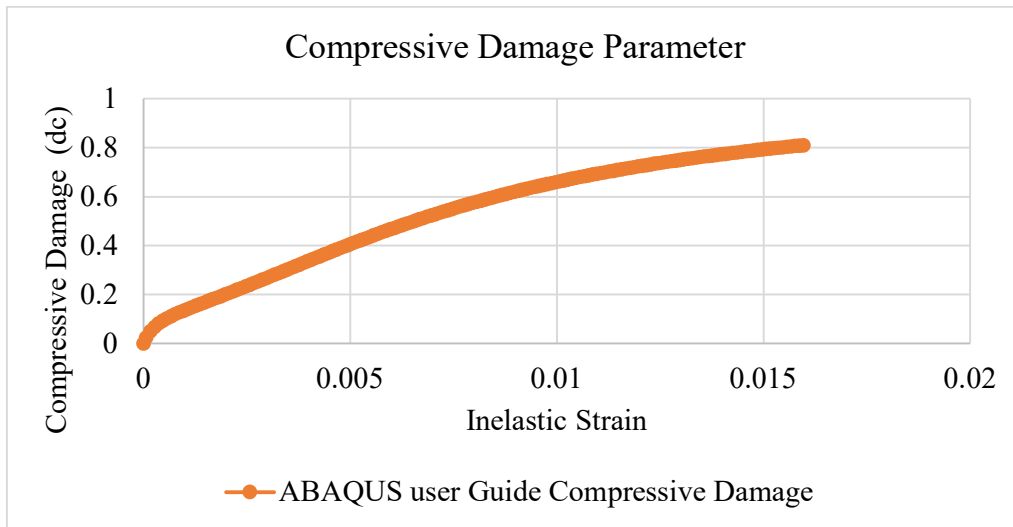


Figure 3.11 Damage evolution for concrete under compression according to ABAQUS equation (3-13)

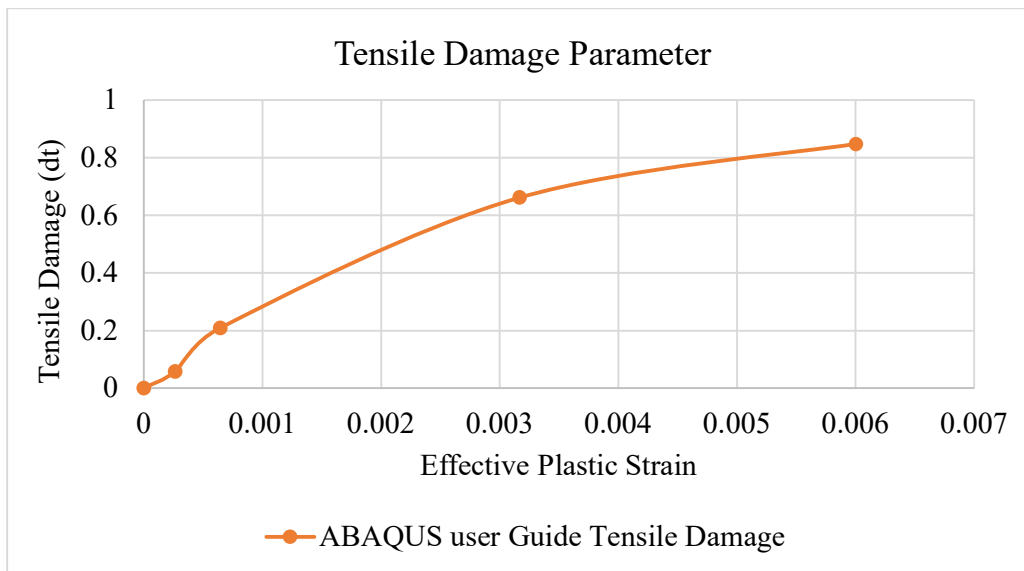


Figure 3.12 Damage evolution for concrete under tension according to ABAQUS equation (3-14)

3.5.2.2 Steel Material and Reinforcement Modeling

The reinforcement of concrete structures is provided in ABAQUS software by means of rebars. These rebars are one dimensional rods and were defined as embedded inside the concrete elements using the embedment constraint. The bond between the concrete and reinforcement steel is considered as a perfect bond. The steel plates were used as solid material on the top and bottom of column surface, and at the loading point on the beam tip for better distribution of load on the area without disturbing the elements with high punching shear stress.

To describe the material behavior of rebars, metal plasticity models are typically used. Steel material was defined using bi-linear method where for the reinforcement steel the elastic-plastic with linear strain hardening was assumed as steel behavior. Steel plates are defined as elastic material because their function is to distribute load without reaching steel plasticity. The yield stress for the steel reinforcement was considered with two different value for different samples through ABAQUS, for the column all the samples was defined with 460 MPa as yield stress while for the longitudinal beam rebars half of the samples (6480/2) were defined with 460 MPa and the remaining with 660 MPa because the beam rebar yield strength is considered as one of the factor that may affect the shear strength of the joint. The steel density is entered equal to 78.5 kN/m^3 . The steel modulus of elasticity for reinforcement rebars is considered as $E_s = 200 \text{ GPa}$, and Poisson's ratio = 0.3, while for steel plates the modulus of elasticity is considered as $E_s = 200 \text{ GPa}$, and the Poisson's ratio = 0.25. The reinforcement steel modeled as linear element as shown in Figure 3.13. The stress-strain curve entered in ABAQUS for the beam and column rebars main steel reinforcement is shown in Figure 3.14 while Figure 3.15 is

stress-strain curve of steel reinforcement used for beam only as one of the changing parameters.

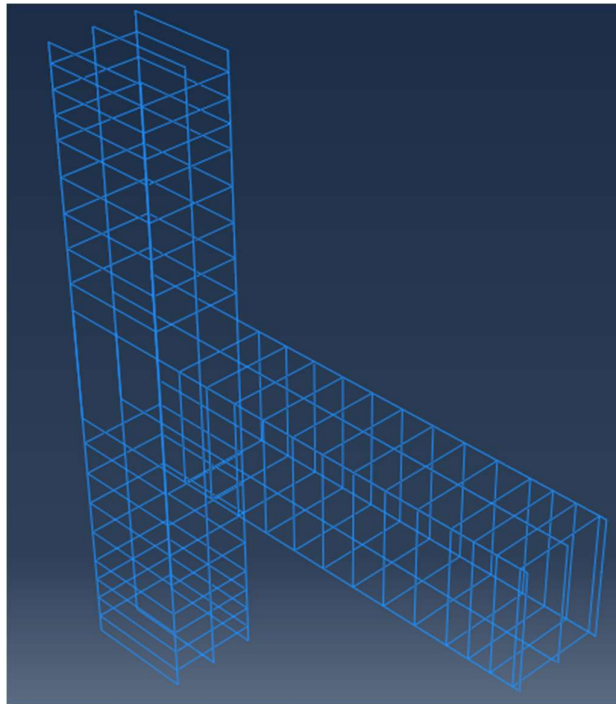


Figure 3.13 Reinforcement Modeling in ABAQUS

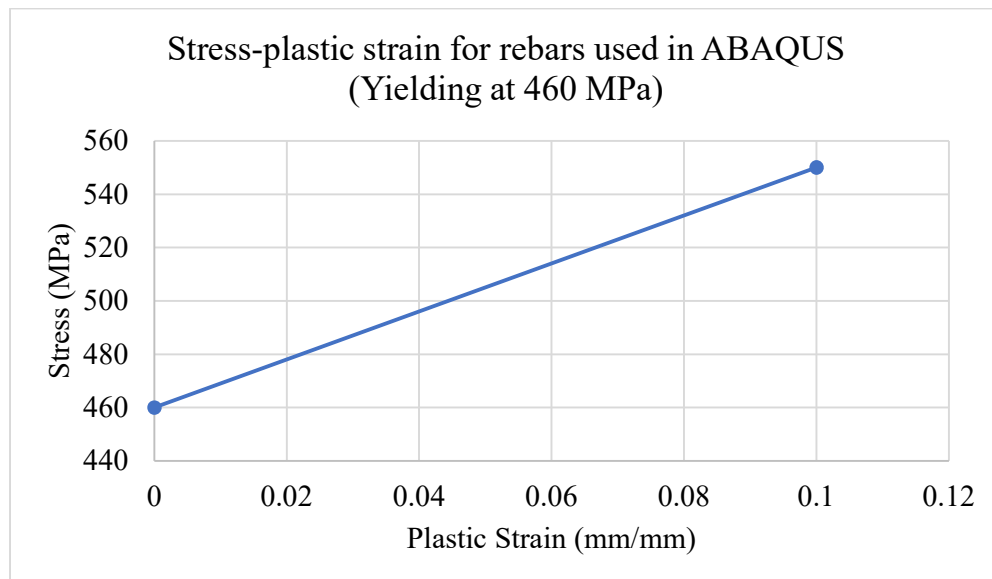


Figure 3.14 Stress-inelastic strain for rebars used in ABAQUS
(Yielding at 460 MPa)

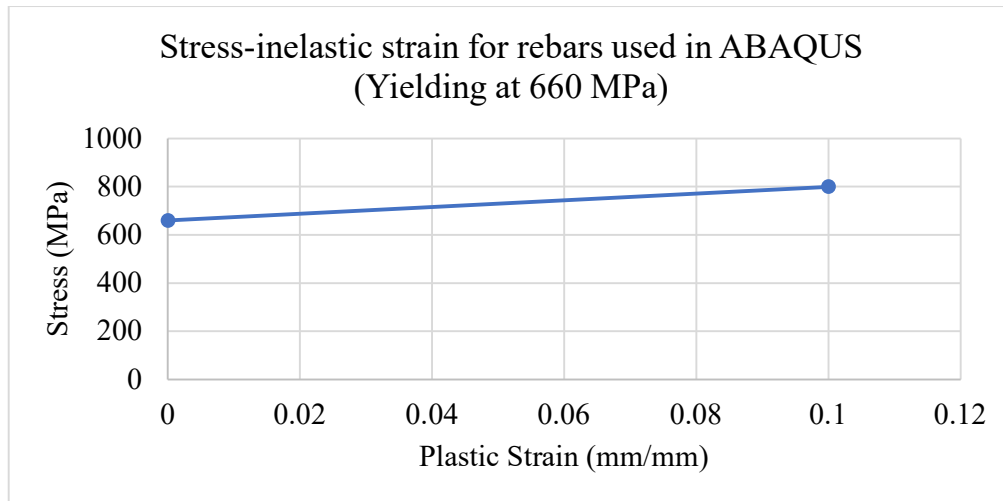


Figure 3.15 Stress-inelastic strain for rebars used in ABAQUS (Yielding at 660 MPa)

3.5.3 Element types

To model the concrete and the loading steel plates, the eight noded 3D hexahedral element C3D8R in ABAQUS is used, which is 8-node linear brick reduced integration element. This element has three translation degrees of freedom at each node. Moreover, the reinforcement steel rebars are modeled as two-node linear truss element T3D2 in ABAQUS, with three translation degrees of freedom at each node.

3.5.4 Loading, Boundary Condition and Meshing

The top end of the column surface was constrained in x and z-direction, and the bottom end of the column was constrained in x, y, and z-direction, simulating the experimental test setup's boundary condition. Two separate load steps are generated in ABAQUS software using dynamic explicit analysis simulation. In step one, the column top surface axial load was applied. While the next step was introduced by applying a controlled displacement at a reference point on the center of the loading plate of the beam as loading step of beam. The reference point for the beam

loading is interactive with the upper coupling nodes of the loading plates using a tie constraint. In addition, a tie constraint was used to achieve a full bond between the contacting surfaces of the loading plate and the beam.

The beam's tip was constrained in y-direction for the displacement application which was taken as 36 mm downward for all specimens. The axial load was applied as pressure on the top of column for the full simulation. Axial column load values were varied from specimen to specimen because it is one of the parameter considered in the study which may affect the joint strength. Figure 3.16 shows the loading and boundary condition for the calibrated numerical sample with M-BCJ specimen of Ajmal, (2016).

In the meshing stage, concrete elements, steel plates, and reinforcement steel were meshed with small uniform mesh. The size of meshing was 30 mm which gave the needed convergence for precise results when compared to the experimental load-displacement curve of Ajmal, (2016). Figure 3.17 shows the meshing of the numerical simulation of the calibrated sample with Ajmal, (2016), experimental beam-column connection M-BCJ specimen.

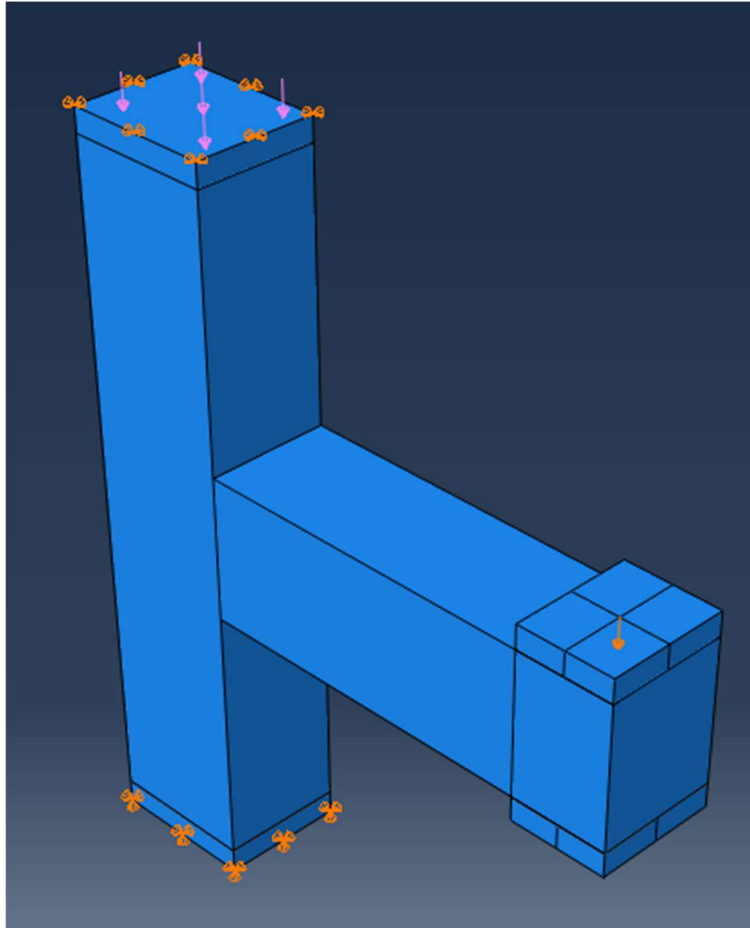


Figure 3.16 The load and boundary conditions for the calibrated numerical model

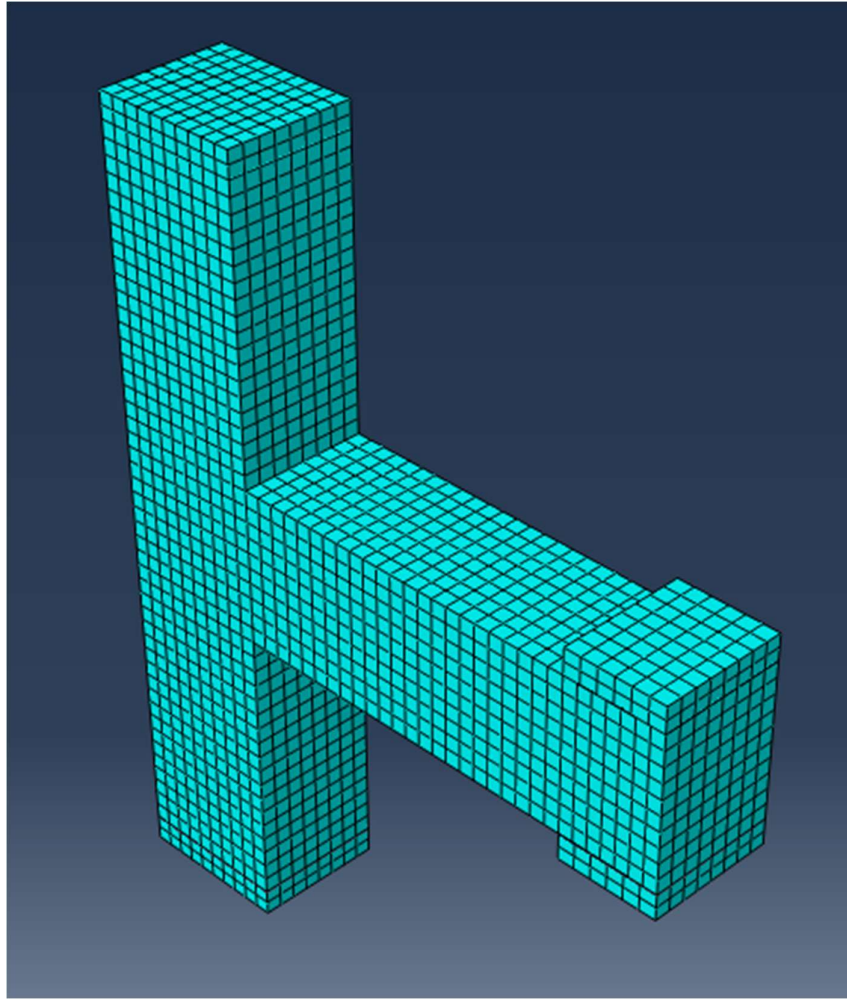


Figure 3.17 The meshing of the numerical simulation of the calibrated sample

3.6 ABAQUS Analysis Results

3.6.1 Results Comparison with the Calibration Specimen

In this research, numerical simulation was done to calibrate Ajmal, 2016, tested connection (M-BCJ) as mentioned previously in section 3.3. The numerical simulation for the mentioned calibrated sample was loaded up to the failure, where the beam tip was pushed up to 36 mm displacement. To check the agreement between the experimental load-displacement curve of the M-BCJ specimen and the numerical simulation result, load-displacement curve result was extracted from ABAQUS software as shown in

Figure 3.18. The maximum load for M-BCJ was 118.5 kN with 18 mm displacement, while in the simulation it gave a maximum load of 127.3 kN with 18 mm displacement. The difference is about 7.6% error between the experimental result maximum load and the calibrated sample result. From the comparison, it has been noticed that the simulation gave acceptable agreement with the experimental result for the same specimen. Therefore, the numerical simulation for the data collection was done depending on the calibrated CDP model to predict the behavior of the concrete material with different compressive strength and tensile behavior.

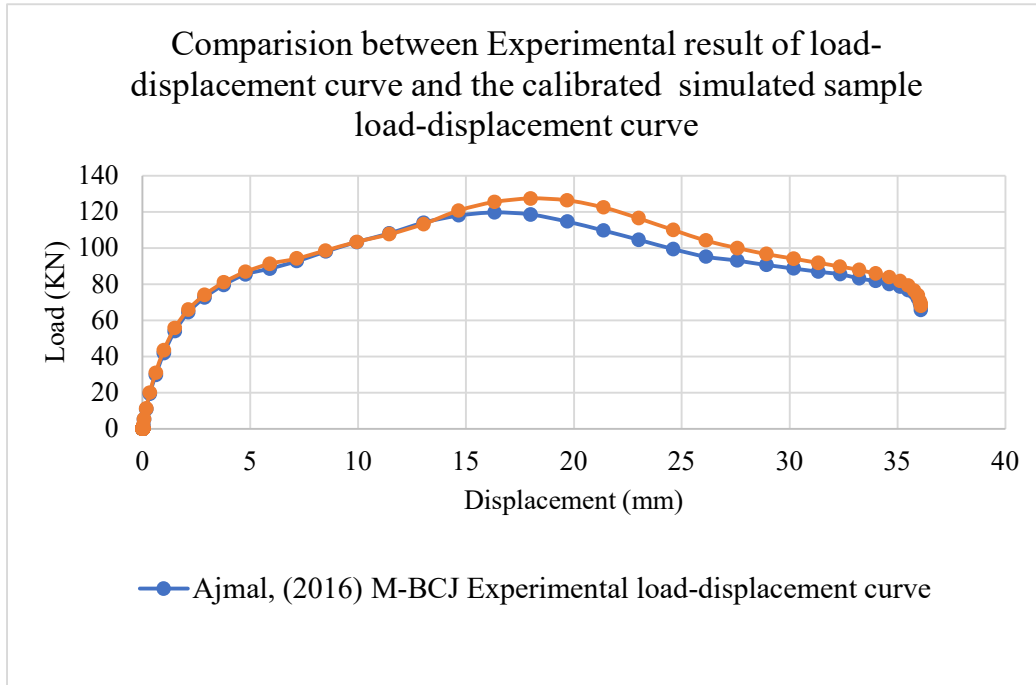


Figure 3.18 Comparison between experimental result of load-displacement curve and the calibrated simulated sample load-displacement curve

Figure 3.19 shows the maximum stress in steel at ultimate load corresponding to 18 mm displacement for the simulated calibrated sample, which indicated that there is no yielding in the steel reinforcement. The maximum stress in steel was 438 MPa at the ultimate load and that value is less than the entered yield stress of steel for the calibrated sample (460 MPa). The stresses S_{11} , S_{22} and S_{12} in concrete are shown in Figure 3.20, Figure 3.21, and Figure 3.22 at ultimate load, respectively. Figure 3.23 shows the tension damage evolution in concrete at ultimate load while Figure 3.24 shows the compression damage evolution in concrete at ultimate load.

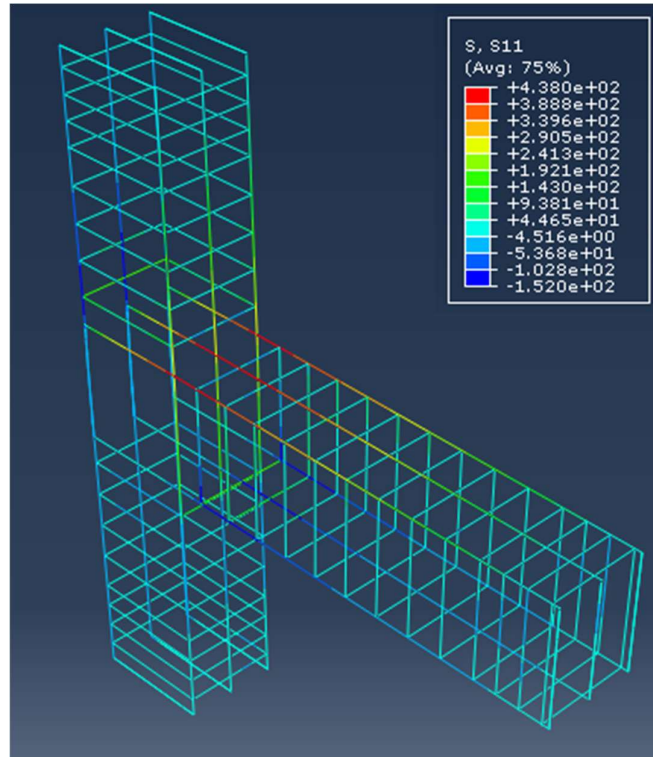


Figure 3.19 Steel stresses at the ultimate load corresponding to 18 mm displacement for the simulated calibrated sample

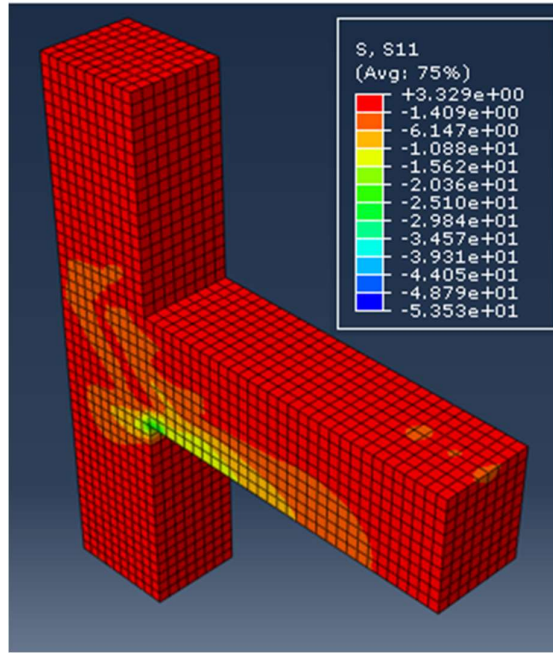


Figure 3.20 Stress S_{11} in concrete at the ultimate load corresponding to 18 mm displacement for the simulated calibrated sample

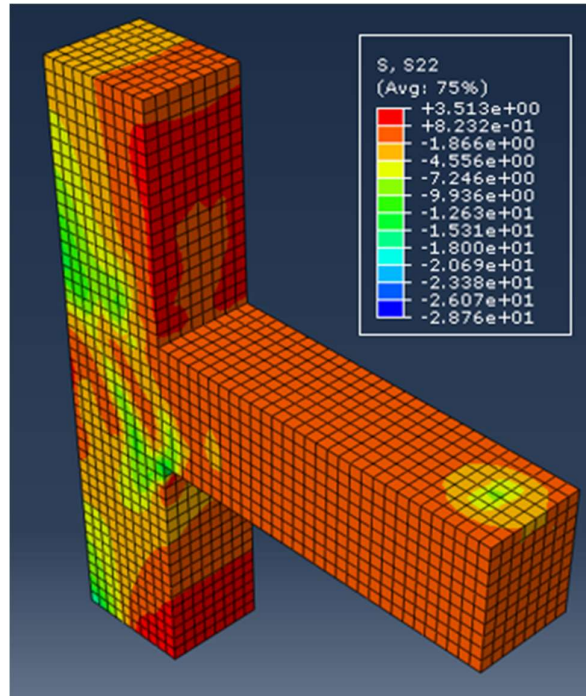


Figure 3.21 Stress S_{22} in concrete at the ultimate load corresponding to 18 mm displacement for the simulated calibrated sample

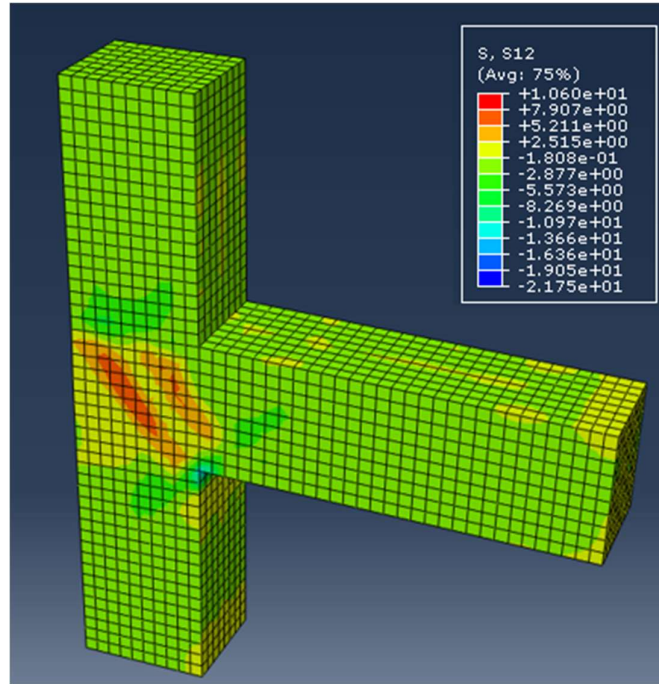


Figure 3.22 Stress S_{12} in concrete at the ultimate load corresponding to 18 mm displacement for the simulated calibrated sample

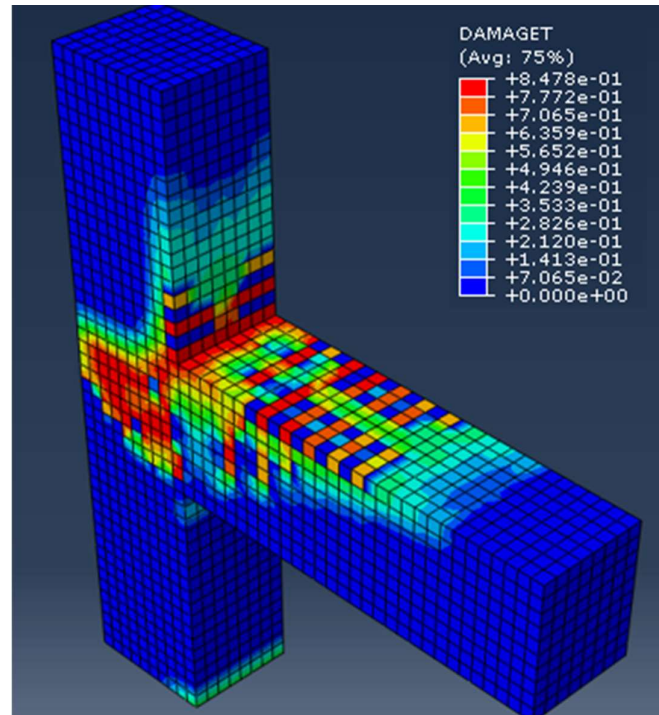


Figure 3.23 Concrete tension damage at the ultimate load corresponding to 18 mm displacement for the simulated calibrated sample

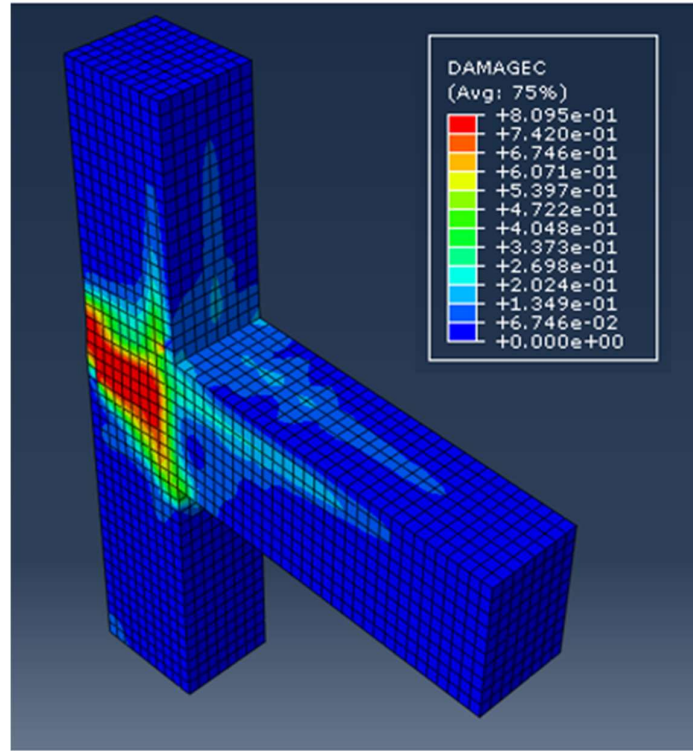


Figure 3.24 Concrete compression damage at the ultimate load corresponding to 18 mm displacement for the simulated calibrated sample

3.6.2 Failure mode of the simulated specimens

6480 samples were simulated in ABAQUS using the variation shown in Table 3.2. At failure, maximum load was extracted for all the samples and beam rebars stresses were observed and compared with the yield strength of the steel. If the beam rebars are yielded, it means that the connection failed in flexural not in shear, and therefore, those specimens were discarded and not used in data for ML. Only the joint shear failure connection samples were used for machine learning which were 4320 and those were used later in Chapter 4 as ML training, validation, and testing data.

3.6.3 Shear Strength Calculations for Exterior RC-BCJ

As mentioned in section 2.2, the joint horizontal shear strength can be calculated using equation (3-15), where the tension force in beam rebars (T_b) and the load (P) at the failure of the joint are required. To extract the maximum load (P), the load-deflection curve of each specimen was extracted. Moreover, for the beam rebar tension (T_b), the stress at rebars S_{11} was extracted at the failure point of the connection and from the stress value the force was found using equation (3-16). From the defined geometry of the calibrated specimen in section 3.3 and depending on the mentioned details in section 2.2, the required details for the calculation were taken (e_{face} , L_C , L_B A_s). The calculation of shear capacity for the mentioned 4320 joint failure samples was calculated and used as an output for each connection sample used in developing the proposed ANN model. The following steps show the shear strength of the calibrated sample:

$$V_{jh} = T_b - V_C \quad (3-15)$$

$$T_b = S_{11} * A_s \quad (3-16)$$

Where:

$$T_b = S_{11} * A_s = 438 \times 942.478 = 412.805 \text{ kN}$$

S_{11} : Tension stress in beam's rebars at the ultimate load, extracted from ABAQUS results

S_{11} from Figure 3.19 = 438 MPa in tension rebars

$$A_s = \frac{3 \times \pi \times 20^2}{4} = 942.478 \text{ mm}^2$$

$L_B = 900 - 100 = 800 \text{ mm}$ (as in numerical simulation for P load location)

A_j = according to ACI as mentioned in section 2.3, $x=0$ since width of column and width of beam are the same which equal to 250 mm taken as

fixed value referring to the sample used for calibration which tested by Ajmal, 2016.

Therefore, $b_{effective} = \text{minimum}((b + h), (b + 2X))$, where for all sample $b = 250$ mm, but h is varying. For calibrated sample, $h = 300$ mm.

$$b_{effective} = \text{minimum}((250 + 300), (250 + 2(0))) = 250 \text{ mm}$$

$$A_j = b_{effective} \times h$$

$$A_j = 250 \times 300 = 75000 \text{ mm}^2$$

$$V_c = \frac{P \times e_{face}}{L_c} = \frac{127.3 \times 800}{1400} = 72.743 \text{ kN}$$

$$V_{jh} = 412.805 - 72.743 = 340.062 \text{ kN}$$

$$v_{jh} = \frac{V_{jh}}{A_j} = \frac{340062}{75000} = \underline{\underline{4.534 \text{ MPa}}}$$

Experimental shear strength of joint in section 3.3 (M-BCJ) = **4.21 MPa** (Ajmal, 2016)

The calculation tables for the 4320 samples were processed using Excel software. Also, python script was used for running the simulations for 6480 samples and for extracting the load-displacement curves of samples result. Stress S_{11} for 6480 samples was extracted manually. Appendix (3) presents part of the 4320 samples data (150 samples).

3.7 Summary

In this chapter, the required data for ML was produced using FE analysis software ABAQUS. The variation in the values of the input parameters has made 6480 possibilities of different exterior connections to be simulated. The selected design parameters are column depth, beam depth, concrete compressive strength, beam tension reinforcement total area (by changing the rebar diameter), beam tension reinforcement yield strength, axial column load as ratio of its capacity. The modeling of these samples was started by drawing geometry in ABAQUS and defining the material properties of their parts. Mander, (1988) model was used for defining the compressive behavior of the concrete and calibrated with the experimental result of Ajmal, (2016), M-BCJ specimen. In addition, the tensile behavior of concrete was defined according to the modified model of Massicotte et al., (1990).

The modeling of samples through ABAQUS was continued by applying the loads and boundary conditions and ended by meshing the parts and running the analysis. After the analysis was finished, the load-displacement curves for all the samples (6480 samples) were extracted using Python script and collected in an Excel sheet. Later, calculations of the shear strength of the samples were done. The final data consisted of 4320 samples with joint failure samples were used in Chapter 5 to develop the proposed ANN prediction model for shear strength of the RC-BCJ.

Chapter Four

Machine Learning

Technique

Chapter 4 Machine Learning Technique

4.1 Introduction

As mentioned previously in Chapter 2, machine learning techniques have proved efficiency and reliability in solving many civil engineering problems. Many recent studies utilize different machine learning techniques for solving complex issues that are hard to solve using traditional statistical approaches.

In this study, artificial neural network (ANN) has been used to develop a prediction model for the shear strength of the beam-column joint region (unreinforced) using the feedforward backpropagation network (FFBPN).

ANN is nonlinear statistical modeling that is capable of capturing the weak and unknown relationship between the input and output variables by accounting for outliers and non-linear interactions among these variables (Sathelly, 2018). It maps the inputs to the output through non-linear processing units, making the process to be complex. Each neuron will work as a processing unit by connecting with each former layer nodes as shown in Figure 4.1. The subsequent layer neurons' value depends on the former layer neurons' connections.

ANN is built by a series of neurons (nodes) that are organized in layers. The architecture of the neural network and the established connections between the processing elements and the related parameters govern the behavior of the network. The neurons in each layer of the networks will be connected consecutively with each other. These connections will be weighted with a weight (W_{ij}) which indicates the connection strength between i^{th} neuron in a layer and j^{th} neuron in the following layer in the network (see Figure 4.1).

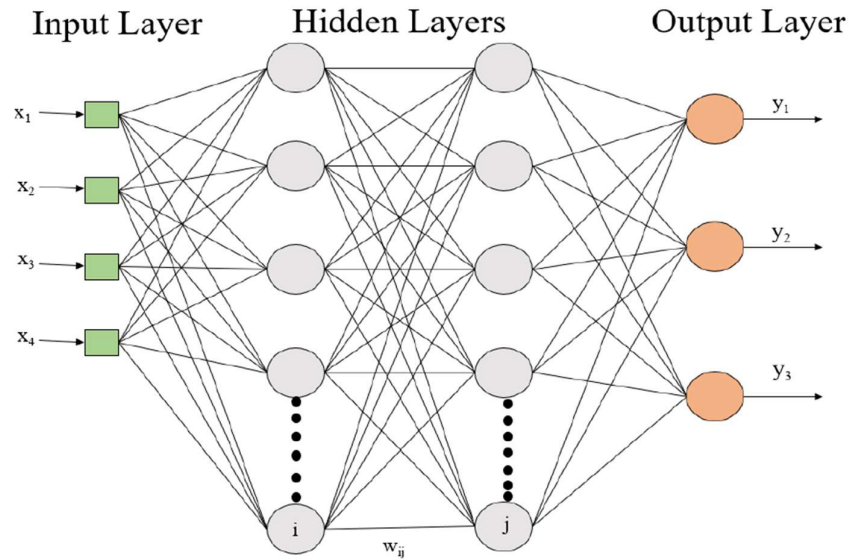


Figure 4.1 General structure of Artificial Neural Network with two hidden layers (Sathelly, 2018)

Using artificial neural network (ANN) in regression model can be very helpful compared to other traditional regression methods. ANN can develop its own features rather than use the step of features engineering in the traditional regression methods. That is done through the process of creating the hidden layer(s) by combining the given input parameters together by its own, which is possible to create relationship between the input parameters with connections that humans may not have previously thought about.

In addition, ANN can model complex non-linear hypotheses while mapping the inputs to the output parameters, which allows the model to capture the nonlinearity in the relationship between the variables (Bauchy, 2020).

On the other hand, there are some weaknesses and drawbacks in ANN. If compared with polynomial regression, for example, ANN is

typically slower to be trained because it involves much more parameters, and therefore, the computing time is more for training and using the final developed model.

Moreover, there is a major drawback in ANN which is the fact that ANN needs a lot of training data. Without enough training data (like several thousand or hundreds of data), utilizing ANN could be very challenging due to the large number of parameters in its network. There is no rule for the minimum required amount of data for developing accurate model, and it all depends on the type of data and number of dimensions in the problems (features numbers). The more features (input parameters) you have, the more data will be required for better performance of the model. That is because the training of the model will consider finding out the coefficient and weights of all connections in the network depending on the minimum error. These different weight values are responsible for connecting the parameters together and computing the output value and therefore, if the required data for ANN is not provided then the other regression approaches may provide better performance.

Another disadvantage of ANN is that it is a black box because it has very low interpretability. The developed model using ANN will give an answer without knowing how this value has been reached. The weights that are finally reached with the minimum error (best performance after many trials) cannot explain any meaning and are presented in complex equation, not a direct one. Also, while training the model, due to its low interpretability, sometimes it works well, and another time will fail without any reason. This is why it is hard to understand what is happening inside the network. Therefore, usually it is recommended to train the network many times and check its performance before finalizing the developed model. Many performance measures are being used in different machine

learning techniques, but in this research the available approaches in ANN tool in MATLAB MathWorks software (The MathWorks Inc., 2019) were used in the modeling step which will be discussed in section 4.3.

For the purpose of developing ANN model for prediction of the shear strength of the beam-column joint region, MATLAB software (The MathWorks Inc., 2019) was used in this research which provides a neural network tool (nftool). The procedure followed in developing the ANN model in this research will be presented in section 4.3.

4.2 Multi-Layer Feed Forward Neural Network

As mentioned previously in chapter 2.6, multi-layer feed forward neural network (ML-FFNN) is the most used network due to its capability of generalization. The architecture of ML-FFNN consists of one input layer, one or more hidden layers, and one output layer. The complexity of the issue that wanted to be solved will play a big role in defining the number of hidden layers and the number of neurons in each hidden layer. With a greater number of hidden layers, and a greater number of neurons, complex networks will be created, where the neural network with two or more hidden layers is called deep network. Figure 4.2 shows typical architecture of multi-layer feed forward neural network.

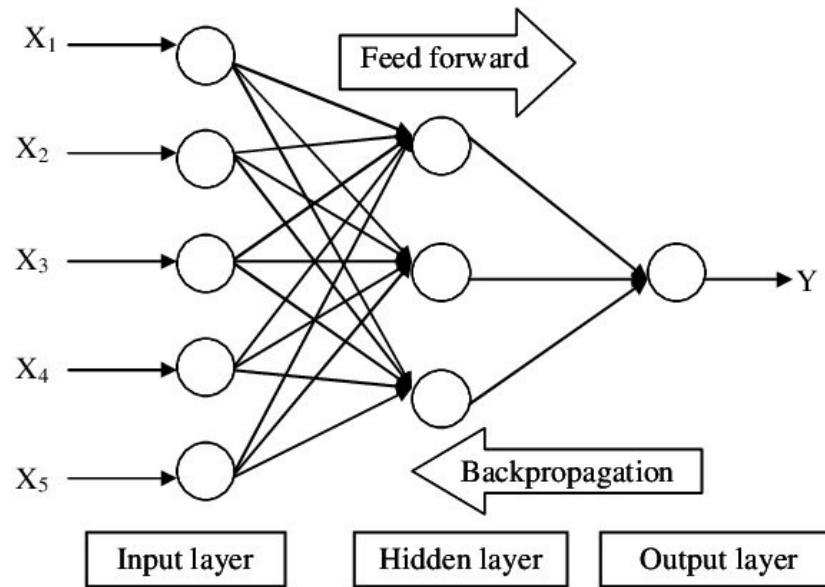


Figure 4.2 Typical architecture of multi-layer feed forward neural network (ML-FFNN) (Hakim, Noorzaei, Jaafar, Jameel, & Mohammadhassani, 2011)

The input layer will be the responsible layer for entering the data in the network through its neurons where these data will be transformed to the hidden layer using the weighted connections between the input layer and the hidden layer neurons (W_{Hidden}). The input data will be processed mathematically to the next layer using Equation (4-1), where W is the connection weight, R is the number of elements in input vector, S is number of neurons in next layer that the calculation is done for, P is the neuron value of the former layer, and b is the bias value. In the matrix $[W]$, Equation (4-2), the row and column indices refer to destination neuron for the weight, and the input source of that weight, respectively. Thus, the indices in $W_{1,2}$ indicate that the strength of the signal from the second input element to the first (and only) neuron is $W_{1,2}$ (The MathWorks Inc., 2004).

$$a = f(W \times P + b) \quad (4-1)$$

$$W = \begin{bmatrix} W_{1,1} & W_{1,2} & \dots & W_{1,R} \\ W_{2,1} & W_{2,2} & \dots & W_{2,R} \\ W_{S,1} & W_{S,2} & \dots & W_{S,R} \end{bmatrix} \quad (4-2)$$

Where:

a: is the next layer neurons value vector

f: transfer function (will be discussed in 4.2.1)

W: is the connection weight

R: is the number of elements in input vector

S: is number of neurons in the next layer that the calculation is done for

P: is the neuron value of the former layer (input values)

b: is the bias value

Each input variable will be multiplied by a weight and all those multiplications will be summed and finally the bias will be added to the summation. The value of summation and the added bias will be entered into a transform/activation function through the processing element (Figure 4.3) in the next layer which will give the neurons of the next layer their values.

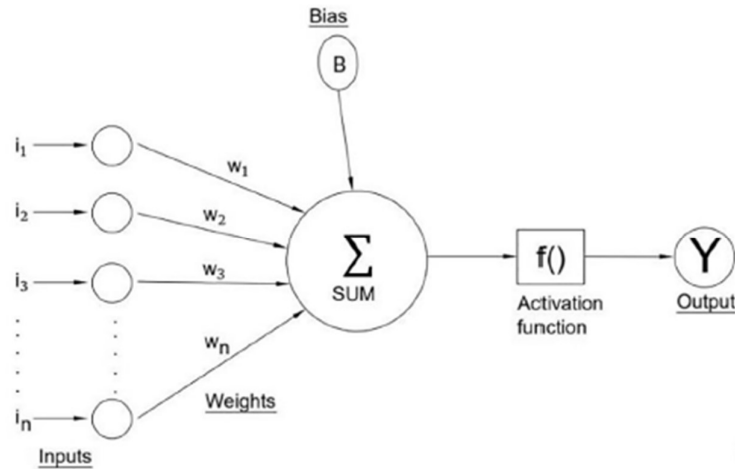


Figure 4.3 Processing Element (Alagundi & Palanisamy, 2022)

Each neuron will take its value through the same mathematical process, but the connections weight varies which depends on the strength of the relation between i^{th} neuron to the j^{th} neuron (see Figure 4.1). The connection weight is being changed in the training process until a minimum error is reached. The error is minimal where the output variables are very close to the target values (the provided output values in the learning data used for training the network).

This process in ANN will create a final model with the optimum weights that give the minimum error, where these weights change each time the training algorithm is run, and hence, different values for weights will be generated.

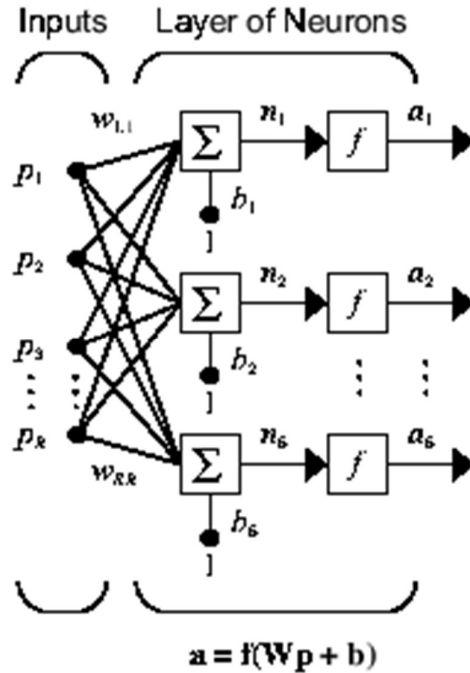


Figure 4.4 Interconnection in the architecture of artificial neural network (The MathWorks Inc., 2004)

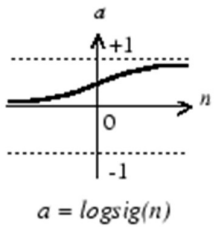
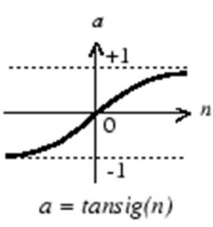
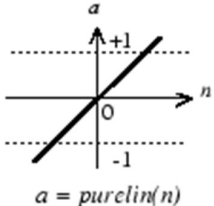
Figure 4.4 shows a typical interconnection in the architecture of artificial neural network, where R is the number of elements in input vector, and S is number of neurons in layer. Each element of the input vector (p) is interacting with each neuron input through the weight matrix (W). The i^{th} neuron gathers its weighted inputs and bias to produce its own scalar output $n(i)$. The different neurons $n(i)$ together will represent an S -element net input vector (n). Then, the neuron of outputs layer will form a column vector (a). Equation (4-1) shows the expression for (a) and equation (4-2) shows the connections weight matrix $[W]$.

In most of the networks the neurons number in the following layer is not the same number of its inputs where the hidden layer number of neurons is higher than the input layer.

4.2.1 Transfer Function

In the output layer and hidden layer(s), activation function will be used in their nodes. The activation function in the hidden layer is a nonlinear transfer function which allows the network to capture the nonlinearity in the relationship between input and output parameters. The output layer node(s) can also use the nonlinear function but in most of the cases found in literature, the linear (linear function) for output layer was providing good performance for the network results. The nonlinear function in the hidden nodes (processing units) can be one of the two nonlinear functions as shown in the Table 4.1, where these are the available functions in MATLAB software (nftool) for ANN. The transfer functions described in Table 4.1 are the most used transfer functions for multilayer networks, according to MATLAB neural network toolbox user's guide (The MathWorks Inc., 2004), but other differentiable transfer functions can be created and used if desired. To reach the network output, neurons can use any transfer function (The MathWorks Inc., 2004).

Table 4.1 Transfer Functions available in MATLAB Neural Network toolbox

Log-Sigmoid Transfer Function (nonlinear)	Tan-Sigmoid Transfer Function (nonlinear)	Linear Transfer Function (linear)
 $a = \text{logsig}(n)$	 $a = \text{tansig}(n)$	 $a = \text{purclin}(n)$
$f(x) = \frac{1}{1 + e^{-x}}$	$f(x) = \frac{2}{1 + e^{-2x}} - 1$	$f(x) = x$

• Multilayer networks often use the log-sigmoid transfer function (logsig). • The function (logsig) generates outputs between 0 and 1 as the neuron's net input goes from negative to positive infinity.	• Multilayer networks can use the tan-sigmoid transfer function (tansig). • The function (tansig) generates outputs between -1 and 1 as the neuron's net input goes from negative to positive infinity.	• The linear function can be used for the output neurons
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4.2.2 Scaling of Data using Normalization

It is important to preprocess the data for machine learning before using them in the learning stage and feeding them to the network. Normalization is one method of scaling and preprocessing the data which is important for better convergence of the developed ANN model. The idea in normalization is to make the data in a limited range and hence, reaching the optimal values for the coefficient/weights in the training stage will be faster which enable the transfer function to work better. The reason is that if the data are within limited range, the neural network will identify the trends and patterns in the data in a better way than if the data has different ranges. The normalization step is available within the transfer function in MATLAB MathWorks software, which ensures that the data entered in the nonlinear function makes the function work easily.

The min-max normalization (The MathWorks Inc., 2019) approach was used in this research, which makes the data in the range $[-1,1]$ using equation (4-3), which will enhance the training of the model. As a result, less iteration in training will be needed and higher speed of learning will occur. This normalization method is provided within the neural network

toolbox (nftool) and made as default for better training. The input and output data are advised to be normalized before being used in the network training (Alagundi & Palanisamy, 2022). Equation (4-3) will be applied in both input and output data of training set in this research, where it is important to notice that the minimum and maximum variables within the training data will be used in the equation and hence these values will be fixed as a constant for future use of the neural network model including testing and validation data. Normalized data will only be used for the future usage of model.

$$a_n = 2 \times \left(\frac{a_i - a_{min}}{a_{max} - a_{min}} \right) - 1 \quad (4-3)$$

Where:

a_i : is the data variable that needs to be normalized.

a_n : is the normalized data variable.

a_{min} : is the minimum value in training set variable that is used to train the model (will remain constant in future use of the ANN model)

a_{max} : is the maximum value in training set variable that is used to train the model (will remain constant in future use of the ANN model)

4.2.3 Training Process and Different Data Sets

As mentioned previously in section 3.4, a wide range of values for the provided data for ML is preferable for better generalization of the ANN model and to achieve accurate results from ANN models (Alagundi & Palanisamy, 2022). Therefore, the computed data from finite element analysis software ABAQUS that has been simulated and calibrated with the experimental data of Ajmal study, (2016), in section 3.3 has been used for the ANN model. The total number of data that has been provided finally for the ANN modeling was 4320 samples of different exterior beam-

column connections which failed in joint, refer to Appendix (3) which provides part of the data (150 samples).

While designing neural network models, there are many hyperparameters which have to be treated well to reach an accurate model without overfitting or underfitting. The two hyperparameters are the number of hidden layers and the number of neurons (nodes) in each hidden layer. With more hidden layers the model will be complex and accurate, but it will be hard to generalize the model for future input data for the benefit of applying the model generally (Bauchy, 2020). In addition, the number of neurons in the hidden layer may lead to an overfitted model if a lot of neurons were used. On the other hand, a low number of neurons in hidden layer can produce an under-fitted model which makes the model unable to capture the complexity of the relationship between inputs and output parameters. Therefore, the proper way of tuning those hyperparameters is by dividing the data into training, testing, and validation sets. The data provided in the form of 7 inputs and 1 output (one connection details of the decided inputs and output is shown in Table 4.2) was divided into training, testing, and validation sets of data. There were 3024 samples (70%) used for training, 648 samples (15%) for testing, and 648 samples (15%) for validation of the ANN model.

Table 4.2 Inputs and Output parameters for one of the exterior connection samples

Input Parameters							Output Parameter
Column Depth h_c (mm)	Beam Depth h_b (mm)	concrete cylinder compressive strength f'_c (MPa)	Beam tension Reinforcement total Area (mm ²)	Beam tension reinforcement Yield Strength f_y (MPa)	Column Axial load as ratio of its capacity	Joint Area A_j (mm ²)	Shear strength of the joint v_j (MPa)
150	150	17	603.185	460	0.05	37500	4.458

Training data sets are used to train the ANN model which starts with random initial weights of connections. The training process in ANN is supervised by the training method where the desired output will be provided with the inputs of the training data. Therefore, the network will optimize the weights in the connections and obtain the best possible weights that provide predicted output value with minimum error when compared to the expected output data of training. In the training process of multilayer feed-forward neural network, many iterations will be done to determine optimum weights. During the training process, back-propagation will be considered as the most successful and commonly used training method in applications of neural network (Sanad & Saka, 2001). In back-propagation method of training, the inputs are propagated from the input layer and then through the hidden layer(s) to the output layer. Then, the error of the difference between the predicted and the expected output value will be backpropagated from the output layer to the input layer for the purpose of modifying the weights and reaching the minimum error. However, it is advised to train the model many times (about 10 times could

be good), then choose the best model with minimum error because the model could fall in local minimum error rather than global minimum error.

The backpropagation training method will be implemented in MATLAB software using the backpropagation algorithm called “trainlm” which represents the Levenberg-Marquardt algorithm. This algorithm is a training function for the network that updates the bias and weight values according to Levenberg-Marquardt optimization. This algorithm is the first-choice function for the supervised training method which is the fastest in the toolbox of MATLAB software. In the other hand, Levenberg-Marquardt algorithm does require more memory when compared to other algorithms. This function uses the Jacobian in its calculation which assume the evaluation of the model using a mean or sum of squared error and hence the trained model (trainlm) will be evaluated using mean squared error (MSE) or sum squared error (SSE) performance function (Stoyanova, 2017). Further details about performance analysis will be presented in section 4.2.4.

Moreover, the benefit of validation set is to maintain good generalization of the model by comparing the error of the training set and validation set, if the error is small for both then the model is accurate and generalized well. On the other hand, with small error for training set and high error for validation set, that indicates the model is not generalized well which means overfitted model.

In addition, the testing set will be used as testing data for the developed model by checking how accurate the model will predict the value of output and compare it with the expected value. The difference in testing data compared to validation data is totally unknown data to the model which has not been used for training the model and for validating it.

Testing data is useful to check how the developed model is dealing with future data after developing the model.

4.2.4 Evaluation Measures and Performance Analysis

Throughout the training process, the training function will use one of the performance measures available in MATLAB software. In this study the Levenberg-Marquardt algorithm has been used for training the model, in this function the suitable performance function is either MSE or SSE as mentioned in section 4.2.3. Therefore, this study has used MSE for performance analysis through the training process which has been used to check the error between the predicted and expected output of the network during the training. After the training, MATLAB produces regression analysis for the three sets of data in terms of coefficient of correlation (R) which is a statistical measure showing how strong is the relationship between variables. R value can evaluate the differences between the expected and predicted output. In other words, the R value will be 1 if the predicted output is exactly equal to the expected output of the network. In addition, error histogram will be available too by the MATLAB neural network toolbox showing the error between predicted and expected output for training, validation, and testing sets. The root mean square error (RMSE) is another performance indicator for the regression models and a useful function in performance verification due to its unit (as the output value unit) that allows the user to estimate how big or small the error is. For example, the output variable in this research is the shear strength of the beam-column joint region in megapascal unit (MPa) which will be the same unit of RMSE. RMSE is computing the average magnitude of the error and it is a quadratic scoring method (Ganasan, et al., 2021). RMSE was used in this study for the purpose of optimizing the number of neurons

in the hidden layer, which was done using a small script in MATLAB to compare the error in training, testing, and validation sets.

The optimum number of neurons in hidden layer has two criteria: the smallest error between predicted and expected output for the three data sets, and the matching of error between the training and validation sets. When the trained model gives the same or close amount of error for the training and validation sets that means that the prediction ANN model is generalizing well and is not biased to the trained data (Bauchy, 2020). Equation (4-4), (4-5), and (4-6) showing the equations that have been used for different evaluation measures. Figure 4.5 shows the flow chart of ANN model development process.

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (A_i - Y_i)^2}{n}} \quad (4-4)$$

Where:

RMSE: root means square error.

A_i : Expected output value.

Y_i : Predicted output value.

n : number of data points.

$$MSE = \frac{1}{n} \sum_{i=1}^n (A_i - Y_i)^2 \quad (4-5)$$

Where:

MSE: mean squared error.

A_i : Expected output value.

Y_i : Predicted output value.

n : number of data points.

$$R = \frac{\sum_{i=1}^n (A_i - \hat{A})(Y_i - \hat{Y})}{\sqrt{\sum_{i=1}^n (A_i - \hat{A})^2 \sum_{i=1}^n (Y_i - \hat{Y})^2}} \quad (4-6)$$

Where:

R: Coefficient of correlation.

A_i : Expected output value.

$\hat{A}$: Average expected output value.

Y_i : Predicted output value.

$\hat{Y}$: Average predicted output value.

n : number of data points.

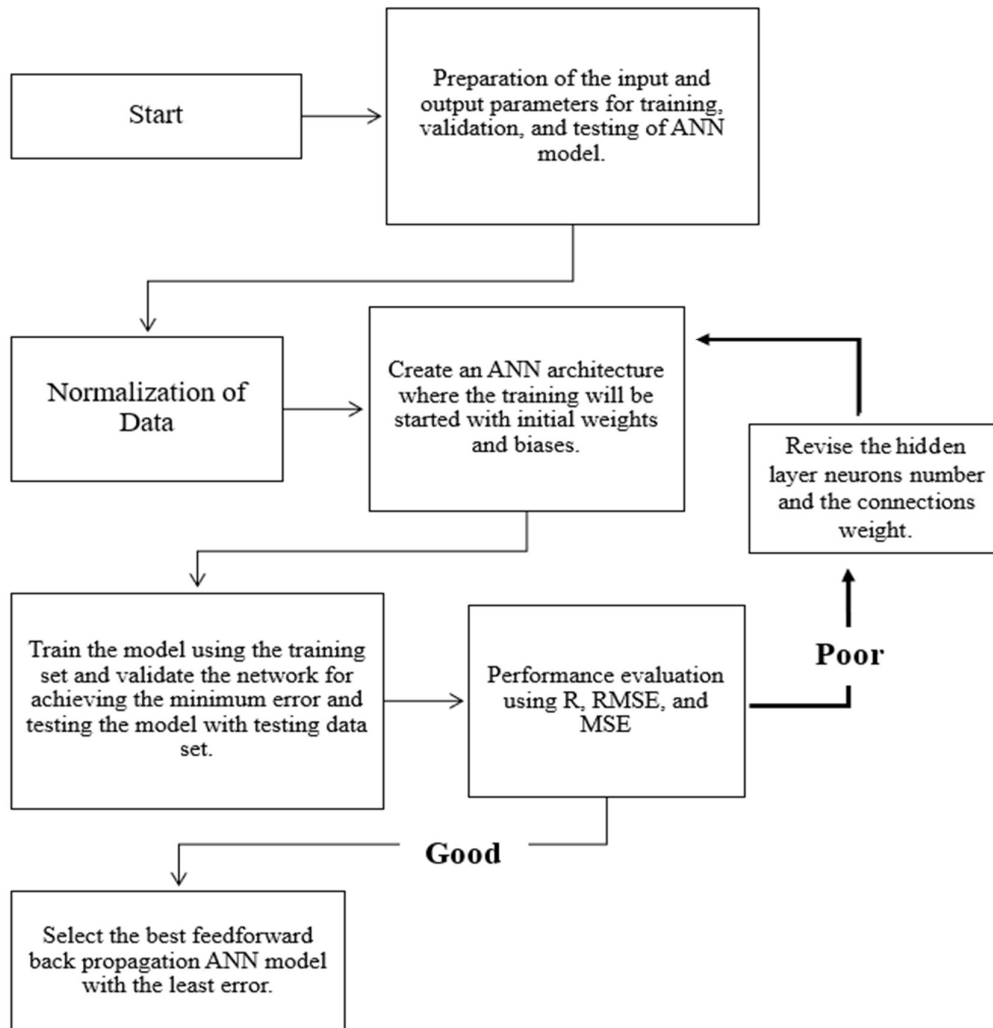


Figure 4.5 Flow chart of ANN model development process

4.3 Neural Network Modeling using MATLAB

Software

To develop artificial neural network model to predict the shear strength of unreinforced exterior beam-column joint, a large data of exterior connections was simulated using nonlinear finite element analysis-based software called ABAQUS as shown previously in Chapter 3.

The data required for the ANN was used as inputs and output parameters in the learning process, where the total number of inputs was seven and one output for each sample. Figure 4.6 shows a graphical sketch of an unreinforced exterior beam-column connection, the input and output parameters are taken from the geometry and details of the connection. The seven input parameters are column depth (h_c) in mm, beam depth (h_b) in mm, concrete cylinder compressive strength (f_c') in MPa, beam tension reinforcement total area (A_{st}) in mm^2 , beam tension reinforcement yield strength (f_y) in MPa, axial column load as ratio of its capacity (P_y), refer to Equation (4-7), and the joint area (A_j) in mm^2 , refer to Equation (4-8). The joint area formula is mentioned in chapter 2.3, Equation (2-5), and presented in equation (4-8). The output parameter is the shear strength of the joint region in (MPa).

$$P_y = \frac{N}{b_j \times h_c \times f_c} \quad (4-7)$$

Where:

P_y : is the column axial load as ratio of column's capacity (approximately)

N : is the column axial load in (N)

b_j : joint width where it is equal to column width b_c in (mm) (refer to section 2.3)

h_c : column depth in (mm)

f_c : is the concrete compressive strength in column in (MPa)

$$A_j = b_j \times h_j \quad (4-8)$$

Where:

A_j : is the joint area in (mm^2)

b_j : is the joint width where it is equal to column width b_c in (mm) (refer to section 2.3)

h_j : is the depth of joint which is equal to the column depth h_c in (mm)

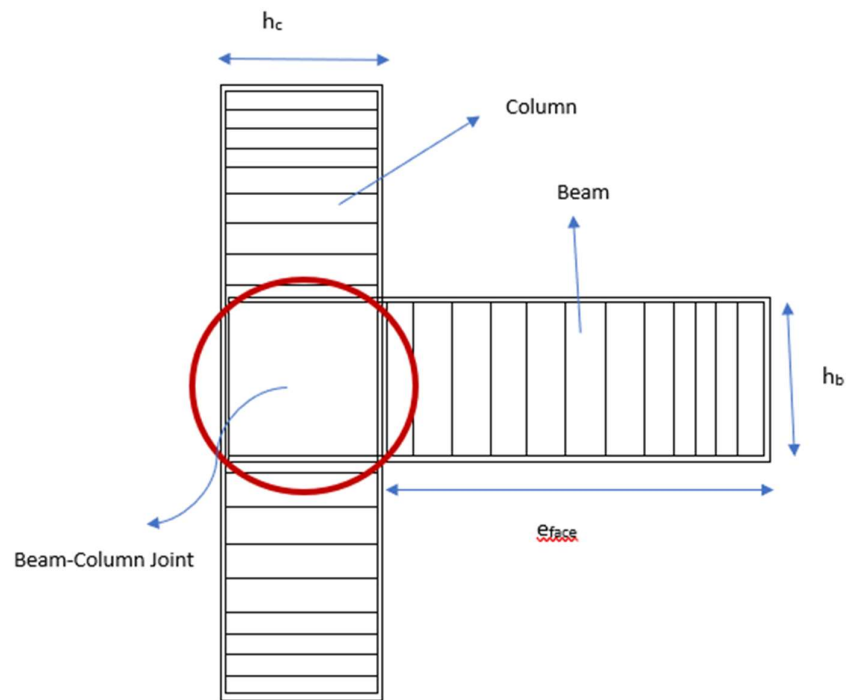


Figure 4.6 Graphical sketch of unreinforced exterior beam-column connection

Table 4.3 shows the different inputs and output parameter that have been considered in the proposed ANN model. Table 4.4 shows the statistical information of input and output variables. The input and output parameters in the histogram represent the data used for developing ANN model of this research are shown in Figure 4.7, Figure 4.8, Figure 4.9, Figure 4.10, Figure 4.11, Figure 4.12, Figure 4.13, Figure 4.14. The figures mentioned show that the data used to develop the ANN has good variations of values, allowing the ANN model to be trained with different examples and capturing the nonlinearity between the variables with better performance.

Table 4.3 The different inputs and output parameters

Variables	Description
Input Variables	
X_1	Column depth (h_c) in mm
X_2	Beam depth (h_b) in mm
X_3	Concrete compressive strength (f_c') in MPa
X_4	Beam tension reinforcement total area (A_{st}) in mm^2
X_5	Beam tension reinforcement yield strength (f_y) in MPa
X_6	Axial column load as ratio of its capacity (P_y)
X_7	The joint area (A_j) in mm^2
Output Variable	
Y	The shear strength of the joint region in (MPa)

Table 4.4 Statistical information of input and output variables

Variable	Units	Minimum	Maximum	Mean	Standard Deviation
Column Depth (h_c)	(mm)	150	600	301.424	146.795
Beam Depth (h_b)	(mm)	150	600	352.986	159.078
Concrete Compressive Strength (f_c')	MPa	17	60	35.201	13.888
Beam Reinforcement Area (A_{st})	mm ²	603.186	1472.622	1118.672	348.607
Beam Yield Strength (f_y)	MPa	460	660	577.639	98.443
Axial Column load as ratio (P_y)		0.05	0.15	0.099	0.041
Joint Area (A_j)	mm ²	37500	150000	75355.903	36698.671
Shear strength of BCJ (V_j)	MPa	0.457	9.253	4.523	1.429

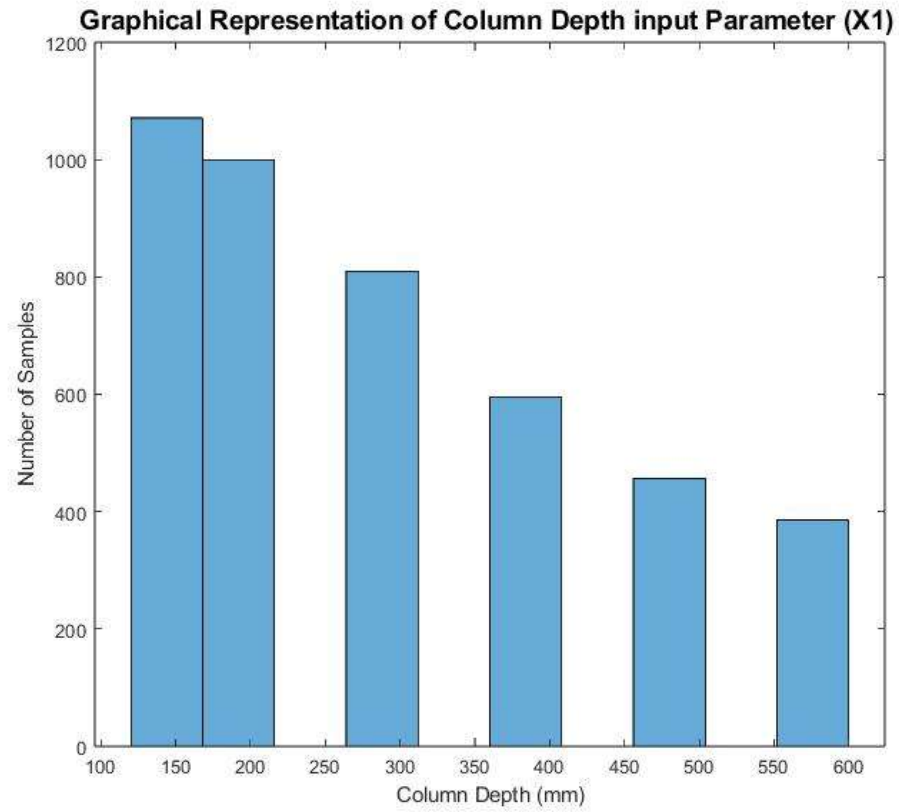


Figure 4.7 Graphical Representation of Column Depth input Parameter (X1)

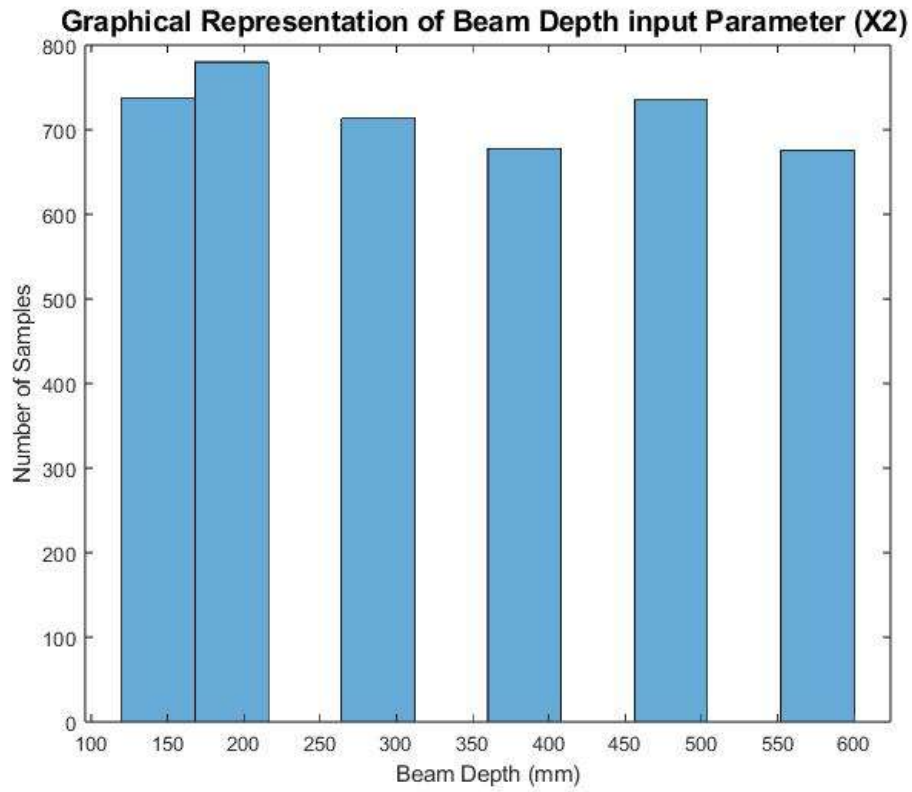


Figure 4.8 Graphical Representation of Beam Depth input Parameter (X2)

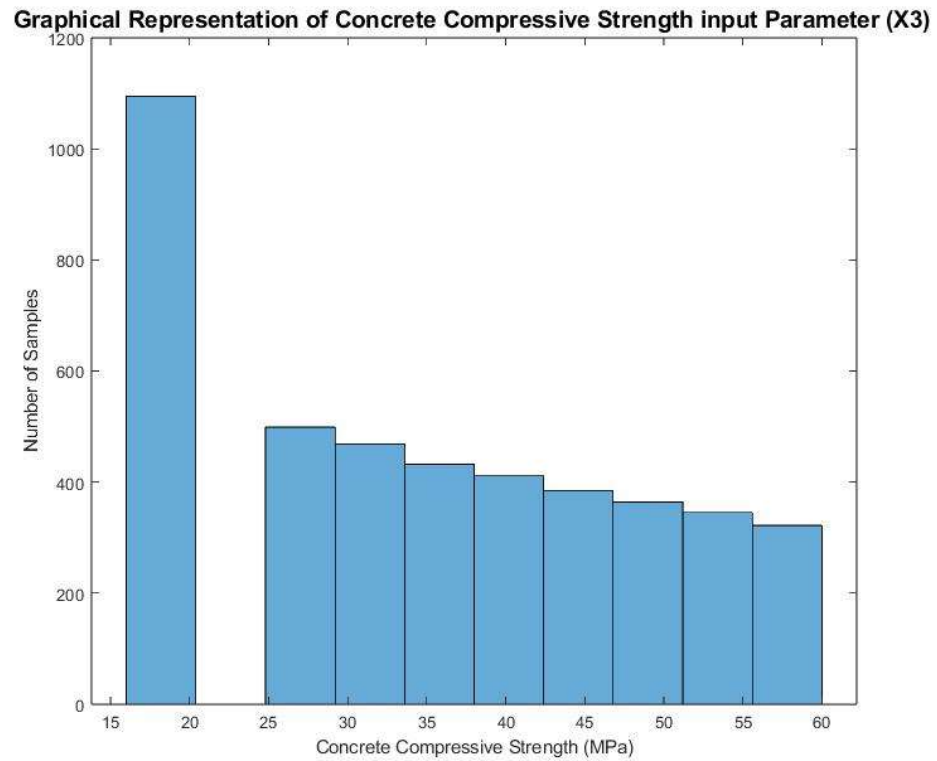


Figure 4.9 Graphical Representation of Concrete Compressive Strength input Parameter (X3)

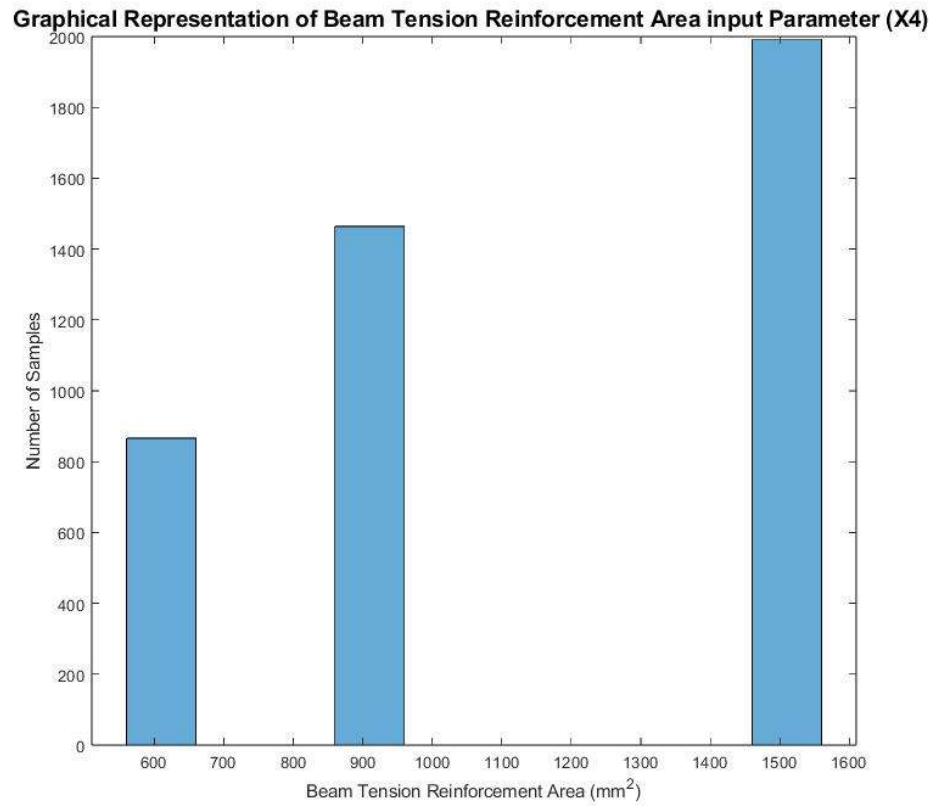


Figure 4.10 Graphical Representation of Beam Tension Reinforcement Area input Parameter (X4)

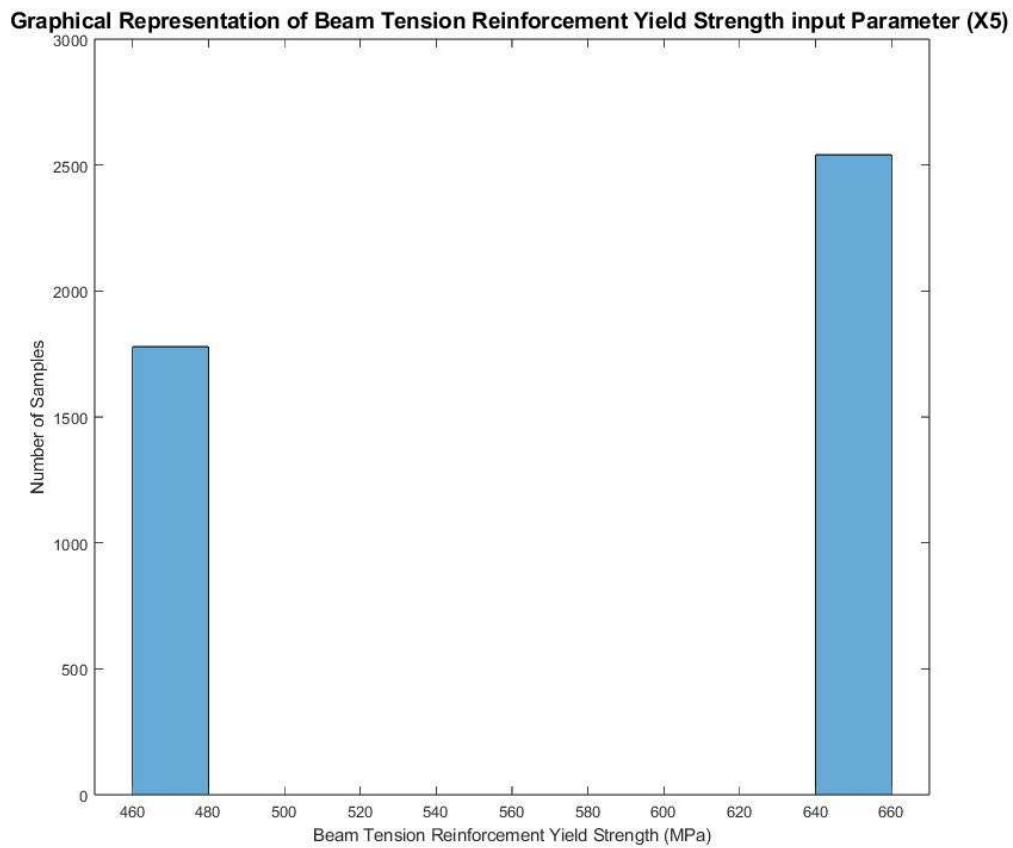


Figure 4.11 Graphical Representation of Beam Tension Reinforcement Yield Strength input Parameter (X5)

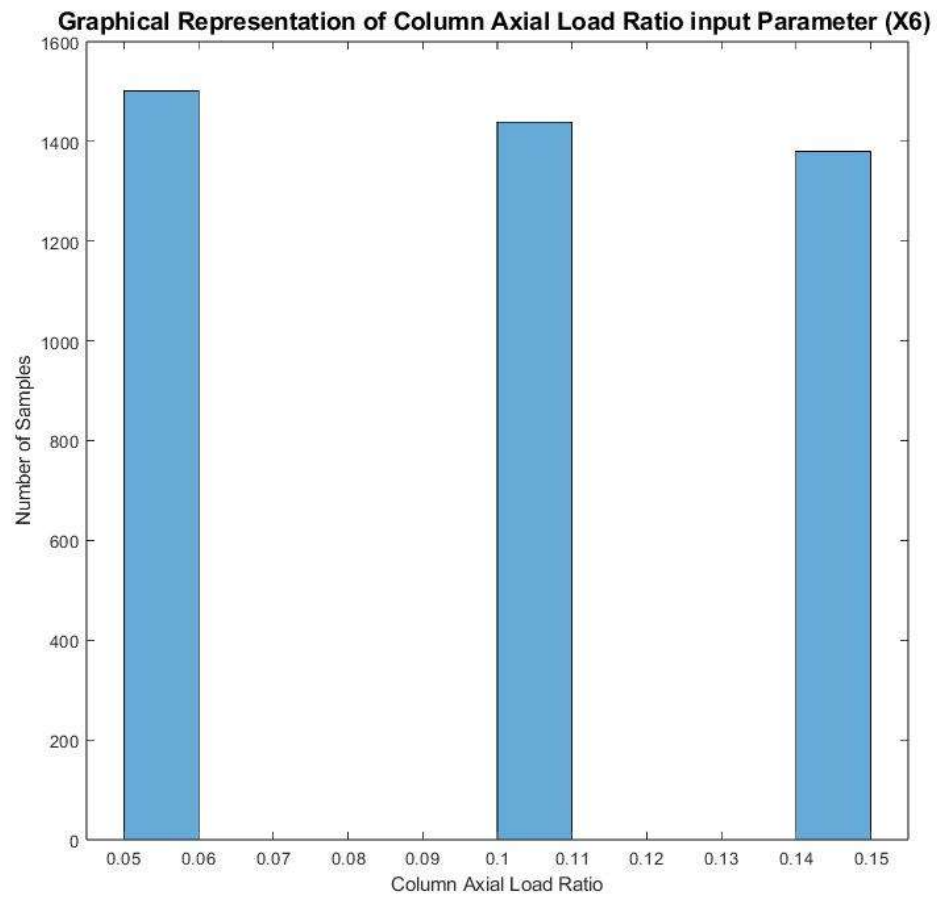


Figure 4.12 Graphical Representation of Column Axial Load Ratio input Parameter (X6)

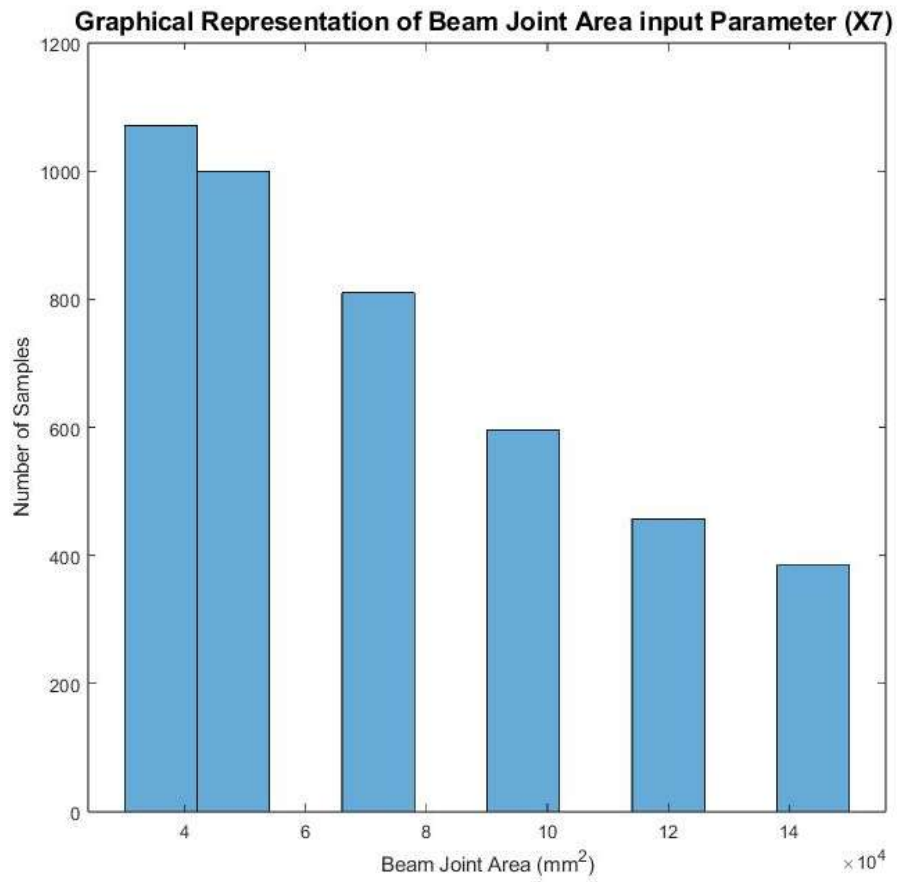


Figure 4.13 Graphical Representation of Beam Joint Area input Parameter (X7)

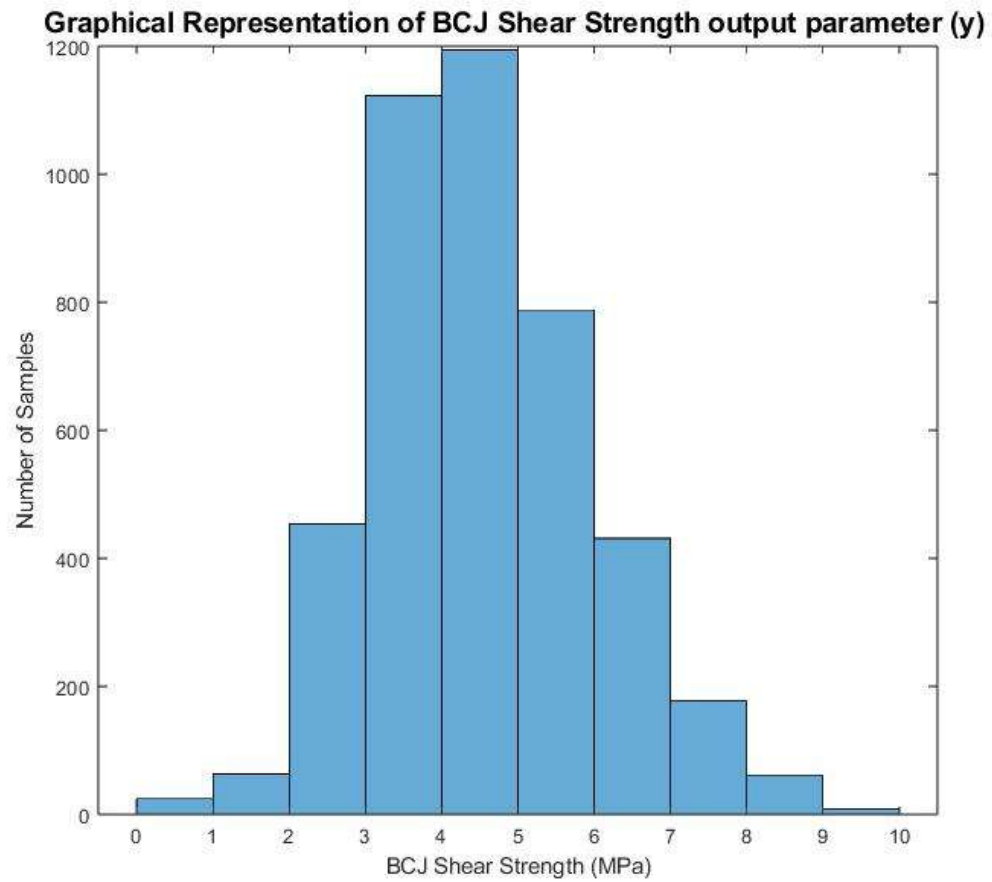


Figure 4.14 Graphical Representation of BCJ Shear Strength output parameter (y)

After identifying the inputs and output parameters for the neural network, the data has to be pre-processed/normalized for a better training process. Therefore, equation (4-3) in section 4.2.2 was used as follows:

Normalization for first input variable: column depth in (mm)

According to Table 4.4, the minimum column depth in the training set is 150 mm, and the maximum is 600 mm.

$$a_{min} = 150 \text{ mm}$$

$$a_{max} = 600 \text{ mm}$$

$$a_n = 2 \times \left(\frac{a_i - a_{min}}{a_{max} - a_{min}} \right) - 1 = 2 \times \left(\frac{a_i - 150}{600 - 150} \right) - 1$$

Where, this equation is applied to the whole data sets of column depth variable.

Normalization for second input variable: beam depth in (mm)

According to Table 4.4, the minimum beam depth in the training set is 150 mm and the maximum is 600 mm.

$$a_{min} = 150 \text{ mm}$$

$$a_{max} = 600 \text{ mm}$$

$$a_n = 2 \times \left(\frac{a_i - a_{min}}{a_{max} - a_{min}} \right) - 1 = 2 \times \left(\frac{a_i - 150}{600 - 150} \right) - 1$$

Where, this equation is applied to the whole data sets of beam depth variable.

Normalization for third input variable: concrete compressive strength in (MPa)

According to Table 4.4, the minimum concrete compressive strength in the training set is 17 MPa and the maximum is 60 MPa.

$$a_{min} = 17 \text{ MPa}$$

$$a_{max} = 60 \text{ MPa}$$

$$a_n = 2 \times \left(\frac{a_i - a_{min}}{a_{max} - a_{min}} \right) - 1 = 2 \times \left(\frac{a_i - 17}{60 - 17} \right) - 1$$

Where, this equation is applied to the whole data sets of concrete compressive strength variable.

Similarly, all the input variables will follow the same procedures. These minimum and maximum values in the training set, Table 4.4, will remain constant for future use of the final ANN model when the normalization process will be done. Note that the units have to be the same as those used in training process of the model, refer to Table 4.4. In addition, output variable was normalized too before the training of the model, which is normalized as follows:

Normalization for the output variable of the data used in developing the ANN model: shear strength of joint in (MPa)

From Table 4.4, the maximum shear strength of joint in the training data was 9.253 MPa, where the minimum was 0.457 MPa.

$$a_{min} = 0.457 \text{ mm}$$

$$a_{max} = 9.253 \text{ mm}$$

$$a_n = 2 \times \left(\frac{a_i - a_{min}}{a_{max} - a_{min}} \right) - 1 = 2 \times \left(\frac{a_i - 0.457}{9.253 - 0.457} \right) - 1$$

Where, this equation applied on the whole data sets of shear strength of joint variable.

Note that the output values of the model result will not be the final, where it has to be returned to the unnormalized version again after reaching a result from the proposed ANN model, refer to Equation (4-9).

The unnormalized result of ANN will be as followed for the output (The MathWorks Inc., 2019):

$$a_{final} = \frac{(a_{ANN}+1) \times (a_{max}-a_{min})}{2} + a_{min} \quad (4-9)$$

Where:

a_{final} : Final result to be considered after using the proposed ANN model.

a_{ANN} : The result from utilizing the ANN proposed model before reversing the normalization.

The development of ANN proposed model has followed the procedure discussed in section 4.2. This research used the MATLAB software for developing the proposed ANN model which has a useful toolbox for neural network fitting is nftool. The data was entered into MATLAB software using text file and during the importing of data within MATLAB, the input and output variables were created to be used in the MATLAB neural network toolbox. Then the normalization of the input and output parameter was done in MATLAB using “mapminmax” function available in the software for normalization.

The next stage was feeding the data to the network after dividing it into 70% training data, 15% validation data, and 15% testing data. The total data used for training the ANN model in this research is 4320 data points, refer to Appendix (3), each one represents different exterior connection sample details. The training process has been done using Levenberg-Marquardt algorithm (LM), which is applied as “trainlm” in MATLAB to train the feed-forward neural network. The training process was repeated many times while tuning the hyperparameters of ANN model to reach better performance.

The hidden layer was one layer that made the problem a shallow neural network rather than a deep network. One hidden layer showed good performance in the many trials of training that have been done and led to a simpler model while maintaining adequate accuracy.

As mentioned previously in section 4.2.4, the overfitting issue in the development of ANN model can be avoided by checking the validation set error and comparing it with the training set error. If both sets have low errors and are very close in error values, that means the model is avoiding the overfitting issue. Also, if the three sets, including the testing set, have low error values, that indicates that the proposed ANN model is generalizing well for future data too, not just the training data.

Figure 4.15 presents the optimization of the number of nodes in the hidden layer, which has been used to compare the MSE of the validation set with the variation of the number of nodes in the hidden layer. In Figure 4.15, the MSE for validation set decreased in the interval of 1 to 13 number of nodes in hidden layer and at 14 and higher it started to increase again. It was noticed that with 13 number of nodes in the hidden layer, the mean squared error in the validation set is low which is used for the final proposed ANN model in this research.

The number of neurons in the hidden layer was optimized after many trials where the performance was checked after each trial until a good accuracy was reached and picked as final proposed ANN model. The best performance was reached with thirteen neurons in the hidden layer. The input layer was created with seven neurons representing the seven input parameters. In contrast, the output layer was created with one neuron representing the output parameter mentioned previously at the beginning of section 4.3.

During the neural network training, the transfer function used is tan-sigmoid function for the hidden layer neurons, and the linear function (purelin in MTALAB) for the output layer. The performance for the model was checked with each trained model until a good performance was reached, and its weights and biases were saved to be used as the final proposed feedforward backpropagated artificial neural network model in this research, which will be presented in the next Chapter, CH 5.

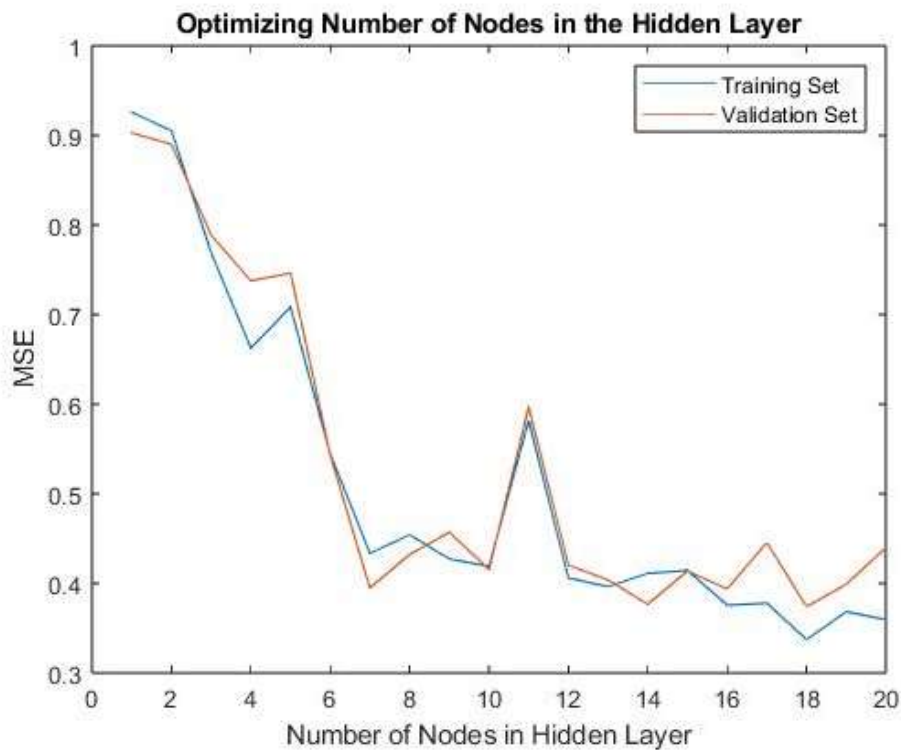


Figure 4.15 Optimizing the Number of Nodes in the hidden layer

4.4 Summary

In general, the methods and procedures implemented in this study can be summarized as follows:

- First, the data was computed using simulation of 6480 exterior connections samples using nonlinear FEM analysis Software ABAQUS where one connection was calibrated with the experimental specimen of Ajmal, (2016), (M-BCJ) specimen.
- The input and output parameters were identified, where the output is the shear strength of the unreinforced exterior beam-column joint.
- The required normalization for enhancing the training of the model is done.
- Feeding the data for the network training, validation, and testing of feed-forward neural network.
- The trained network performance is checked, and if the error is high, the model is retrained and new weights of connections are created, and the performance check is repeated for the newly trained model.
- The number of neurons in the hidden layer changes from one trail to another to optimize the number of neurons in the hidden layer, which gives the minimum error between the predicted and expected output value.
- After many trials of training and changing the number of neurons in the hidden layer, the final proposed ANN model was selected which contains one input layer of seven nodes, one hidden layer of 13 nodes, and one output layer with one node.

The performance check, final weight of the connections and the biases of the final proposed ANN model are detailed in the next chapter, CH 5.

Chapter Five

Results, Comparisons and Discussion

Chapter 5 Results, Comparisons and Discussion

This chapter presents the results of the developed feedforward artificial neural network proposed model that has been described in Chapter 4. The results of the final chosen model for predicting the shear strength of the joint are discussed and compared with the ACI-318 code and other experimental tests from the literature in the following pages.

5.1 Proposed ANN Model Performance Results

The final proposed feedforward artificial neural network model was selected depending on the least error of MSE, RMSE, and R. Where with MSE and RMSE, the closest to zero is a better-performed model, and for the R-value, the closest to one is a better-performed model. Many training trials for the model were done to reach the optimum number of hidden layer neurons that give better performance according to MSE, RMSE, and R evaluation measures. The best performance was reached with the following ANN architecture details: one input layer with seven neurons for the seven input parameters mentioned in Chapter 4, one hidden layer with thirteen neurons representing parameters created from the network itself, one output layer with one neuron representing the output of the network, which is the shear strength of the RC-BCJ in the exterior connection. The final architecture for the proposed ANN model is presented in Figure 5.1, while in Figure 5.2 the structure of the proposed ANN model with connections of weights and bias is presented, refer to Table 4.3 in section 4.3 for the notations in the figure.

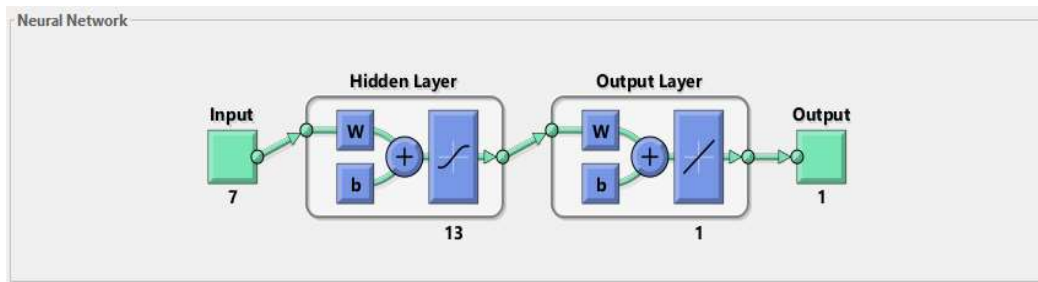


Figure 5.1 Final architecture for the proposed ANN model

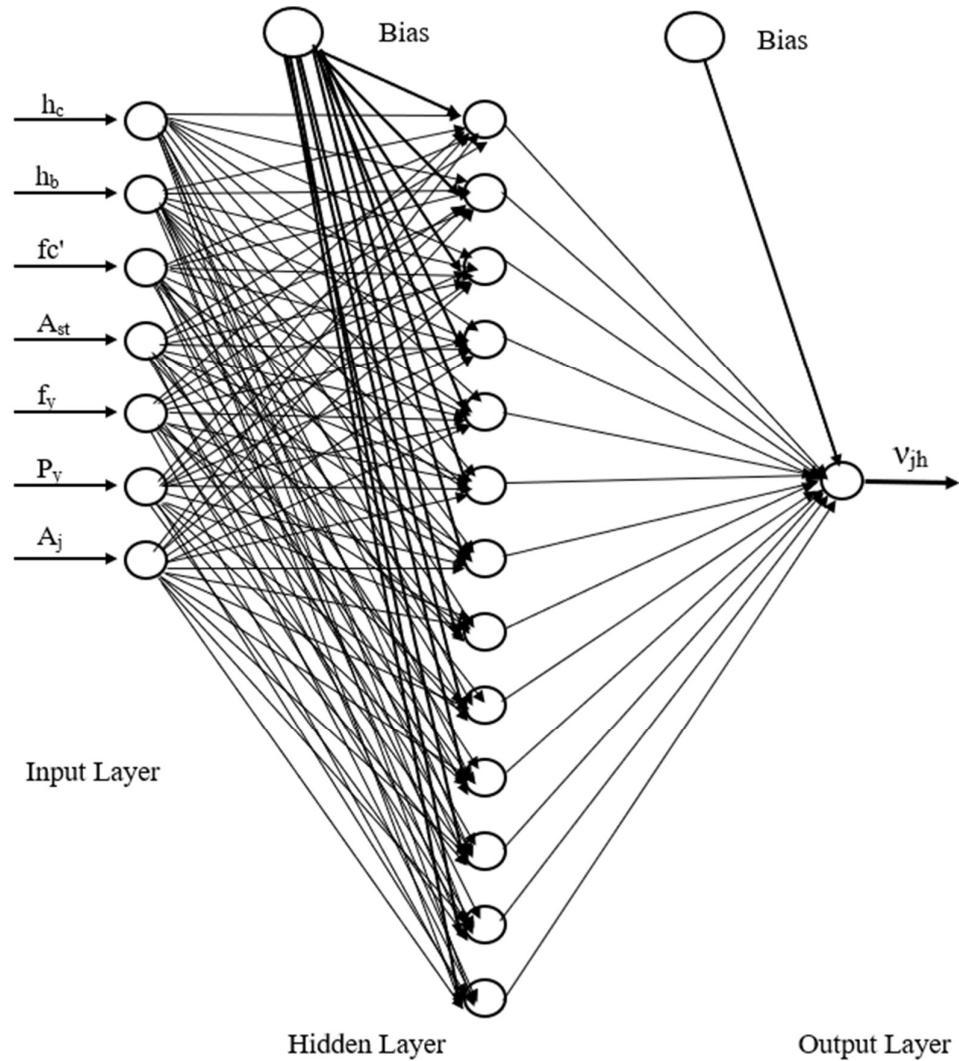


Figure 5.2 Structure of the proposed ANN model with connections of weights and bias

Table 5.1 shows the result of performance done for the proposed ANN model with different evaluation measures for training, validation, and testing sets. Table 5.2 presents the performance of the proposed model for the full data sets. From the previous tables it can be seen that the proposed model is accurate and capable of predicting the shear strength of the exterior RC-BCJ with high accuracy.

Table 5.1 Performance check results with different evaluation measures for training, validation, and testing sets

Model	Training Data (3024 Samples)			Validation Data (648 Samples)			Testing Data (648 Samples)		
	RMS E	MSE	R	RMS E	MSE	R	RMS E	MSE	R
ANN Proposed Model	0.347	0.1207	0.961	0.351	0.141	0.967	0.367	0.172	0.956

Table 5.2 Performance results for proposed model for the full data sets

Model	Training Data (4320 Samples)		
	RMSE	MSE	R
ANN Proposed Model	0.392	0.154	0.9615

The error histogram is presented in Figure 5.3 for the proposed ANN model, which presents the error for the full data sets of a total of 4320 connection samples. In Figure 5.3, the total error range has been divided into 20 bins (vertical bars) by default from the MATLAB software. As shown in Figure 5.3, the total error for the developed proposed model ranges from -0.8176 (leftmost bin) to 0.3691 (rightmost bin). Most of the data set lies in the error range of (-0.06813, 0.05679), which is considered a well-performed ANN model in predicting shear strength for the BCJ.

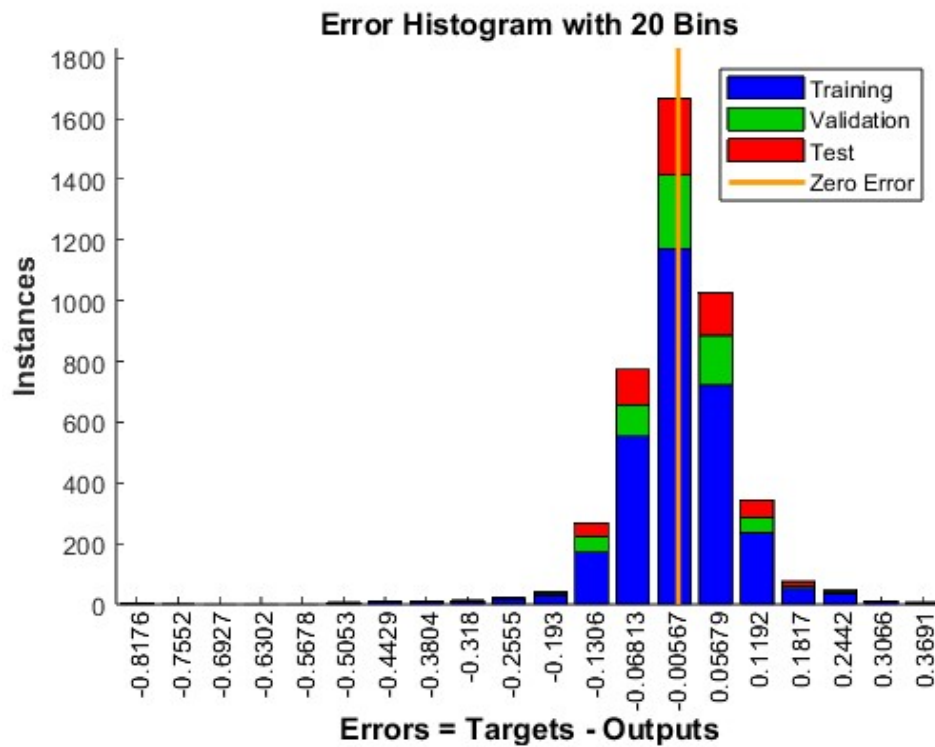


Figure 5.3 Error Histogram of the data sets

Figure 5.4 shows the regression plots for the performance of the final proposed ANN model, where the R-value is 0.961, 0.967, 0.956, for training, validation, and testing sets, respectively. For all data sets, R value is 0.962, which means 96.2% accuracy of proposed model. The coefficient of correlation (R) values converge for the three sets of data, which means that the overfitting problem has been avoided, as mentioned previously in section 4.2.4. On the other hand, all the R values are close to 1, indicating that the under-fitting problem has been avoided too, as discussed previously in section 4.2.4. From the mentioned results of regression plots for the proposed model, it is clear that the prediction of shear strength of the exterior RC-BCJ is accurate, and the model achieved the required accuracy for acceptance.

After reaching the best performance model after many trials, the generation of function from the developed model was done using (genFunction) function available in the nftool in MATLAB software. From the function of the proposed model, the connections' weight and biases are extracted and used for the next section 5.2. These weights of connections and biases will be used on future input parameters to let the proposed ANN model predict the shear strength of the RC beam-column joint.

The MATLAB script used for developing final proposed ANN model is available in Appendix (4), while the proposed model's final connections weight and biases in matrix form are presented in Appendix (5). The following section will discuss the steps that can be followed to get used to the final proposed ANN model with future applications.

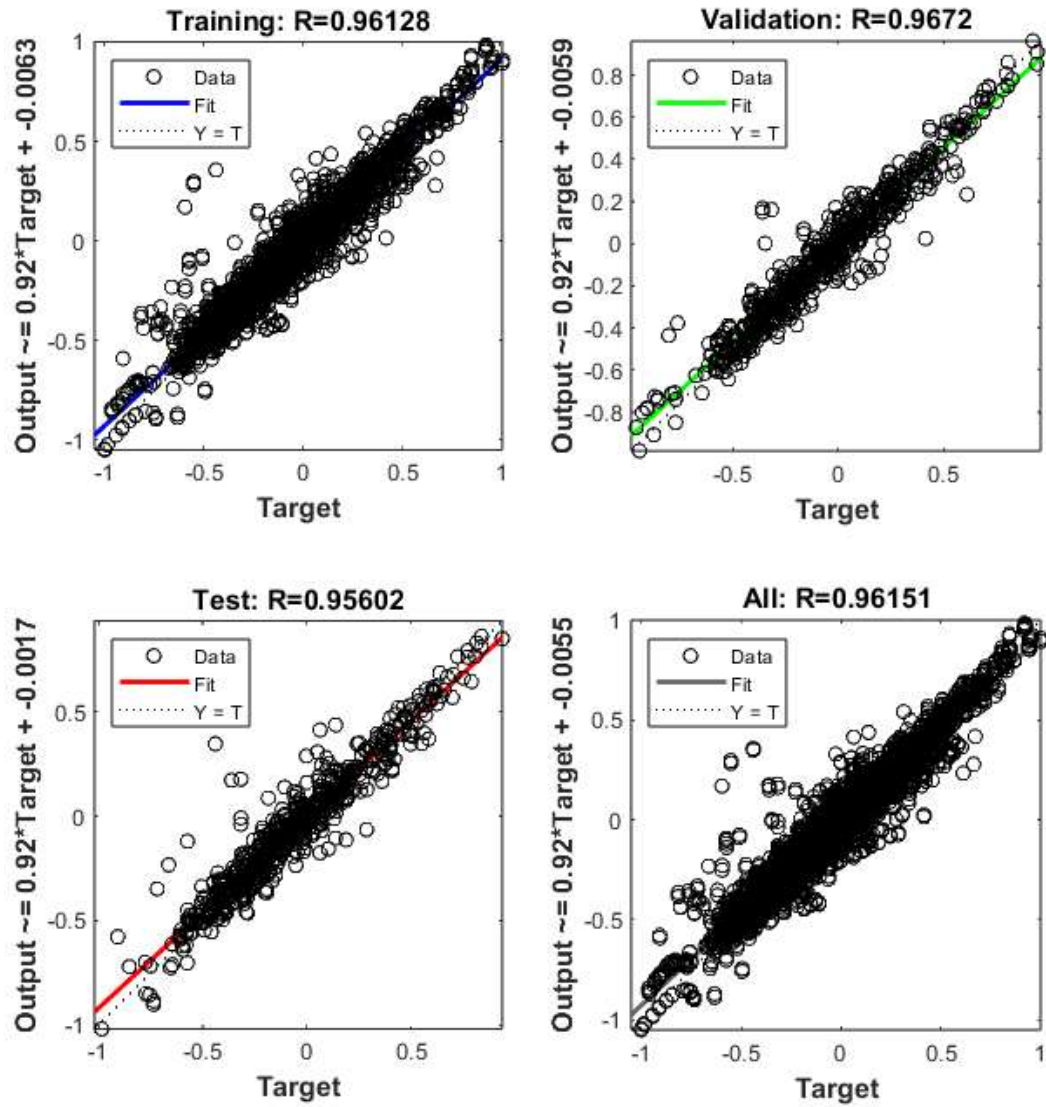


Figure 5.4 Regression Plots for performance of the proposed model using the training, validation, and testing data in addition to graph for the full data sets

5.2 The Proposed ANN Model

The proposed ANN model has successfully mapped the input parameters to the output, which means that the proposed model can predict the joint shear strength of exterior RC-BCJ. This section explains the procedure for applying the proposed ANN model in predicting joint strength for future input parameters.

The proposed neural network model is presented in terms of mathematical equations to predict the shear strength of exterior RC beam-column joint using 7 input parameters which can be easily collected from exterior RC connection geometry and reinforcement details, refer to section 4.3. The inputs and output variables are presented in Table 5.3. While computing the shear strength for the joint, the input variables are multiplied with the associated weights of the proposed ANN model and then biases will be added as shown in equation (5-1) to (5-13). These equations are passed through the hyperbolic sigmoid function (tansig activation function) as it is presented in equation (5-14) to (5-26).

The summation function for each hidden neuron is represented in equation (5-1) to (5-13), while the transfer function for each hidden neuron is presented in equation (5-14) to (5-26). For the output layer neuron, Equation (5-27), presents the weights associated with the neurons value in hidden layer to connect it to the output layer which these weights are multiplied with the values obtained by Equation (5-14) to (5-26) and then bias value of the output layer is added. Equation (5-28) shows the output result of the proposed ANN model, in this research the linear transfer function for the output layer neuron is used. The output of the proposed ANN model is not the final result for shear strength since reverse normalization must be done on its value as shown in Equation (5-29) and simplified in Equation (5-30).

Table 5.3 Input and output parameters for the proposed ANN model.

Variables	Description
Input Variables	
h_c	Column depth in mm
h_b	Beam depth in mm
f_c'	Concrete compressive strength in MPa
A_{st}	Beam tension reinforcement total area in mm^2
f_y	Beam tension reinforcement yield strength in MPa
P_y	Axial column load as ratio of its capacity
A_j	The joint area in mm^2
Output Variable	
v_{jh}	The shear strength of the joint region in MPa

Hidden layer neurons value computing:

As mentioned in equation (4-1) in Chapter 4:

$$a = f(W \times P + b) \quad (4-1)$$

Let $W \times P + b = K$, to compute K for the hidden layer neurons. There are thirteen neurons at the hidden layer in the proposed model and these will be computed as follows with future input variables. It is important to note that all the variables in the following equations are normalized before applying the following equation for computing the values for the 13 neurons in the hidden layer. Refer to Table 4.4 and Equation (4-3) in Chapter 4 for more details about the normalization of the input parameters which detailed in section 4.3.

$$K_1 = \{(-0.5185)h_c + (-1.2716)h_b + (-0.6639)f'_c + (-2.4119)A_{st} + (-0.0160)f_y + (-0.0172)P_y + (-0.5546)A_j\} + 1.3476 \quad (5-1)$$

$$K_2 = \{(-0.3564)h_c + (-0.2010)h_b + (0.1107)f'_c + (0.3687)A_{st} + (0.0181)f_y + (0.1010)P_y + (0.0468)A_j\} - 0.1554 \quad (5-2)$$

$$K_3 = \{(1.0215)h_c + (1.5968)h_b + (1.8751)f'_c + (0.1720)A_{st} + (-0.0711)f_y + (0.1343)P_y + (1.3570)A_j\} - 0.9316 \quad (5-3)$$

$$K_4 = \{(-1.1757)h_c + (-1.2049)h_b + (-0.6131)f'_c + (-1.9716)A_{st} + (-0.0044)f_y + (0.0106)P_y + (0.2407)A_j\} + 1.1729 \quad (5-4)$$

$$K_5 = \{(-1.6588)h_c + (1.9250)h_b + (-0.2070)f'_c + (0.3456)A_{st} + (0.0453)f_y + (-0.0128)P_y + (-3.1511)A_j\} - 3.8005 \quad (5-5)$$

$$K_6 = \{(-0.1273)h_c + (3.2528)h_b + (-0.1104)f'_c + (-0.1829)A_{st} + (-0.0090)f_y + (-0.1661)P_y + (1.4606)A_j\} + 4.7283 \quad (5-6)$$

$$K_7 = \{(-0.7594)h_c + (-6.5145)h_b + (0.1309)f'_c + (0.1816)A_{st} + (0.0031)f_y + (0.1362)P_y + (-0.5558)A_j\} - 7.8068 \quad (5-7)$$

$$K_8 = \{(1.1948)h_c + (1.4796)h_b + (-0.5909)f'_c + (-1.1049)A_{st} + (0.0279)f_y + (-1.6679)P_y + (-0.4448)A_j\} + 0.5165 \quad (5-8)$$

$$K_9 = \{(-1.7703)h_c + (1.0275)h_b + (-0.0409)f'_c + (0.6819)A_{st} + (0.0521)f_y + (0.6061)P_y + (-0.4093)A_j\} - 2.2382 \quad (5-9)$$

$$K_{10} = \{(-1.7263)h_c + (2.5915)h_b + (0.1979)f'_c + (0.1240)A_{st} \\ + (-0.0027)f_y + (0.3527)P_y + (-1.1080)A_j\} \\ - 5.0222 \quad (5-10)$$

$$K_{11} = \{(-1.6888)h_c + (1.5962)h_b + (-0.2815)f'_c + (0.3812)A_{st} \\ + (0.0444)f_y + (0.0616)P_y + (-2.0532)A_j\} \\ - 3.0808 \quad (5-11)$$

$$K_{12} = \{(0.7699)h_c + (0.1931)h_b + (0.6702)f'_c + (-0.2095)A_{st} \\ + (-0.0105)f_y + (0.0004)P_y + (-0.7588)A_j\} \\ + 0.8607 \quad (5-12)$$

$$K_{13} = \{(1.8973)h_c + (-3.7958)h_b + (-0.2495)f'_c \\ + (-0.0231)A_{st} + (0.0096)f_y + (-0.2515)P_y \\ + (0.6299)A_j\} + 6.0085 \quad (5-13)$$

The next step is to enter the K values into the activation/transfer function to finally find the neurons values of the hidden layer:

$$f(K_1) = \left\{ \frac{2}{1 + e^{-2(K_1)}} - 1 \right\} \quad (5-14)$$

$$f(K_2) = \left\{ \frac{2}{1 + e^{-2(K_2)}} - 1 \right\} \quad (5-15)$$

$$f(K_3) = \left\{ \frac{2}{1 + e^{-2(K_3)}} - 1 \right\} \quad (5-16)$$

$$f(K_4) = \left\{ \frac{2}{1 + e^{-2(K_4)}} - 1 \right\} \quad (5-17)$$

$$f(K_5) = \left\{ \frac{2}{1 + e^{-2(K_5)}} - 1 \right\} \quad (5-18)$$

$$f(K_6) = \left\{ \frac{2}{1 + e^{-2(K_6)}} - 1 \right\} \quad (5-19)$$

$$f(K_7) = \left\{ \frac{2}{1 + e^{-2(K_7)}} - 1 \right\} \quad (5-20)$$

$$f(K_8) = \left\{ \frac{2}{1 + e^{-2(K_8)}} - 1 \right\} \quad (5-21)$$

$$f(K_9) = \left\{ \frac{2}{1 + e^{-2(K_9)}} - 1 \right\} \quad (5-22)$$

$$f(K_{10}) = \left\{ \frac{2}{1 + e^{-2(K_{10})}} - 1 \right\} \quad (5-23)$$

$$f(K_{11}) = \left\{ \frac{2}{1 + e^{-2(K_{11})}} - 1 \right\} \quad (5-24)$$

$$f(K_{12}) = \left\{ \frac{2}{1 + e^{-2(K_{12})}} - 1 \right\} \quad (5-25)$$

$$f(K_{13}) = \left\{ \frac{2}{1 + e^{-2(K_{13})}} - 1 \right\} \quad (5-26)$$

Now the hidden layer neurons will be as input parameters for the output layer neuron using the following equation:

$$\begin{aligned} Y_{output} = & \{f(K_1) \times (0.5997) + f(K_2) \times (0.6566) \\ & + f(K_3) \times (-0.1274) + f(K_4) \times (-0.6396) \\ & + f(K_5) \times (1.1219) + f(K_6) \times (1.9717) \\ & + f(K_7) \times (1.9659) + f(K_8) \times (0.0292) \\ & + f(K_9) \times (0.2192) + f(K_{10}) \times (-2.3402) \\ & + f(K_{11}) \times (-1.3293) + f(K_{12}) \times (0.5239) \\ & + f(K_{13}) \times (-2.4671)\} - 0.2427 \end{aligned} \quad (5-27)$$

$$\tau = \text{purelin}(Y_{output}) = Y_{output} \quad (5-28)$$

The final step is to reverse the normalization for the output value of proposed ANN model, since the developed model used the normalized version of the output parameters in the training process. That can be done using Equation (4-9) in section 4.3.

The final output value using equation (4-9) will be as follows:

$$Y_{final\ output} = \frac{(Y_{output}+1) \times (a_{max}-a_{min})}{2} + a_{min} \quad (5-29)$$

Where:

$$a_{min} = 0.457\ mm$$

$$a_{max} = 9.253\ mm$$

These values are constant depending on the normalization done for the output parameter in the training process while developing the proposed ANN model. These are the maximum and minimum shear strength of joint values within the used data for training the ANN model. After simplifying Equation (5-29), the final output answer using proposed ANN model for predicting shear strength of reinforced concrete beam-column joint region will be computed using Equation (5-30).

$$Y_{final\ output} = 4.398 Y_{output} + 4.855 \quad (5-30)$$

The flowchart shown in Figure 5.5 summarizes the steps for applying the proposed ANN model for future prediction of exterior BCJ shear strength.

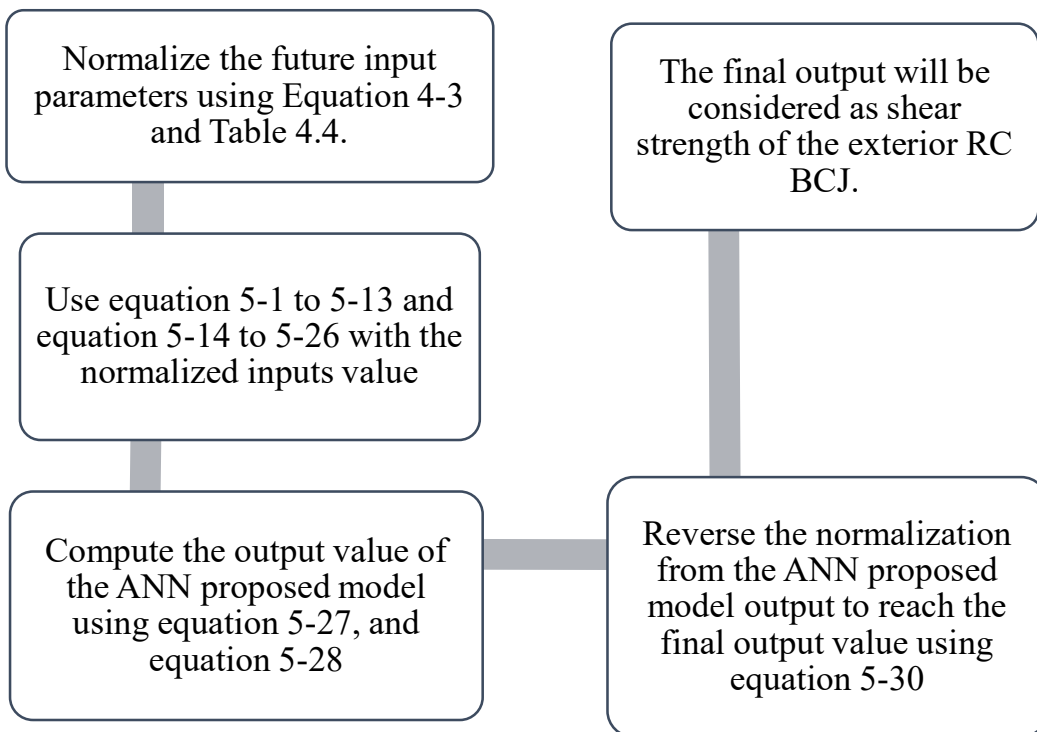


Figure 5.5 Flowchart for the required steps for applying the proposed ANN model of future exterior RC-BCJ shear strength prediction

5.3 Comparison between the Proposed ANN Model and ACI-318, and Literature Experiments Results

In this section, the proposed ANN model results in predicting the shear strength of the exterior RC-BCJ will be compared with ACI-318 results. Furthermore, the proposed ANN model will be utilized to predict the shear strength of 80 experimentally tested exterior beam column joints collected from literature to test the final model performance further. The following sections contain the comparisons made.

5.3.1 Comparison between Proposed ANN model and ACI-318 Code Results

The proposed ANN model developed was compared with the ACI-318 prediction results for shear strength of the joint region of 648 exterior connections (full testing data set). The comparison of the results between the proposed ANN model and ACI-318 in the prediction of shear strength of the RC beam-column joint is presented in Figure 5.6 for 100 samples from testing data set. It can be clearly noticed that the proposed ANN model predicts the shear strength of the joint more accurately than ACI-318 does. In addition, the data points for the performance of proposed ANN model are very close to the best correlation line provided in Figure 5.6. Hence, that indicates the good performance of the proposed ANN model. In Figure 5.7, another comparison plotting form is presented for the same comparison between the proposed ANN model and ACI-318 in the prediction of shear strength of the RC beam-column joint. From Figure 5.7, good agreement between proposed ANN model and FEA results for the shear strength prediction of RC-BCJ while the ACI result is not matching the prediction of FEA which used as alternative for experimental data. That shows the accuracy of the proposed ANN model in predicting RC-BCJ shear strength.

Table 5.4 shows part of the comparison done using the full testing set of 648 connections, which indicates that the proposed model is capable of accurately predicting the shear strength more than the ACI-318 equation mentioned in chapter 2.3, where the comparison is done in terms of shear strength in MPa rather than shear capacity in kN as used in chapter 2.3. The average (prediction/FE analysis result) value for the full testing set of 648 connections for the ACI-318 equation is 1.257, while for the proposed ANN model, it is 1.003. That indicates that ACI-318 prediction equation is overestimating the strength of RC beam-column joint. Moreover, the proposed ANN model is performing better than ACI-318 equation which showed better agreement with FE analysis result.

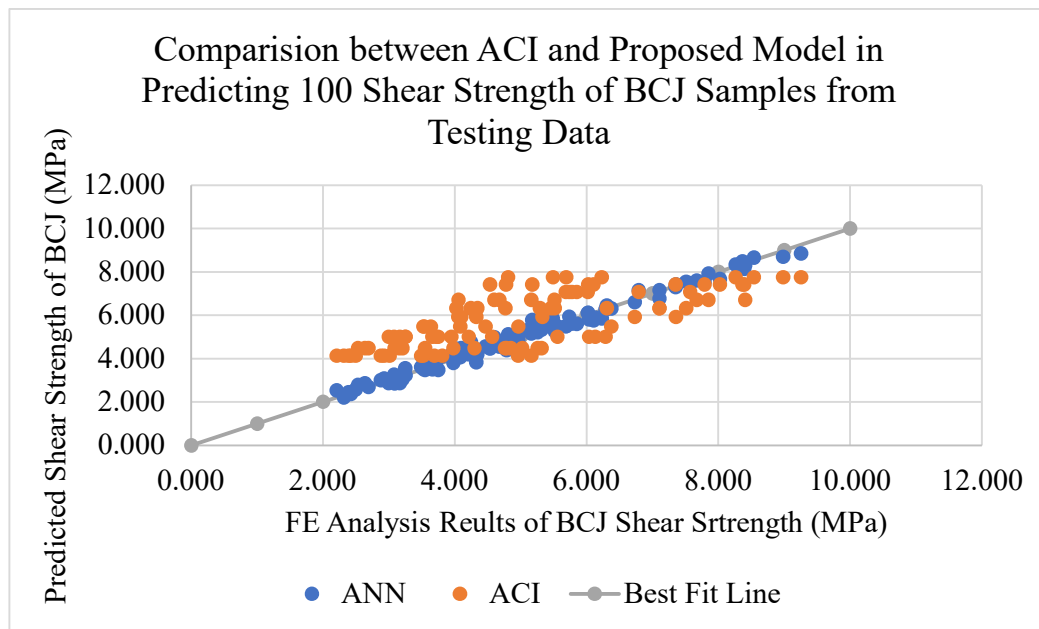


Figure 5.6 Comparison of the results between proposed ANN model and ACI-318 in the prediction of shear strength of the RC beam-column joint

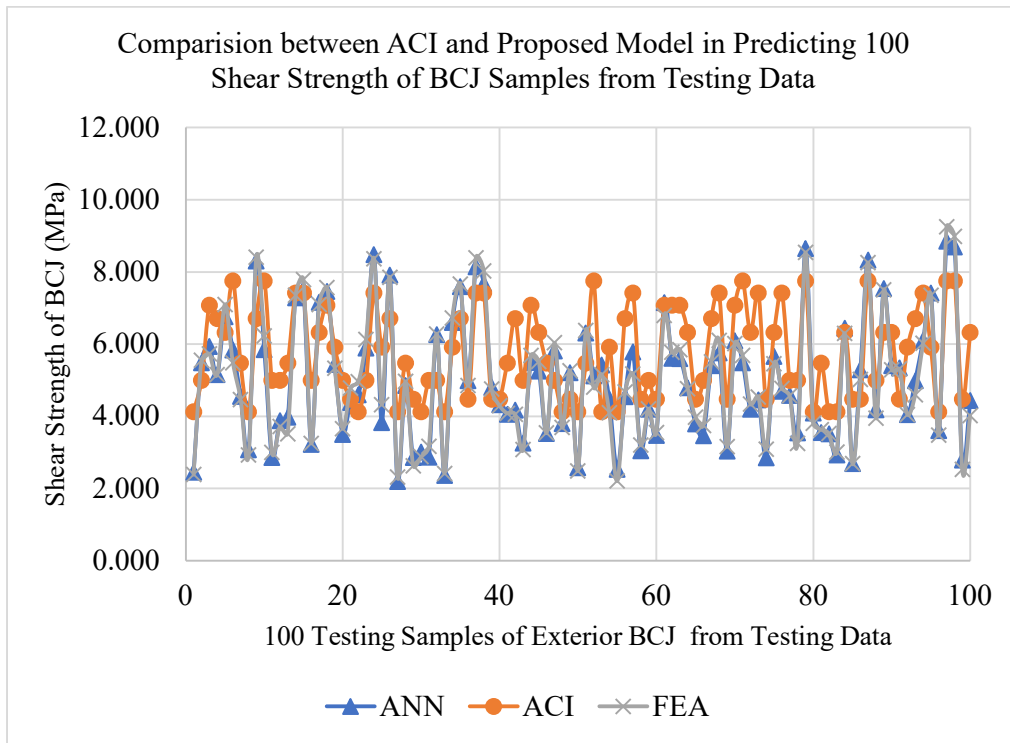


Figure 5.7 Comparison of the results between proposed ANN model and ACI-318 in the prediction of shear strength of the RC beam-column joint

Table 5.4 Part of the comparison of the results between proposed ANN model and ACI-318 in the prediction of shear strength of the joint

Average values for full Testing Data set (648 Connection Samples)				Average ACI Prediction/FEA Result	Average ANN Prediction/ FEA Result
				<u>1.257</u>	<u>1.003</u>
No.	v_{jn} (MPa) (FEA Result)	v_{jn} from ACI-318 (MPa)	v_{jn} from proposed ANN model (MPa)	ACI/FEA result	ANN/FEA result
1	4.459	4.123	4.627	0.92	1.04
2	4.792	4.472	4.932	0.93	1.03
3	5.211	5.000	5.410	0.96	1.04
4	5.736	5.477	5.844	0.95	1.02
5	6.124	5.916	6.231	0.97	1.02
6	6.591	6.325	6.570	0.96	1.00
7	6.761	6.708	6.866	0.99	1.02
8	6.776	7.071	7.125	1.04	1.05
9	6.768	7.416	7.350	1.10	1.09
10	4.468	4.123	4.603	0.92	1.03
11	4.894	4.472	4.906	0.91	1.00
12	5.259	5.000	5.379	0.95	1.02
13	5.821	5.477	5.809	0.94	1.00
14	6.179	5.916	6.191	0.96	1.00
15	6.593	6.325	6.527	0.96	0.99
16	6.737	6.708	6.821	1.00	1.01
17	6.706	7.071	7.078	1.05	1.06
18	4.427	4.123	4.583	0.93	1.04
19	4.900	4.472	4.899	0.91	1.00
20	5.378	5.000	5.394	0.93	1.00
21	5.812	5.477	5.841	0.94	1.01
22	6.217	5.916	6.238	0.95	1.00
23	6.514	6.325	6.585	0.97	1.01
24	6.781	6.708	6.886	0.99	1.02
25	6.789	7.071	7.146	1.04	1.05
26	4.841	4.123	5.071	0.85	1.05

5.3.2 Comparison between Proposed ANN model and Literature Experimental Results

The proposed ANN model was tested using the testing data set and it showed high accuracy in the prediction of the shear strength of BCJ of that totally unknown data to the model. To further test the performance of the proposed ANN model, the proposed model is used to predict the shear strength of 80 RC beam-column joints collected from exterior connection specimens from literature. These 80 specimens were tested experimentally, and therefore the experimental results were compared with the predicted results using the proposed model in this research. The full table for the 80 exterior connection specimens is provided in Appendix (6), which Table 5.5 shows just a sample of it (20 specimens).

Figure 5.8 shows a comparison of the prediction of the proposed ANN model and experimental results for the same specimens, where the best-fit line is presented in the graph for easy comparison. It can be indicated that most of the data points lie under the straight line, and those data points are underestimated when compared to experimental results. In contrast, the points on the top of the best-fit line indicate that the strength of the joint is overestimated when compared to actual (experimental) results. Even though the points do not exactly match the predicted and experimental results, the proposed ANN model still has high accuracy since the points are near the best-fit line and have reasonable error, where 90% of specimens got error less than 30%. The average error for the 80 samples prediction using the ANN proposed model is 17.2%. The possible explanation for the difference between predicted and experimental strength is that some of the literature samples include reinforcement in the joint and some input parameters are out of the used range for training the ANN model. This can provide recommendations for future study to further

increase the input parameters and provide a wider range of values for training the ANN model.

Furthermore, another comparison plotting form for the same 80 specimens is provided in Figure 5.9 which shows the results of RC-BCJ shear strength prediction using the proposed ANN model in comparison with the actual (experimental) result. Figure 5.9 shows good agreement between the ANN and experimental result curves which indicates that the proposed model is reasonably accurate in its prediction.

The average ANN prediction to experimental value for all the specimens of 80 exterior connections is 0.915, where 1 indicates the best performance. The value of 0.915 is very close to 1, and hence, it indicates that the proposed ANN model can predict the shear strength with acceptable accuracy for exterior RC-BCJ. The specimens from the literature were not used in any part of the development of the ANN proposed model. That is a promising performance of the proposed ANN model due to its capability of predicting with reasonable error for totally new data points with future input parameters. Seventy-two out of eighty (90%) exterior connections had errors of less than 30% in the prediction using the proposed ANN model, while 51 (63.8%) specimen results showed errors of less than 20% when compared depending on the predicted to the expected experimental results value.

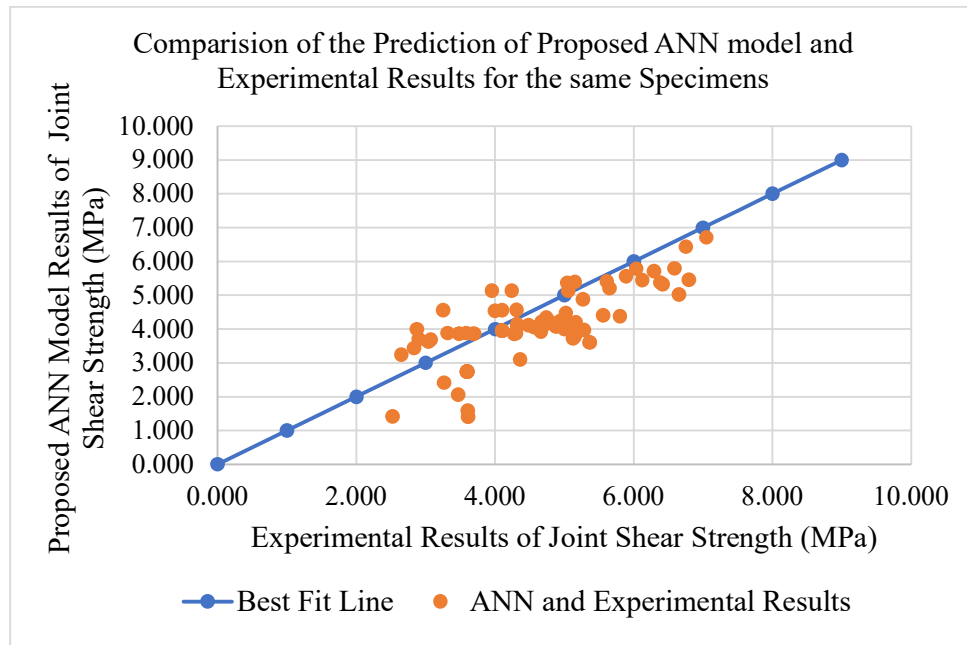


Figure 5.8 Comparison of the Prediction of Proposed ANN model and Experimental Results for the same Specimens

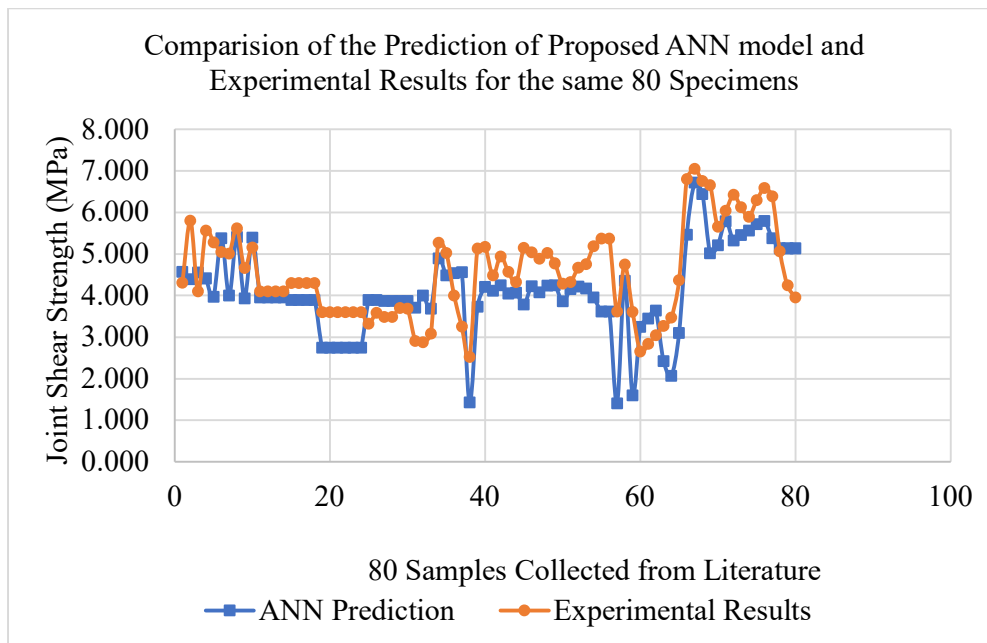


Figure 5.9 Comparison of the Prediction of Proposed ANN model and Experimental Results for the same Specimens

Table 5.5 Sample of the Comparison between the prediction of Proposed ANN model in comparison with the experimental result of data collected from literature.

		Average ANN Prediction/Experimental (for 80 samples)
		<u>0.915</u>
Shear Strength from Experimental Result (MPa)	ANN Prediction (MPa)	ANN Prediction/ Experimental
4.310	4.568	1.060
5.800	4.385	0.756
4.100	4.555	1.111
5.560	4.408	0.793
5.280	3.969	0.752
5.044	5.369	1.065
5.001	3.997	0.799
5.613	5.409	0.964
4.662	3.931	0.843
5.153	5.391	1.046
3.483	3.863	1.109
3.700	3.863	1.044
3.683	3.863	1.049
2.900	3.706	1.278
2.875	3.999	1.391
3.075	3.687	1.199
5.270	4.883	0.927
5.020	4.480	0.892
3.998	4.539	1.135
3.250	4.559	1.403

Chapter Six

Conclusion and Recommendations

Chapter 6 Conclusion and Recommendations

The main research findings, future work recommendations and guidelines for the work carried out in this study are highlighted in this chapter.

6.1 Main Research Findings

The main research findings are provided through the achievement of the research objectives as follows:

Objective 1

“To develop a model for strength prediction of reinforced concrete beam-column joint using machine learning technique.”

This research developed a model for predicting reinforced concrete beam-column joint strength using one of machine learning techniques, Artificial Neural Network. The proposed model uses the feedforward back propagation artificial neural network to develop a model to predict the shear strength of exterior beam-column joints. The proposed ANN model required a large amount of data for training, validation, and testing. Therefore, the required data was produced in this research using nonlinear finite element analysis software “ABAQUS” to simulate the exterior connection rather than the full-scale testing procedure which could be limited to a few numbers of samples collected from literature. A total of 4320 exterior connection samples were used for developing the ANN proposed model. This research focused on joint failure exterior connections only. The proposed model can be applied by extracting simple inputs parameters from any exterior connection, where the inputs are the column depth (h_c) in mm, beam depth (h_b) in mm, concrete cylinder compressive strength (f_c') in MPa, beam tension reinforcement total area (A_{st}) in mm^2 , beam tension reinforcement yield strength (f_y) in MPa, axial column load

as ratio of its capacity (P_y), and the joint area (A_j) in mm^2 . The inputs will have the same unit as used in the developed ANN model. Also, the input parameters for data have to be normalized first before applying the proposed ANN model in section 5.2. The ANN model output will be reversed of normalization before using the value as final output answer of shear strength of the joint area, as shown in Equation (5-30).

Objective 2

“To compare the performance of machine learning model in the prediction of the reinforced beam-column joint strength with the literature.”

The performance of the proposed ANN model was checked using the testing data set of 648 samples which showed a coefficient of correlation value of 0.956, where 1 is the best correlation. In addition, the RMSE for testing data was found to be 0.367 MPa in the prediction of exterior RC-BCJ shear strength. The R and RMSE evaluation measure values are very good and indicate that the proposed ANN model is accurate in its prediction. For further performance check, the ACI-318 prediction for the shear strength of exterior RC-BCJ results was compared with the prediction of the proposed model result of the same testing data set. This comparison revealed that the proposed ANN is predicting the shear strength of RC-BCJ with higher accuracy than the ACI-318 prediction. In this research, the proposed ANN model performance was checked not only with the testing set of data, but also with 80 exterior connection specimens tested experimentally collected from literature. These 80 specimens already have been tested up to failure and their joint shear capacity was calculated depending on experimental approach. Therefore, the results of these samples were compared with the results of proposed ANN model. The proposed model showed high capability of prediction of the shear strength for exterior RC-BCJ collected from literature, where these

samples are completely unknown by the ANN model and have never entered to the model in the training process. Despite that, the prediction of shear strength was 0.915 as average for the 80 connection specimens, where seventy-two out of eighty (90%) exterior connections of the literature were having error less than 30% in the prediction using the proposed ANN model.

It has been found that ANN proposed model is capable of predicting the shear strength of exterior beam-column joints with very high accuracy. Moreover, using the proposed ANN model as an alternative for the long procedure of the FEA and high cost of full-scale testing of BCJ that could be done to calculate the shear strength of RC-BCJ will save efforts and money.

6.2 Recommendations and Comments for this Research

Further recommendations and guidelines for the work that has been achieved in this research are provided accordingly:

- The prediction equation can be used to evaluate exterior joint shear strength without expensive testing or detailed finite element analysis modeling. The proposed ANN model can predict the exterior reinforced concrete beam-column joint shear capacity to evaluate the joint capacity before starting the design calculation by the engineers in design offices.
- The proposed model depends on simple input parameters where the future users of this proposed ANN model could easily collect the input parameters from their preliminary design geometry and reinforcement details.

- The proposed ANN model is helpful for assessing old reinforced concrete structures to check whether retrofitting and strengthening techniques for the beam-column joint are required.

6.3 Recommendations for Future Work

Recommendations for future work are suggested from this thesis study as follows:

- The exterior beam-column joint simulated samples for training the ANN model could be simulated with slab part as it is more realistic on the shear strength of the beam-column joint. Also, different positions of the exterior joint could be considered for a better understanding of exterior joint shear strength.
- The joint region could be considered with different reinforcement arrangements and ratios, which will enable the proposed model to perform better with the reinforced exterior beam-column joint too.
- The axial column loading and the yield strength of the reinforcement for the connection could be varied in a wider range to provide better variation of training data examples.
- More input parameters that could affect the shear strength of exterior RC-BCJ may be included in the ANN model.
- The ANN model could be hybridized with the metaheuristic algorithms to enhance the performance of the machine learning techniques.
- Develop a model for predicting the shear strength of RC-BCJ with different machine learning techniques and compare their performance.
- Develop a prediction model for the beam-column joint strength for the strengthened joints.

- Develop machine learning model to predict the strength of the beam-column joint that contains fiberglass reinforcement.
- Develop machine learning model to predict the strength of interior beam-column joint.

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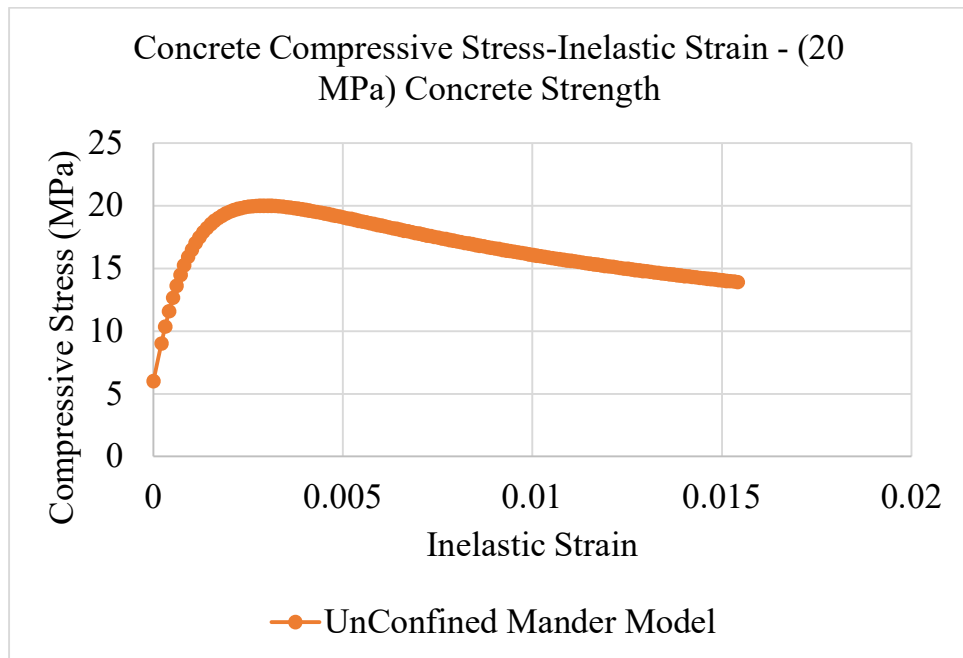
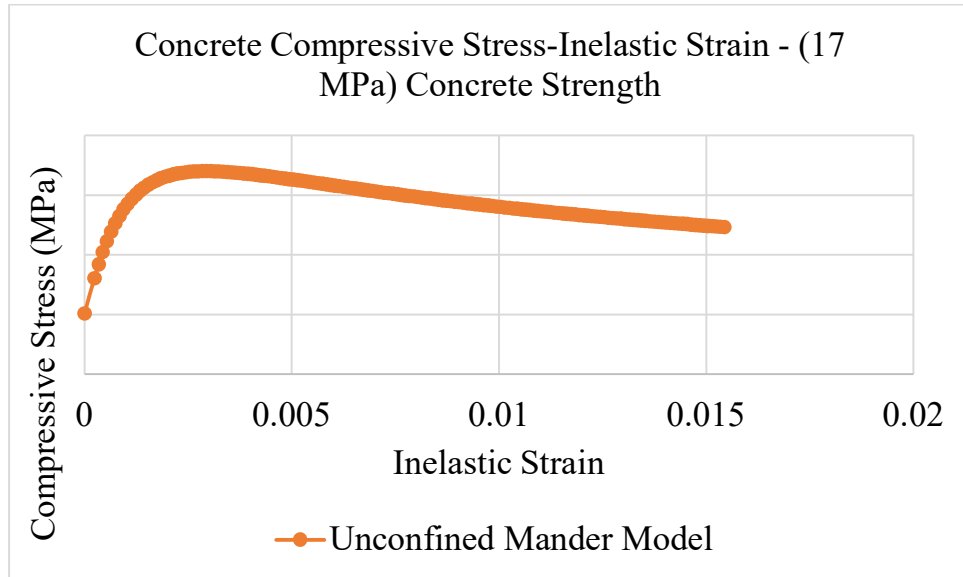
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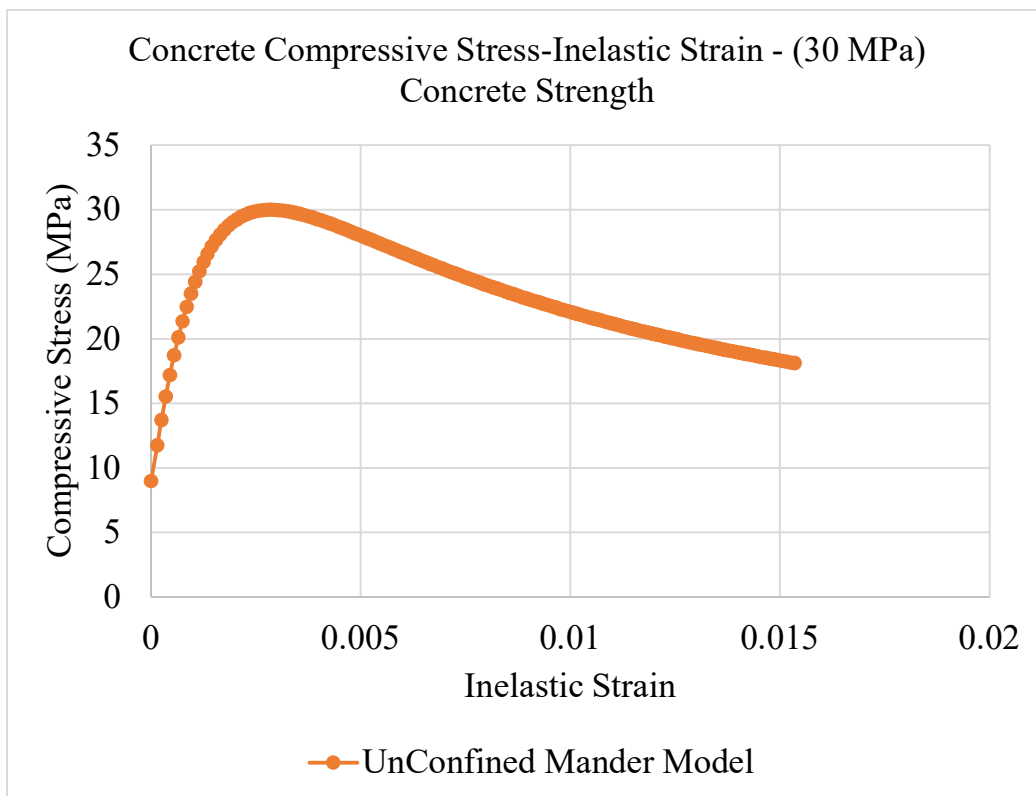
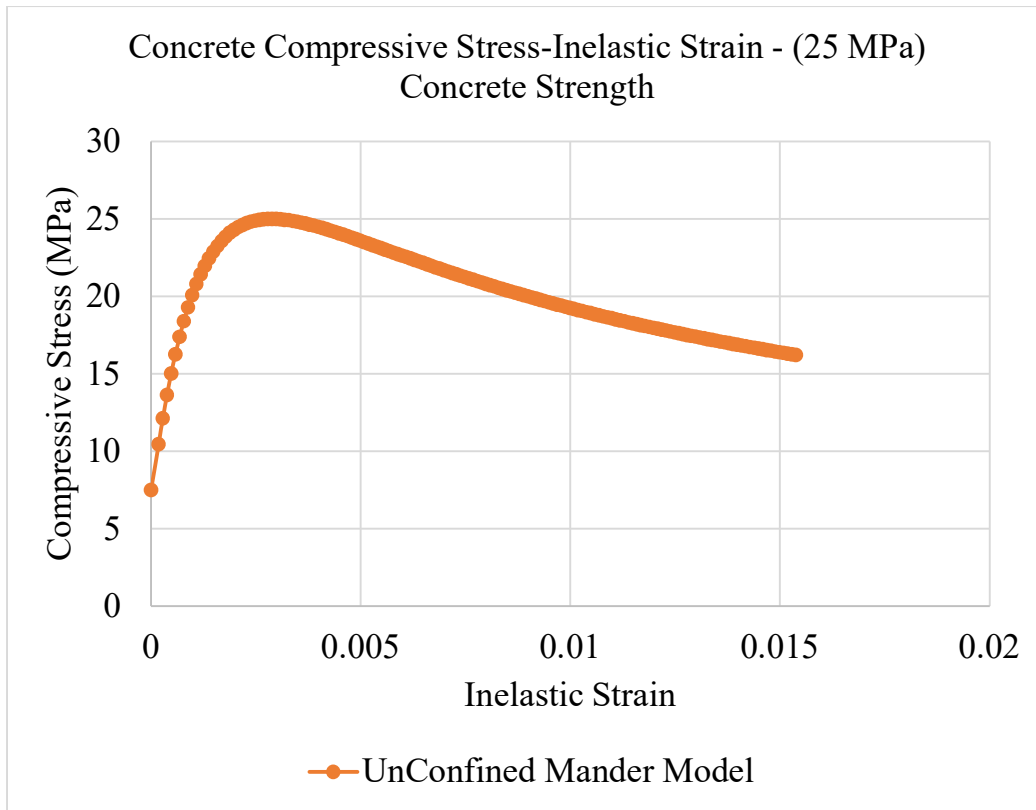
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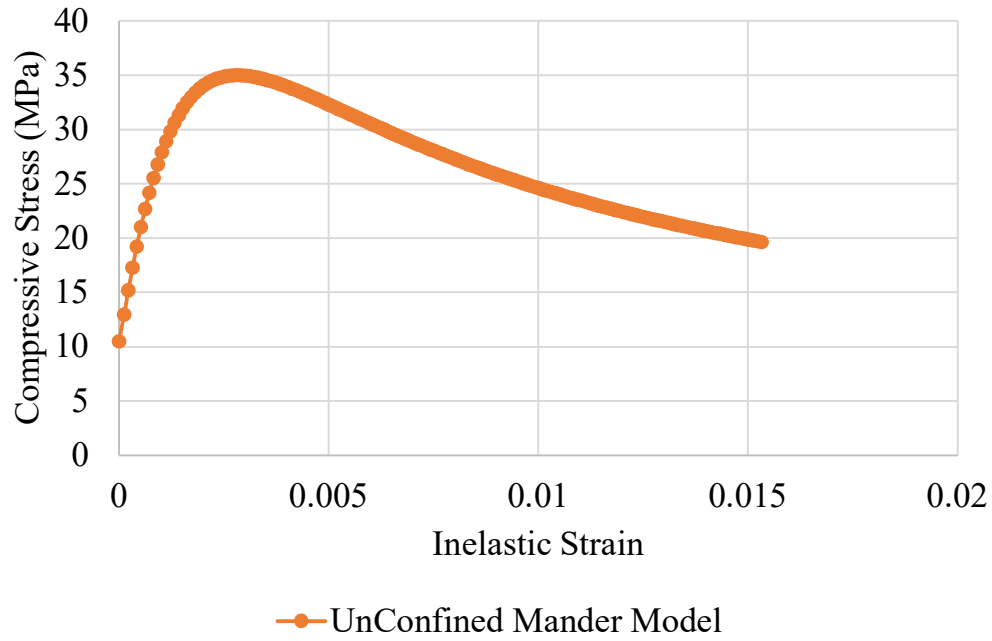
Appendix (1) Produced Concrete Stress-inelastic Strain Curve for different Compressive Strength of Concrete

Concrete behavior in compression is defined in this research using Mander,1988 model and the uniaxial stress-strain curves of concrete for different strength are shown in this appendix.

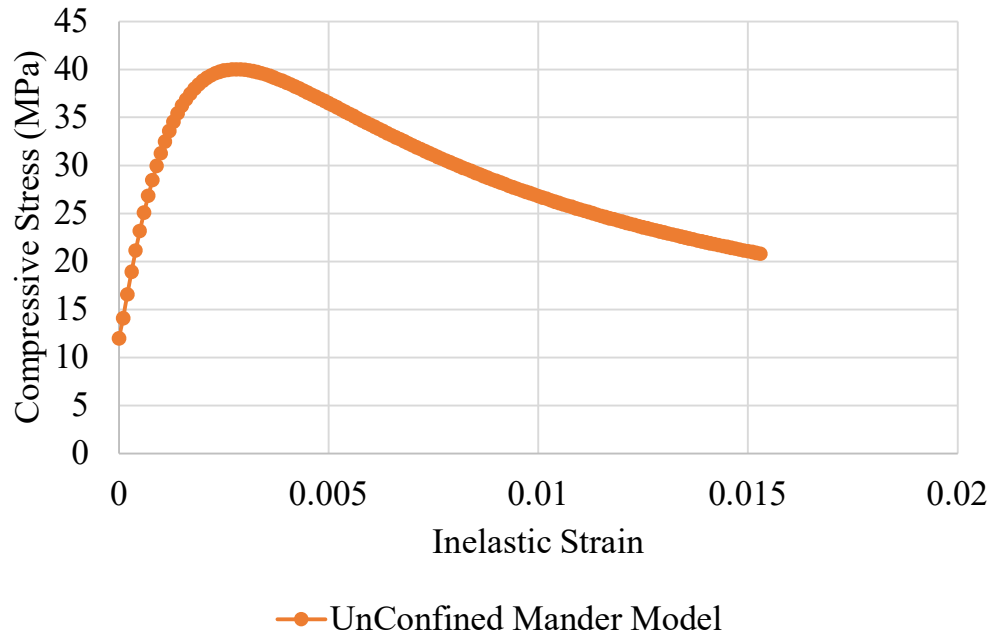




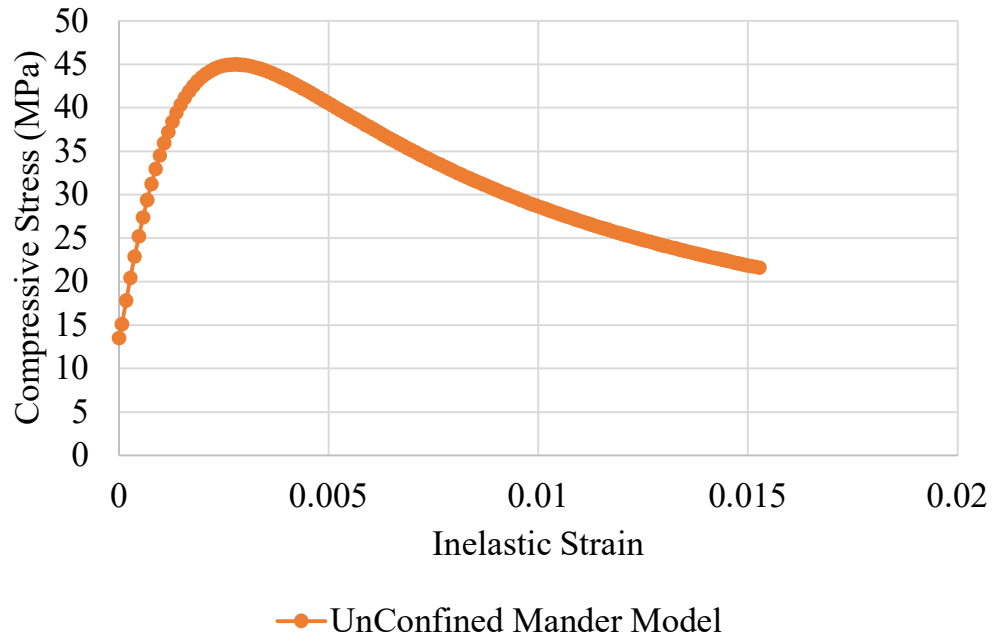
Concrete Compressive Stress-Inelastic Strain - (35 MPa)
Concrete Strength



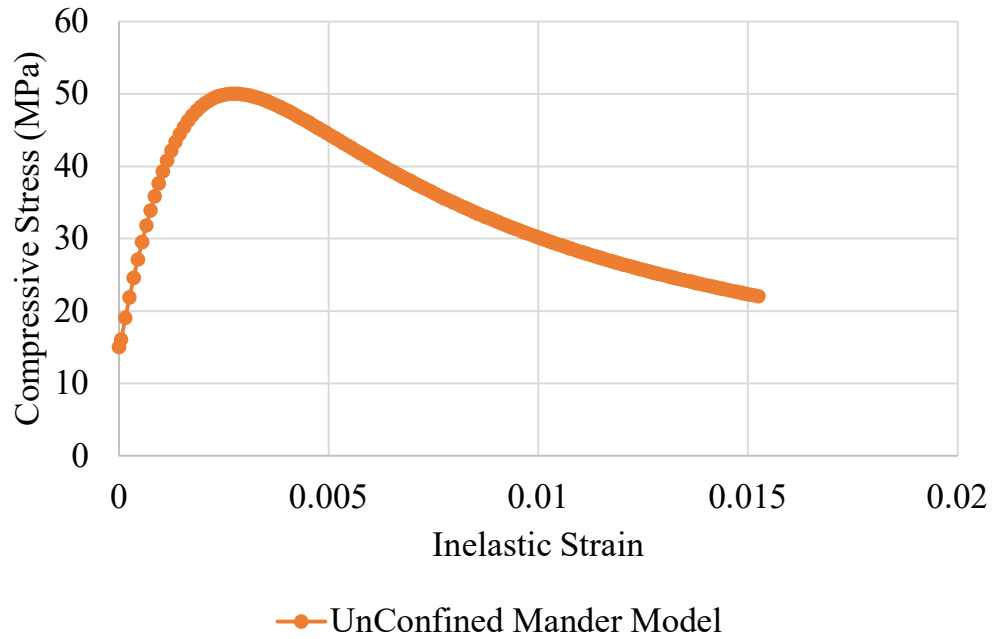
Concrete Compressive Stress-Inelastic Strain - (40 MPa)
Concrete Strength

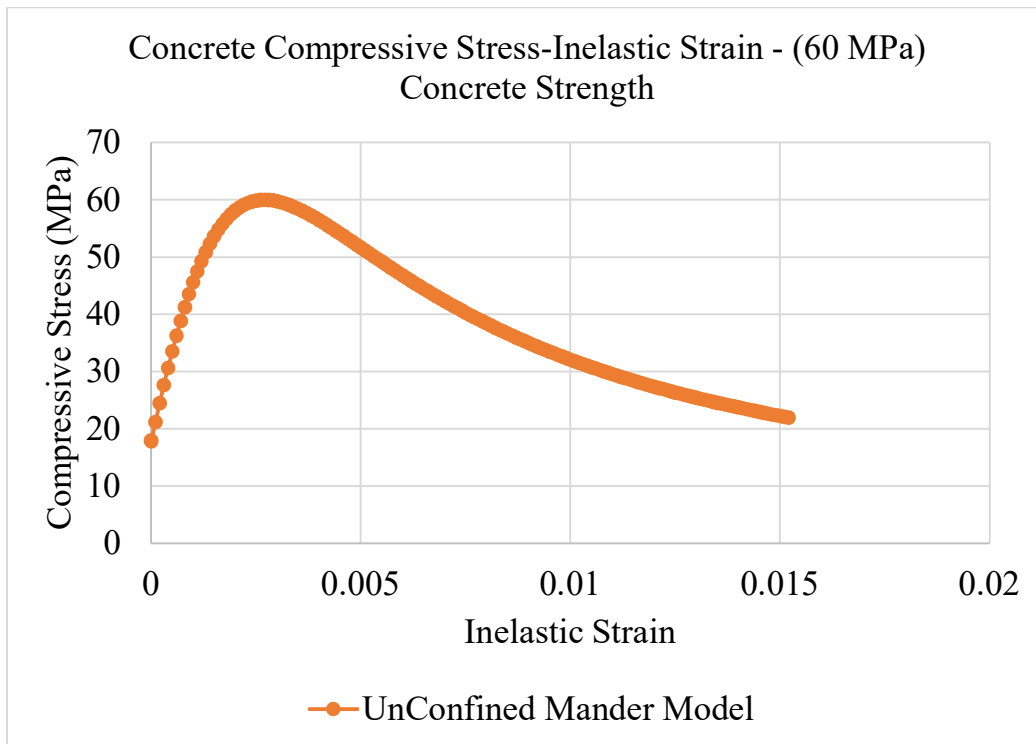
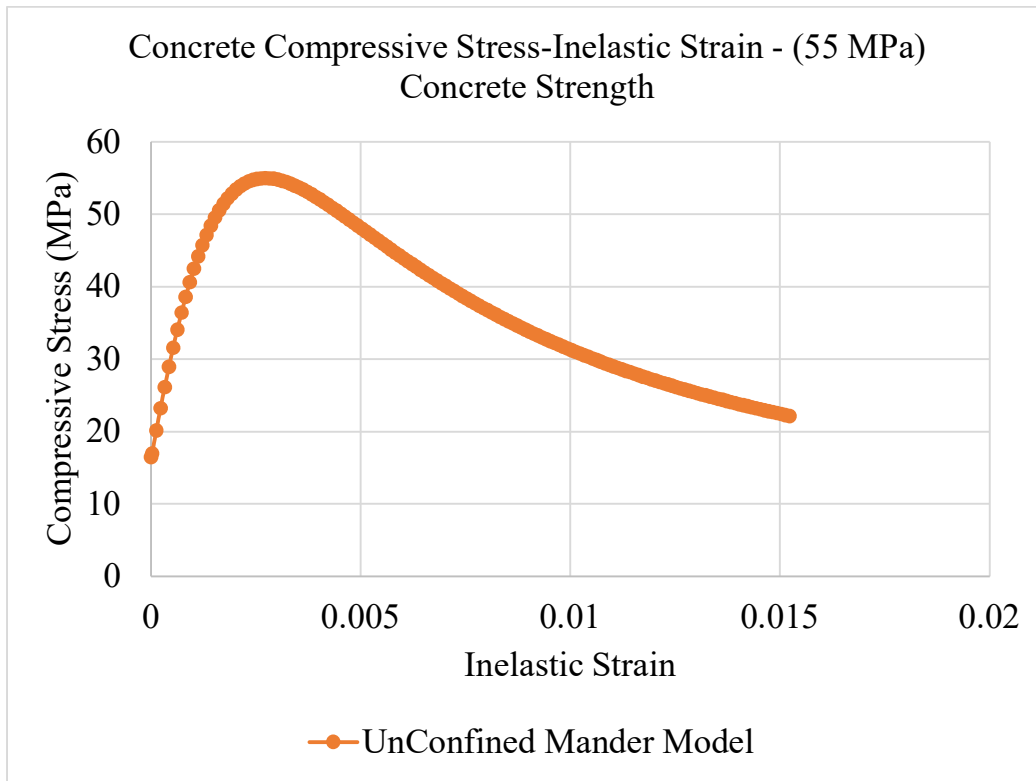


Concrete Compressive Stress-Inelastic Strain - (45 MPa)
Concrete Strength

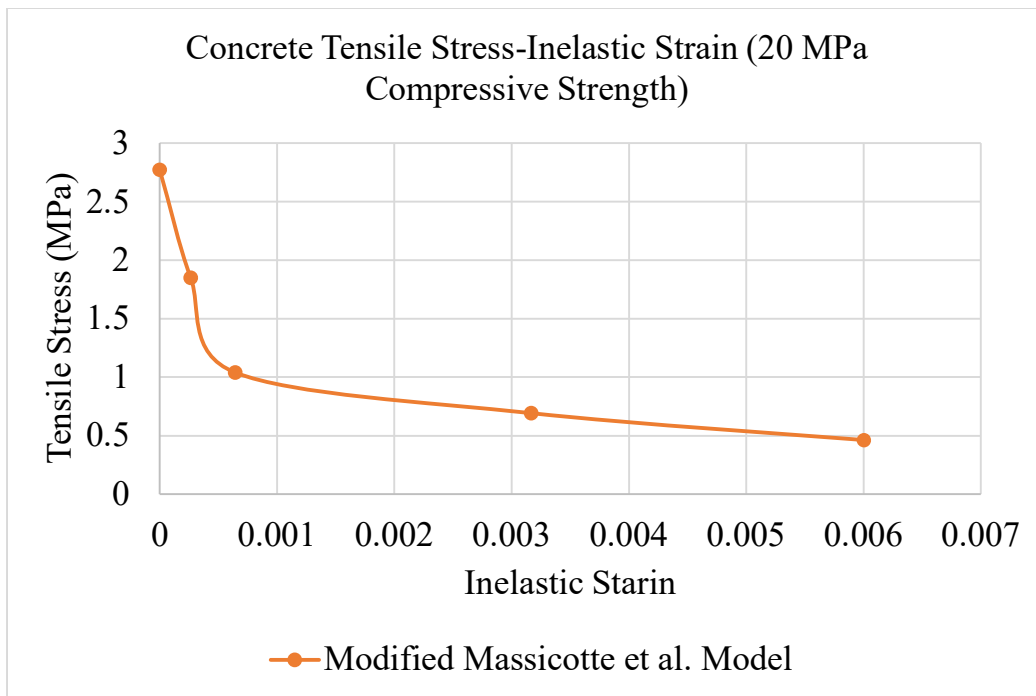
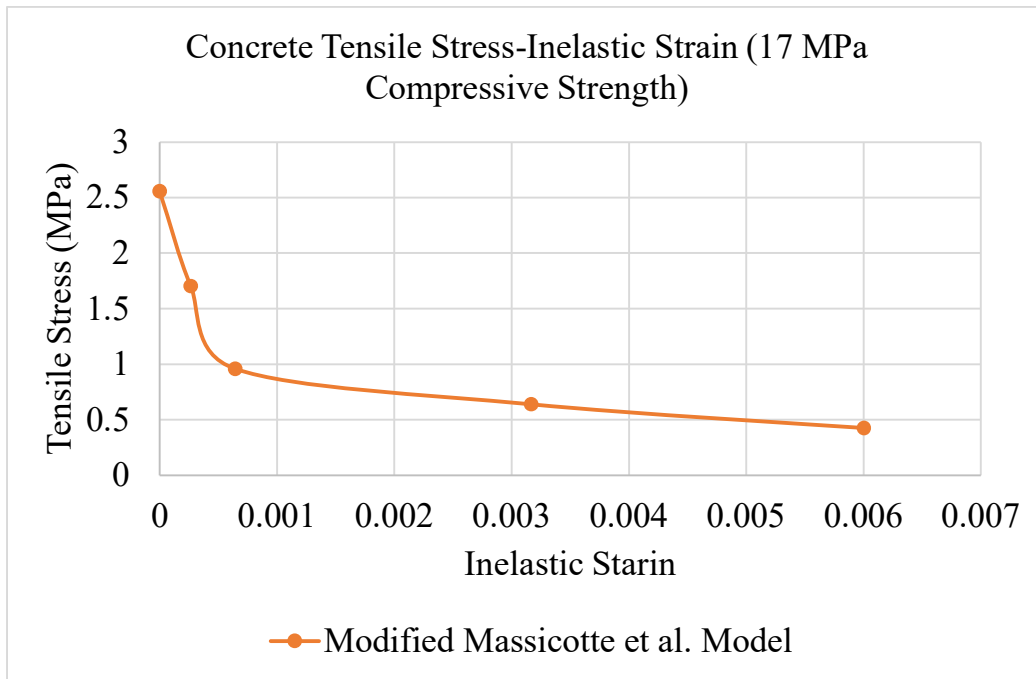


Concrete Compressive Stress-Inelastic Strain - (50 MPa)
Concrete Strength

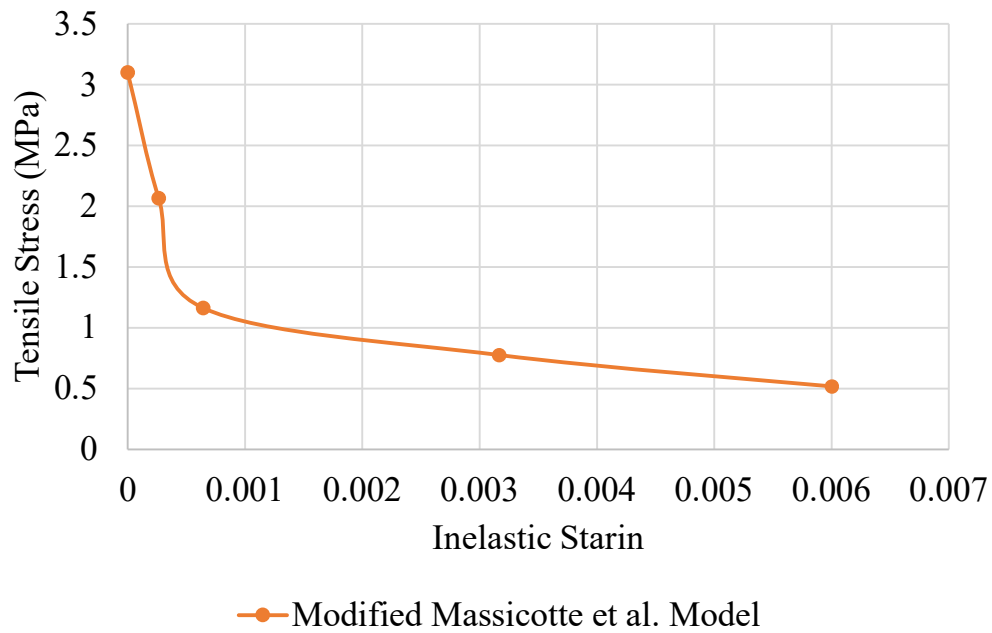




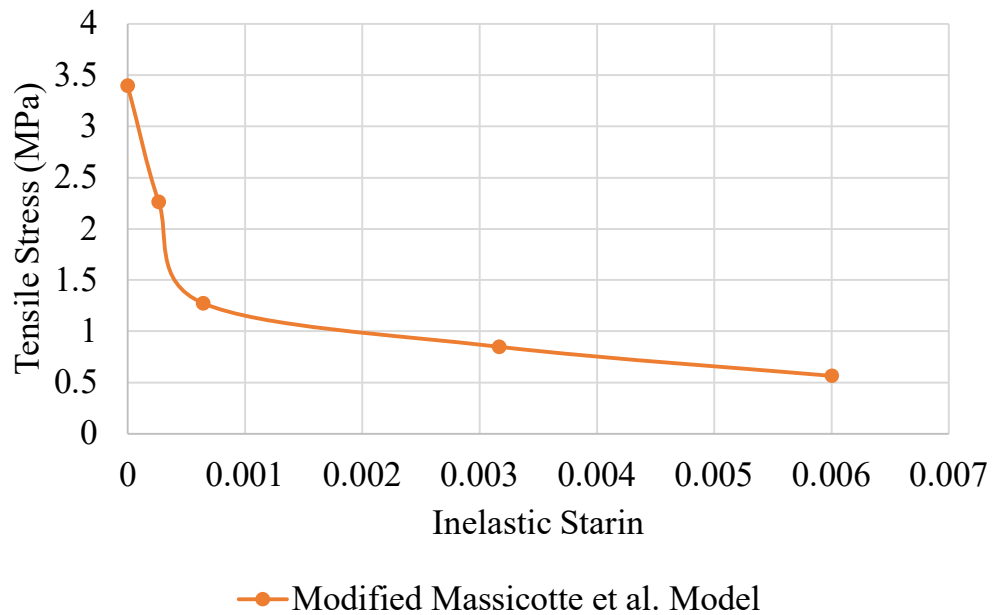
The behavior of concrete in tension was produced using stress-strain model by (Massicotte et al., 1990) and modified by (Allam et al., 2013). The produced curves for different concrete strength are shown in this part of the appendix.



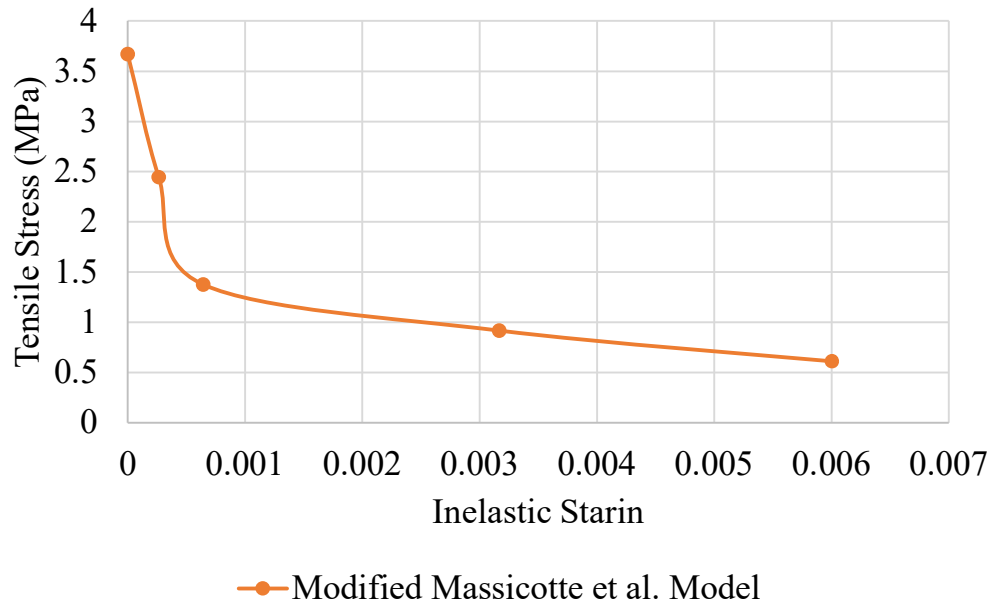
Concrete Tensile Stress-Inelastic Strain (25 MPa
Compressive Strength)



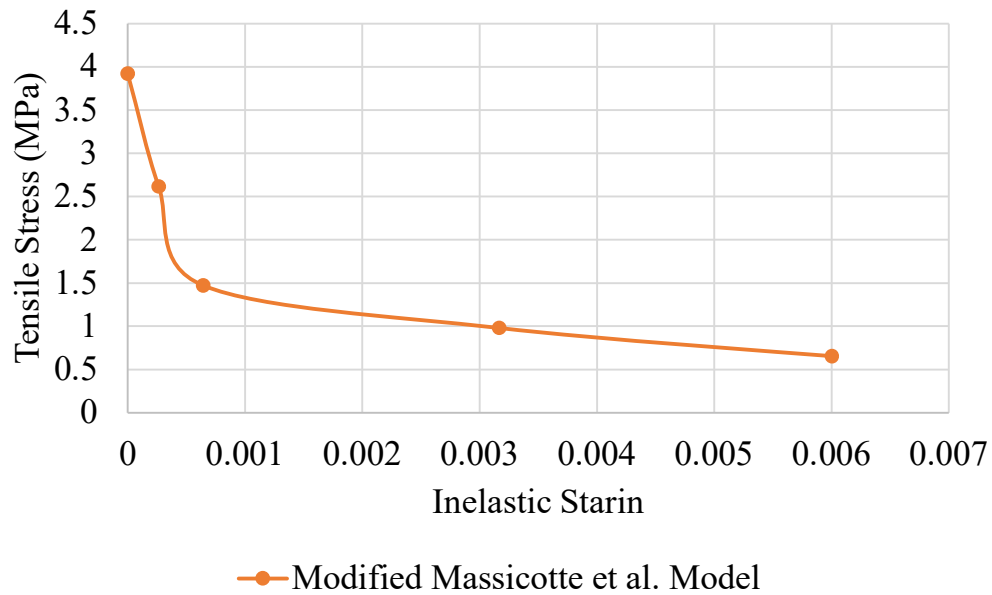
Concrete Tensile Stress-Inelastic Strain (30 MPa
Compressive Strength)



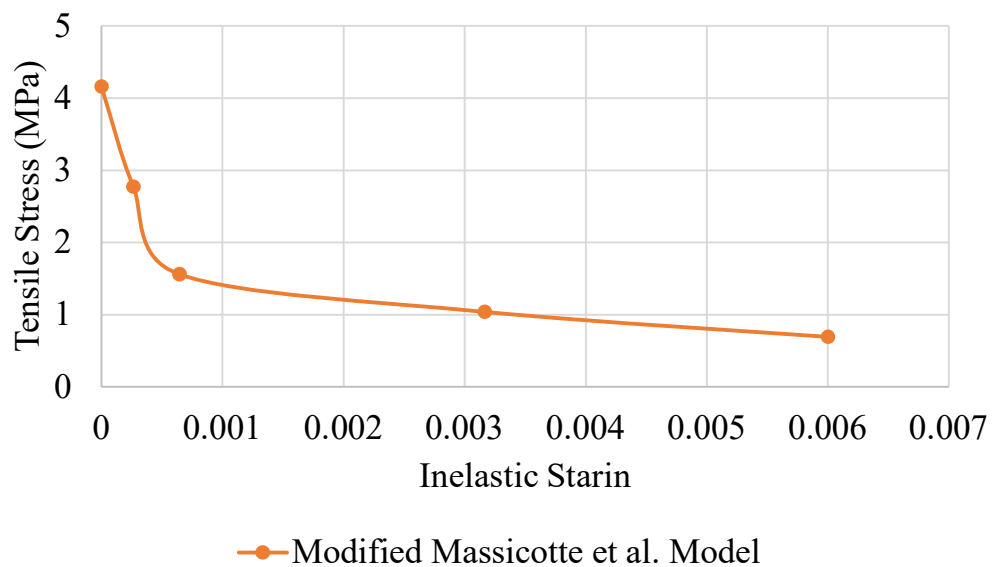
Concrete Tensile Stress-Inelastic Strain (35 MPa
Compressive Strength)



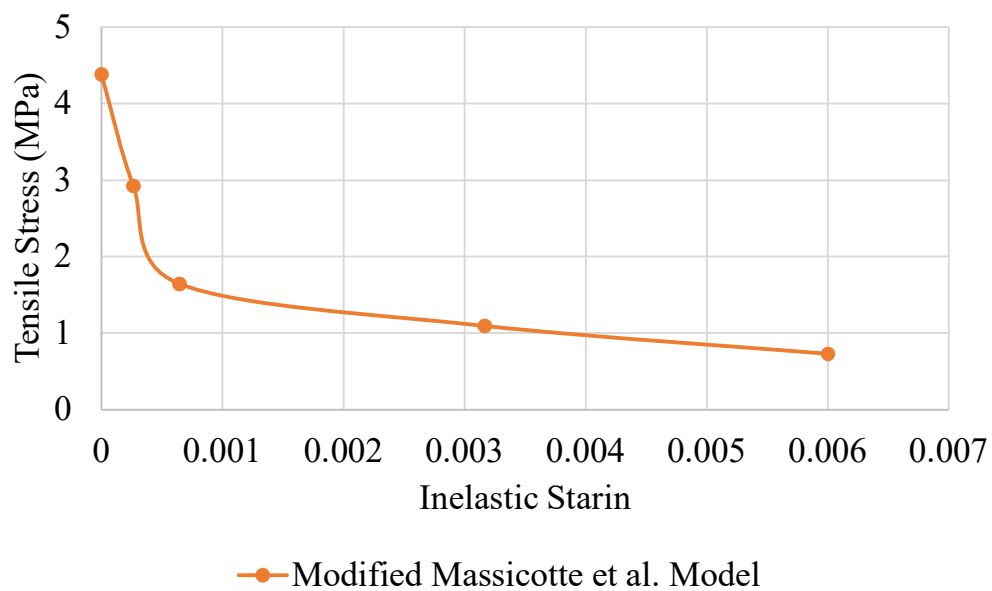
Concrete Tensile Stress-Inelastic Strain (40 MPa
Compressive Strength)



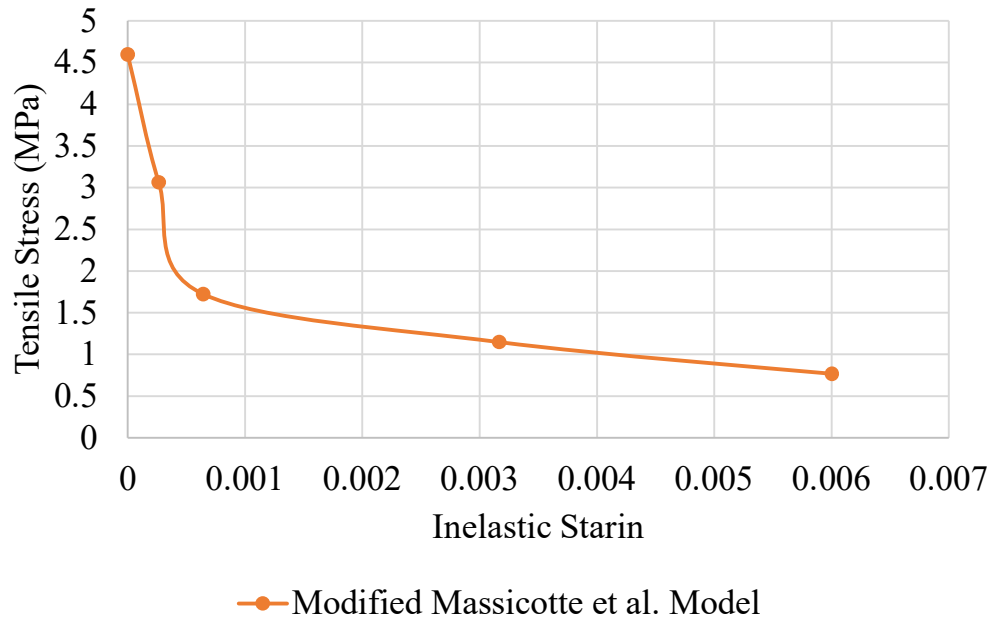
Concrete Tensile Stress-Inelastic Strain (45 MPa
Compressive Strength)



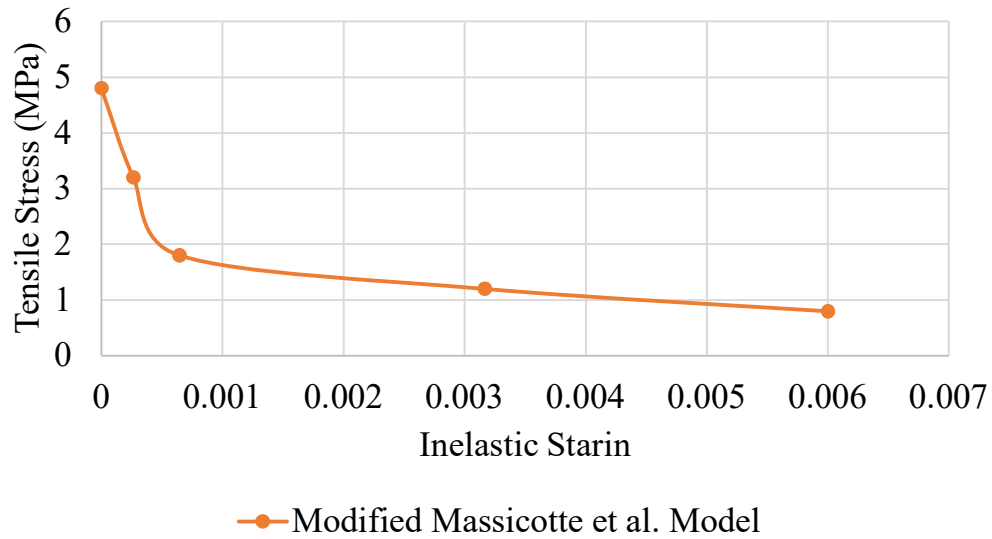
Concrete Tensile Stress-Inelastic Strain (50 MPa
Compressive Strength)



Concrete Tensile Stress-Inelastic Strain (55 MPa
Compressive Strength)



Concrete Tensile Stress-Inelastic Strain (60 MPa
Compressive Strength)

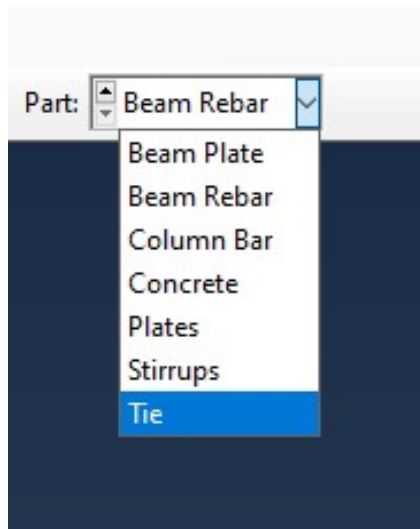


Appendix (2) ABAQUS Modeling

Following is one of the samples modeling steps and results which has been simulated using ABAQUS nonlinear analysis software:

Part Module

The first step was creating the parts of the beam-column exterior connection which consisted of beam plate, beam rebar, column bar, concrete, plates of the column, stirrups for the beam, and ties of the column.



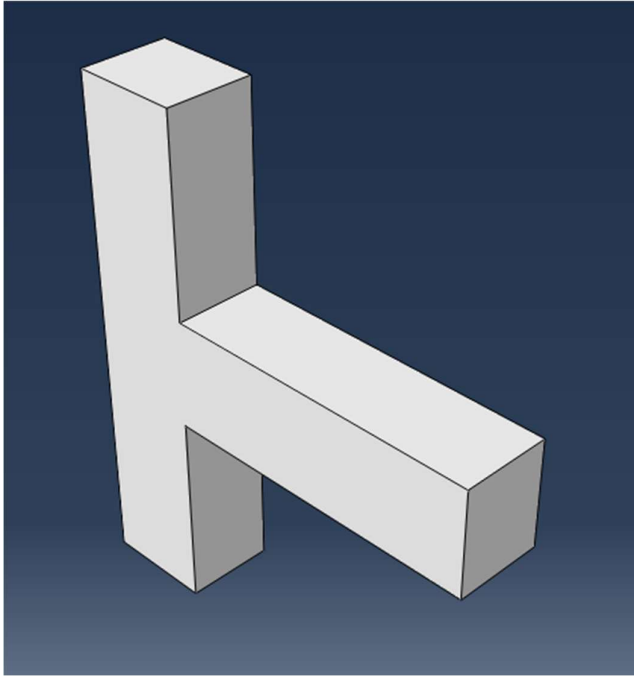
Beam Rebar



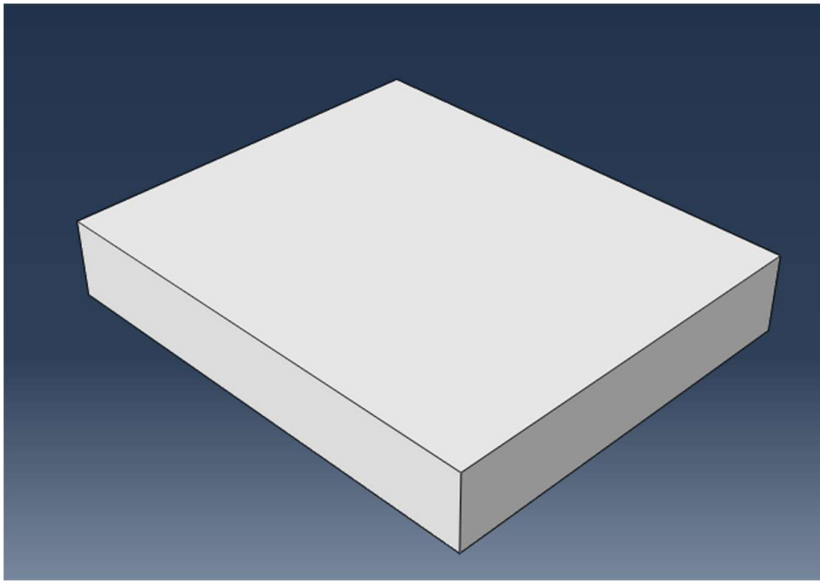
Column Bars



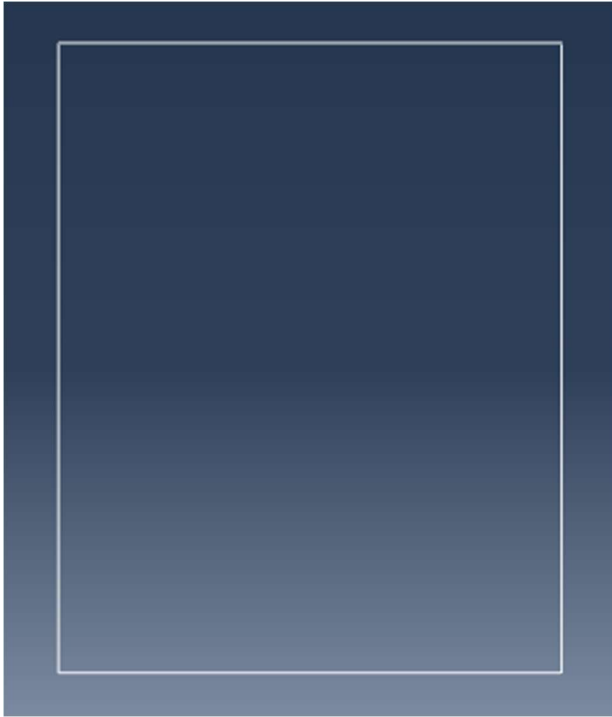
Concrete Part



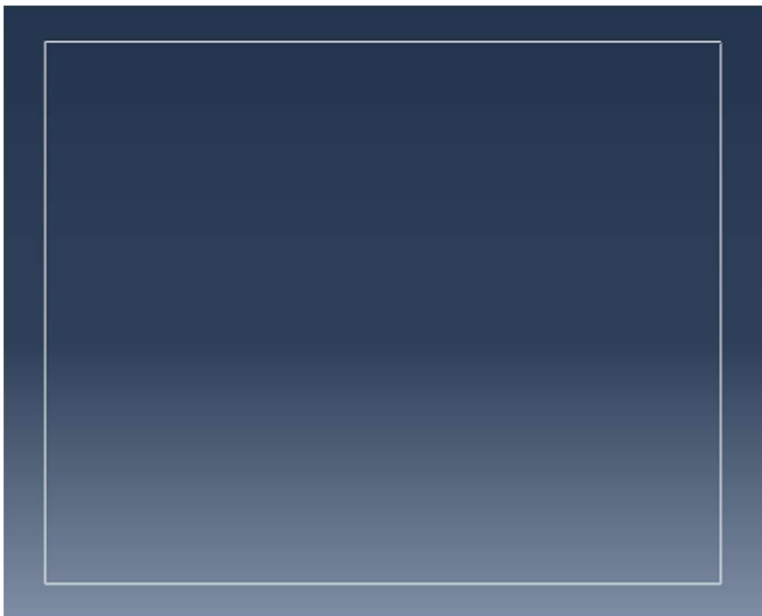
Column Plates



Beam's Stirrups

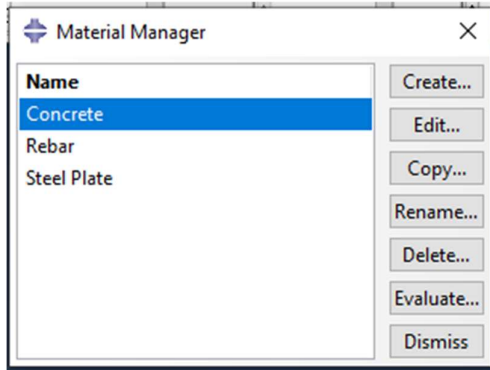


Column's Ties



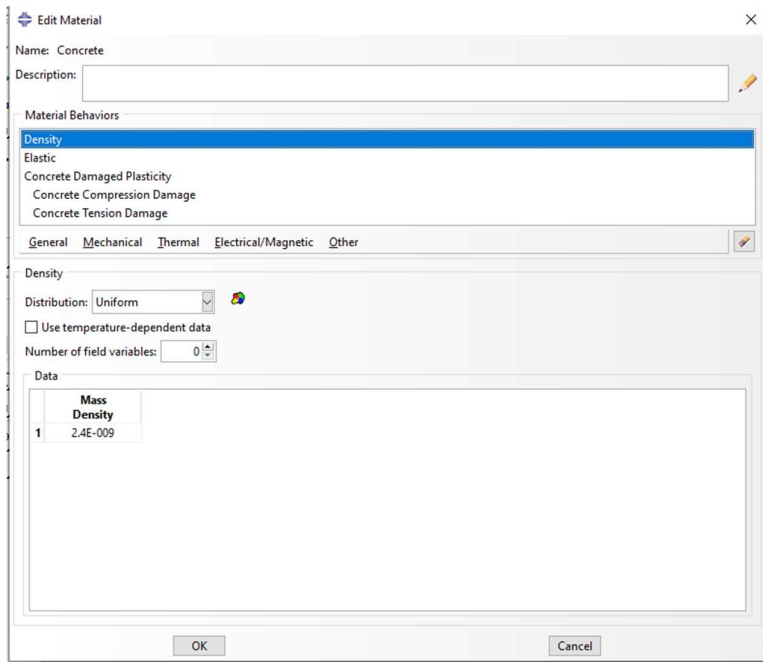
Property Module

Next step is creating the material properties and add them to the library for easy use, where the units used is mega pascal (MPa) for stress, newton (N) for force, ton for mass, second (s) for time, ton for each cubic millimeter (ton/mm^3) for density. The units have to be consistent.



Concrete Material

Density of concrete:



Elastic property of concrete:

 Edit Material ✕

Name: Concrete

Description:

Material Behaviors

- Density
- Elastic**
- Concrete Damaged Plasticity
 - Concrete Compression Damage
 - Concrete Tension Damage

General Mechanical Thermal Electrical/Magnetic Other 

Elastic

Type: Isotropic ▼ Suboptions

☐ Use temperature-dependent data

Number of field variables: 0

Moduli time scale (for viscoelasticity): Long-term

☐ No compression

☐ No tension

Data

	Young's Modulus	Poisson's Ratio
1	19378.59644	0.19

OK Cancel

Plastic property of concrete:

 Edit Material ✕

Name: Concrete

Description:

Material Behaviors

- Density
- Elastic
- Concrete Damaged Plasticity**
- Concrete Compression Damage
- Concrete Tension Damage

General Mechanical Thermal Electrical/Magnetic Other 

Concrete Damaged Plasticity

Plasticity Compressive Behavior Tensile Behavior

☐ Use temperature-dependent data

Number of field variables:

Data

	Dilation Angle	Eccentricity	f_{b0}/f_{c0}	K	Viscosity Parameter
1	36	0.1	1.16	0.67	0

OK Cancel

Compression behavior of concrete in plastic:

Note that the tables in the software are long and this is not the full as shown in the next figures.

The screenshot shows the 'Edit Material' dialog box for a material named 'Concrete'. The 'Material Behaviors' list includes 'Concrete Compression Damage', which is selected. The 'Concrete Damaged Plasticity' section is active, showing the 'Compressive Behavior' tab. The 'Data' table displays the following values:

	Yield Stress	Inelastic Strain
1	5.1	0
2	8.039456272	0.000236823
3	9.200035463	0.000336823
4	10.22819846	0.000436823
5	11.13609988	0.000536823
6	11.93580878	0.000636823
7	12.63881936	0.000736823
8	13.25579422	0.000836823

The dialog box also includes fields for 'Name' (Concrete), 'Description', and 'Material Behaviors' (Density, Elastic, Concrete Damaged Plasticity, Concrete Compression Damage, Concrete Tension Damage). The 'Concrete Damaged Plasticity' section has tabs for 'Plasticity', 'Compressive Behavior', and 'Tensile Behavior'. The 'Compressive Behavior' tab is active, showing options for 'Use strain-rate-dependent data' and 'Use temperature-dependent data', and a 'Number of field variables' set to 0. A 'Suboptions' button is also present. The 'Data' table is scrollable, showing a list of values for 'Yield Stress' and 'Inelastic Strain'.

Tension behavior of concrete in plastic:

Edit Material

Name: Concrete

Description:

Material Behaviors

DensityElasticConcrete Damaged PlasticityConcrete Compression DamageConcrete Tension Damage

GeneralMechanicalThermalElectrical/MagneticOther

Concrete Damaged Plasticity

PlasticityCompressive BehaviorTensile Behavior

Type: Strain

Suboptions

☐ Use strain-rate-dependent data☐ Use temperature-dependent data

Number of field variables: 0

Data

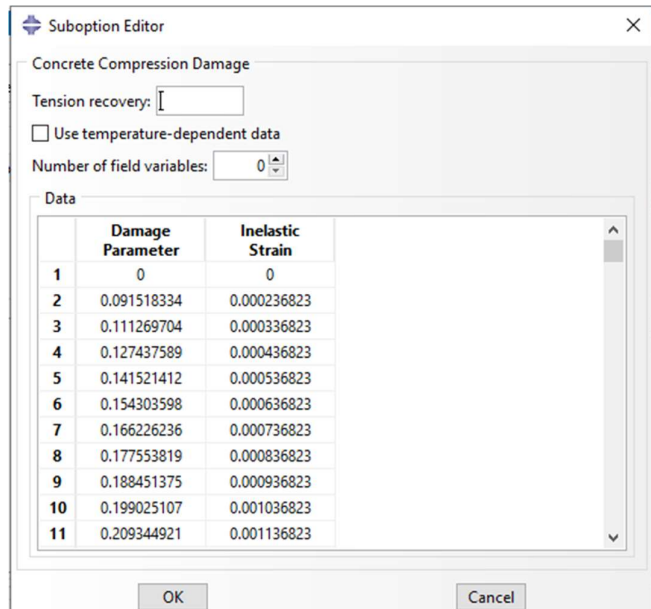
	Yield Stress	Cracking Strain
1	2.556325488	0
2	1.704216992	0.00026383
3	0.958622058	0.000643085
4	0.639081372	0.003165957
5	0.426054248	0.006002128

OK

Cancel

Concrete compression damage:

Note that this is part of the full table for damage of concrete, produced as mentioned in chapter 3.



The screenshot shows a software window titled 'Suboption Editor' with a close button (X) in the top right corner. The main title is 'Concrete Compression Damage'. Below the title, there is a 'Tension recovery:' label followed by an empty text input field. Underneath is a checkbox labeled 'Use temperature-dependent data', which is currently unchecked. Below the checkbox is a label 'Number of field variables:' followed by a spin box set to '0'. The main area of the window is titled 'Data' and contains a table with three columns: an index column, 'Damage Parameter', and 'Inelastic Strain'. The table has 11 rows of data. At the bottom of the window are 'OK' and 'Cancel' buttons.

	Damage Parameter	Inelastic Strain
1	0	0
2	0.091518334	0.000236823
3	0.111269704	0.000336823
4	0.127437589	0.000436823
5	0.141521412	0.000536823
6	0.154303598	0.000636823
7	0.166226236	0.000736823
8	0.177553819	0.000836823
9	0.188451375	0.000936823
10	0.199025107	0.001036823
11	0.209344921	0.001136823

Concrete tension damage:

Suboption Editor ×

Concrete Tension Damage

Type: Strain

Compression recovery:

☐ Use temperature-dependent data

Number of field variables: 0

Data

	Damage Parameter	Cracking Strain
1	0	0
2	0.057692308	0.00026383
3	0.209677419	0.000643085
4	0.662068966	0.003165957
5	0.847826087	0.006002128

OK Cancel

Rebars material for Reinforcement of column and beam

Density of rebars:

Edit Material ✕

Name: Rebar

Description: 

Material Behaviors

- Density
- Elastic
- Plastic

General Mechanical Thermal Electrical/Magnetic Other 

Density

Distribution: Uniform 

☐ Use temperature-dependent data

Number of field variables: 0 

Data

	Mass Density
1	7.85E-009

OK Cancel

Elastic property of rebar:

 Edit Material ✕

Name: Rebar

Description:

Material Behaviors

Density

Elastic

Plastic

General

Mechanical

Thermal

Electrical/Magnetic

Other

Elastic

Type:

Isotropic

☐ Use temperature-dependent data

Number of field variables:

0

Moduli time scale (for viscoelasticity):

Long-term

☐ No compression

☐ No tension

Data

	Young's Modulus	Poisson's Ratio
1	200000	0.3

OK

Cancel

Plastic property of rebar:

 Edit Material ×

Name: Rebar

Description:

Material Behaviors

Density

Elastic

Plastic

General

Mechanical

Thermal

Electrical/Magnetic

Other

Plastic

Hardening:

Isotropic

▼ Suboptions

☐ Use strain-rate-dependent data

☐ Use temperature-dependent data

Number of field variables:

0

Data

	Yield Stress	Plastic Strain
1	460	0
2	550	0.1

OK

Cancel

Steel Plates to apply the loads on

Density of steel plates:

 Edit Material ✕

Name: Steel Plate

Description: 

Material Behaviors

Density

Elastic

General

Mechanical

Thermal

Electrical/Magnetic

Other



Density

Distribution:

Uniform



☐ Use temperature-dependent data

Number of field variables:

0

Data

	Mass Density
1	7.85E-009

OK Cancel

Elastic property of steel plates:

 Edit Material ×

Name: Steel Plate

Description:

Material Behaviors

Density

Elastic

General

Mechanical

Thermal

Electrical/Magnetic

Other

Elastic

Type:

Isotropic

☐ Use temperature-dependent data

Number of field variables:

0

Moduli time scale (for viscoelasticity):

Long-term

☐ No compression

☐ No tension

Data

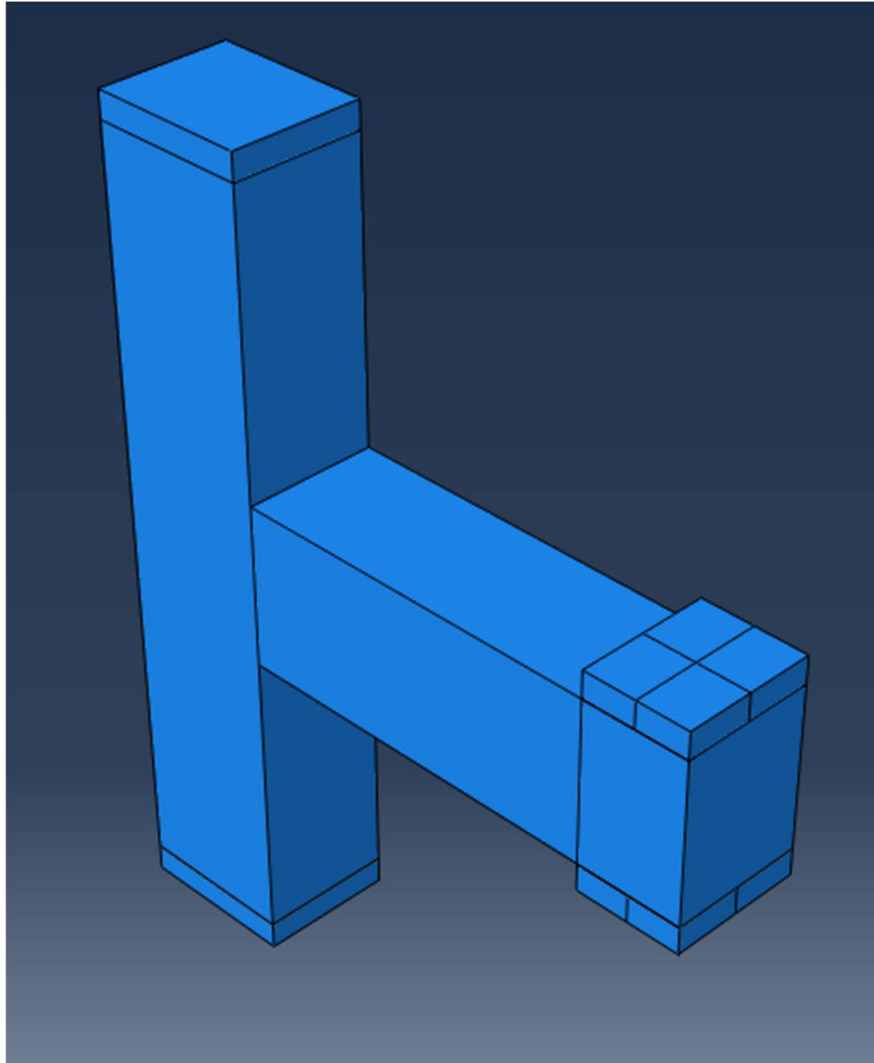
	Young's Modulus	Poisson's Ratio
1	200000	0.25

OK

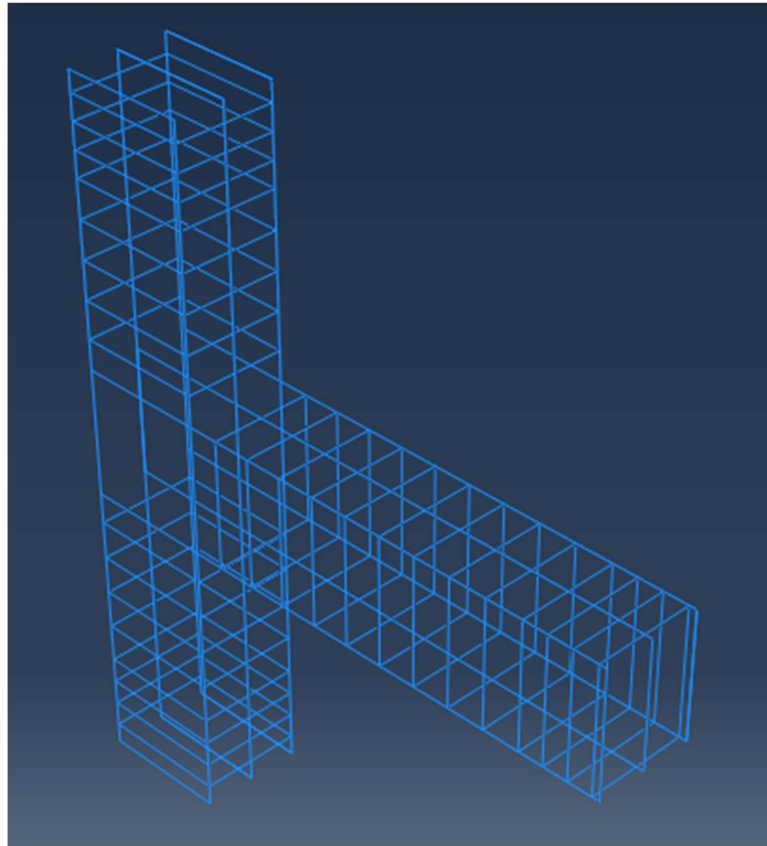
Cancel

Assembly Module

In this step the parts are inserted together, and the reinforcement located in the concrete part as shown in next figure.

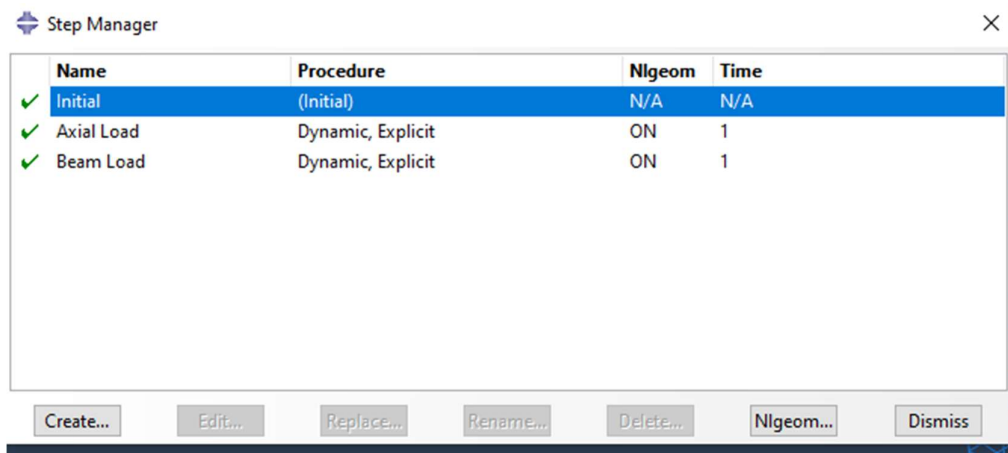


To show the details of reinforcement, the display group tool was used to show the reinforcement only as follow:

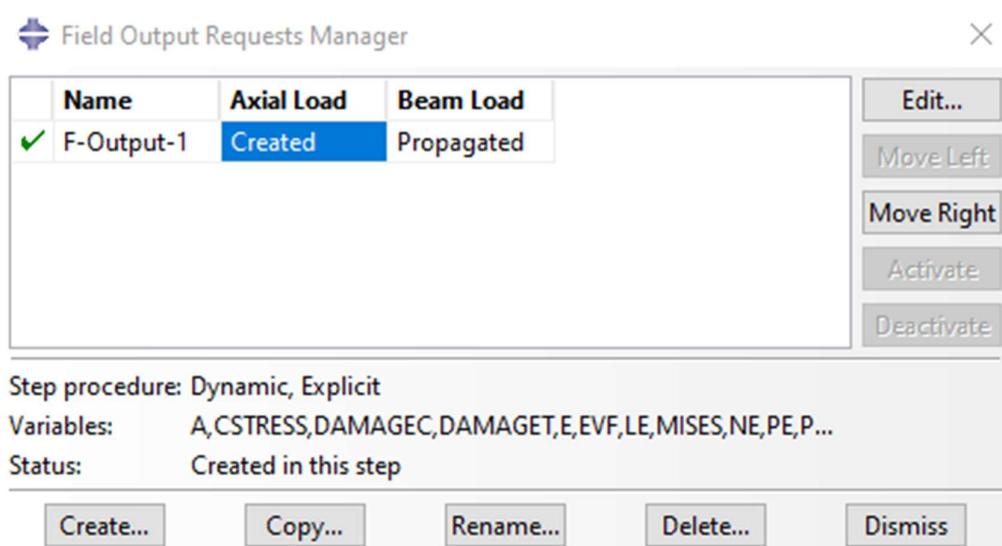


Step Module

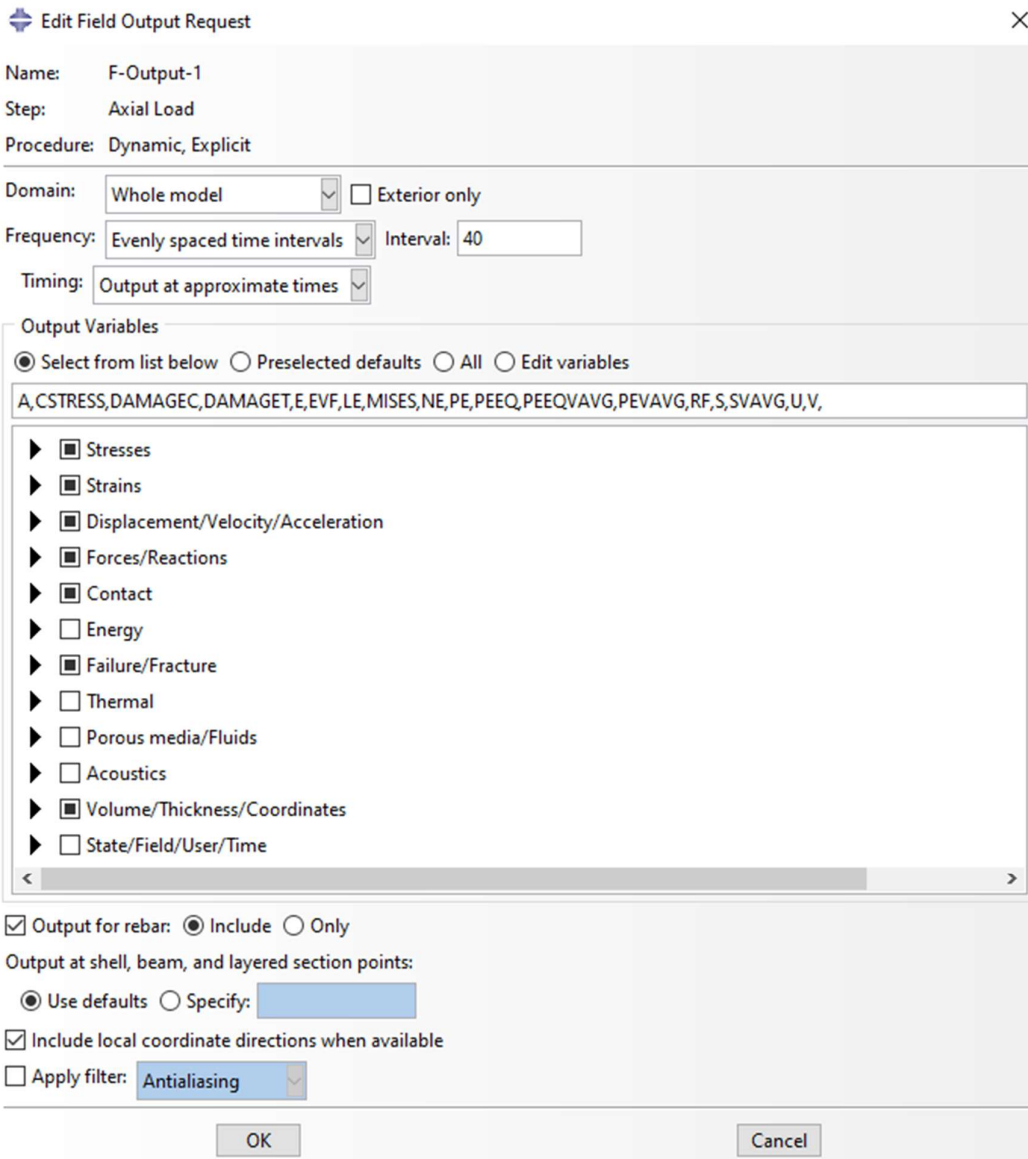
In the step module, the steps were created starting with axial load and after ending it the beam loading step is started. Both steps created as dynamic explicit analysis which give a better performance for analysis result.



Field output was requested from the step module, which is showing the results that the user want to show it and save it after the analysis has been done.



Details of requested field output:



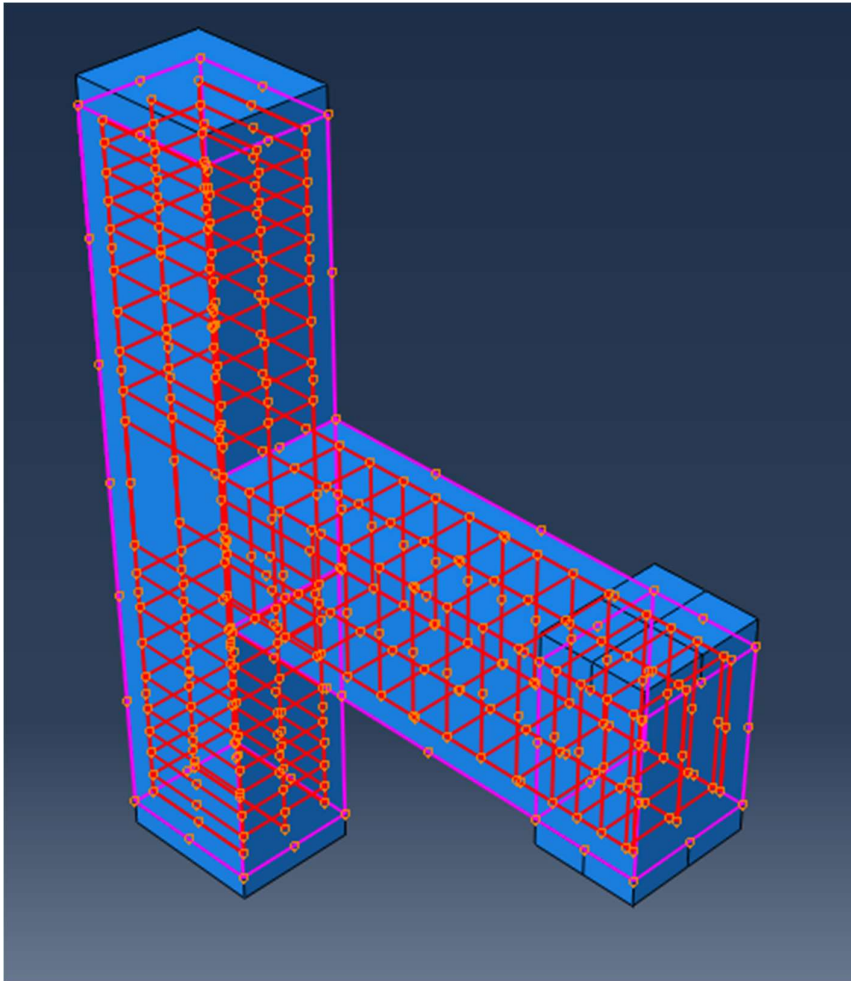
The dialog box is titled "Edit Field Output Request" and contains the following settings:

- Name:** F-Output-1
- Step:** Axial Load
- Procedure:** Dynamic, Explicit
- Domain:** Whole model (dropdown), ☐ Exterior only
- Frequency:** Evenly spaced time intervals (dropdown), Interval: 40
- Timing:** Output at approximate times (dropdown)
- Output Variables:**
 - Radio buttons: ☒ Select from list below, ☐ Preselected defaults, ☐ All, ☐ Edit variables
 - Text box: A,CSTRESS,DAMAGEC,DAMAGET,E,EVF,LE,MISES,NE,PE,PEEQ,PEEQVAVG,PEVAVG,RF,S,SVAVG,U,V,
 - Tree view:
 - Stresses (checked)
 - Strains (checked)
 - Displacement/Velocity/Acceleration (checked)
 - Forces/Reactions (checked)
 - Contact (checked)
 - Energy (unchecked)
 - Failure/Fracture (checked)
 - Thermal (unchecked)
 - Porous media/Fluids (unchecked)
 - Acoustics (unchecked)
 - Volume/Thickness/Coordinates (checked)
 - State/Field/User/Time (unchecked)
- ☒ Output for rebar: ☒ Include, ☐ Only
- Output at shell, beam, and layered section points:
 - Radio buttons: ☒ Use defaults, ☐ Specify: [text box]
- ☒ Include local coordinate directions when available
- ☐ Apply filter: Antialiasing (dropdown)
- Buttons: OK, Cancel

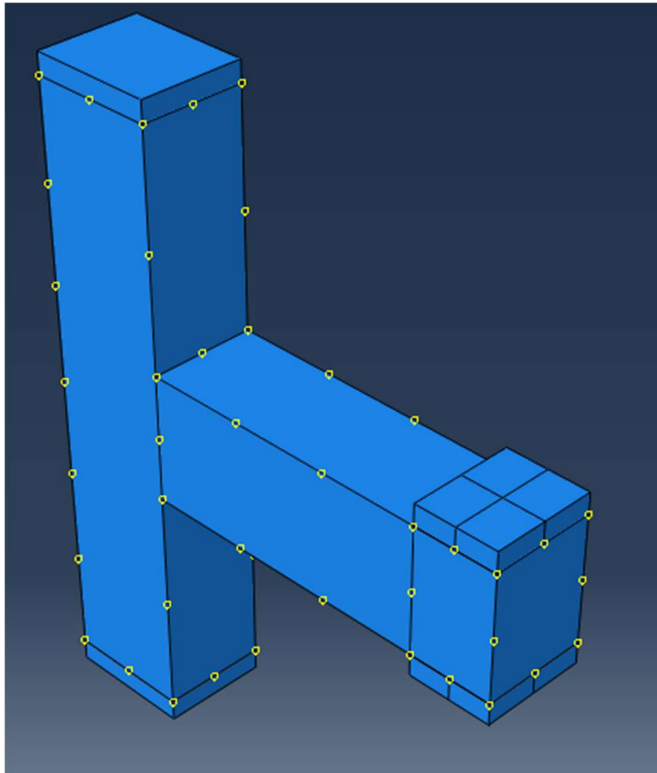
Interaction Module

In this module the constraints were developed as follows, where the rebars were embedded in the concrete as shown in the next figure.

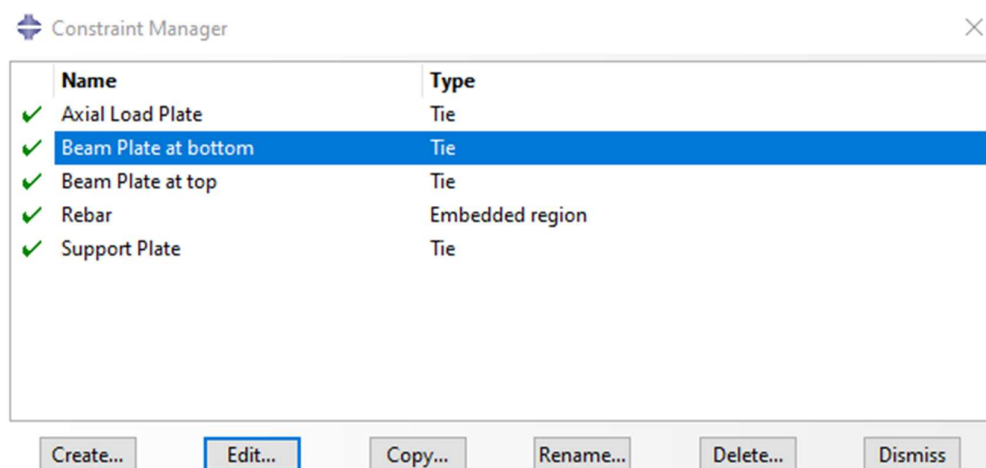
Embedded regions constrain of rebars within the concrete material:



Tie constraint through the exterior connection simulated sample

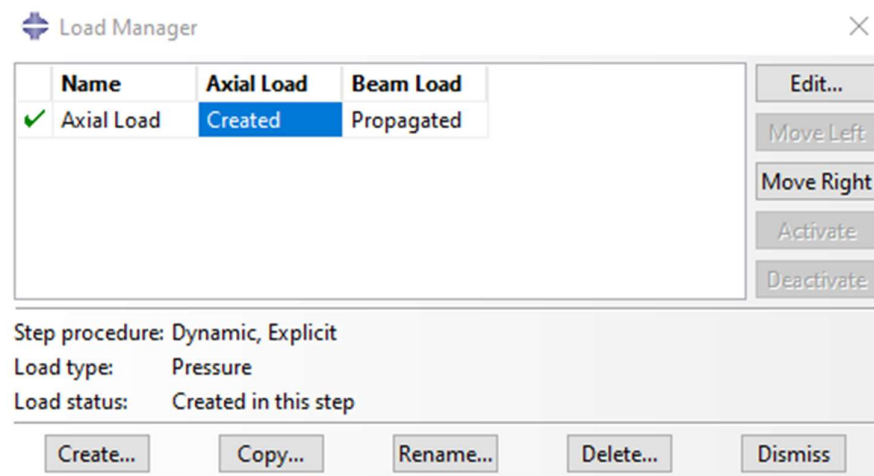
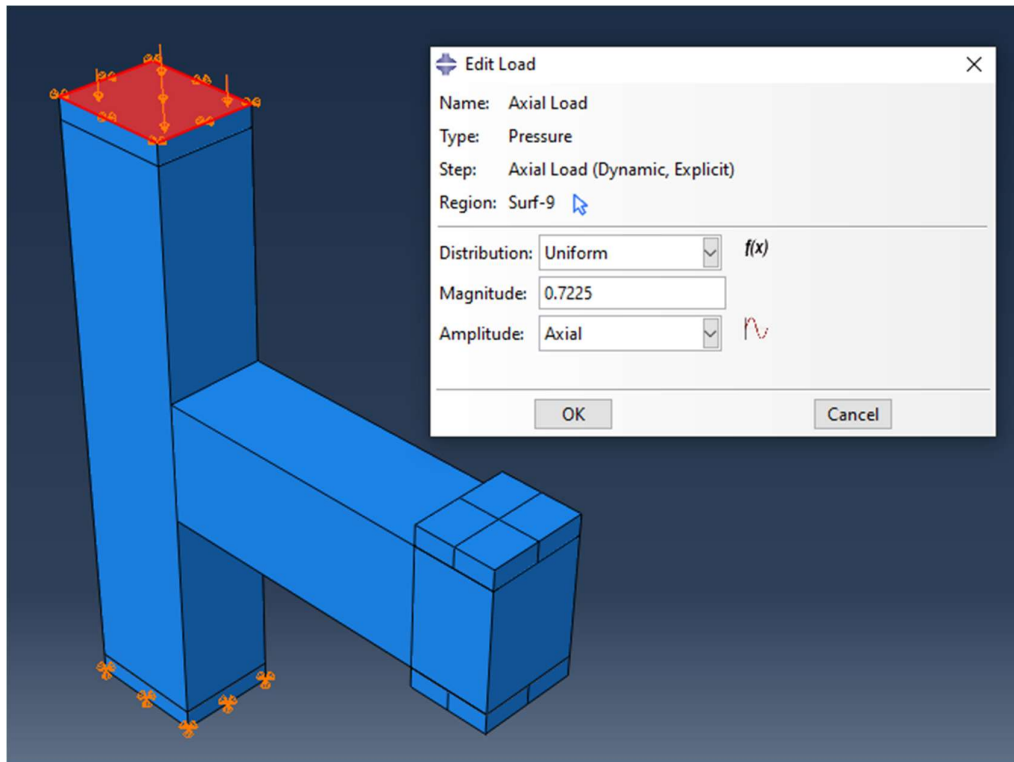


Applied constraint in the interaction module:

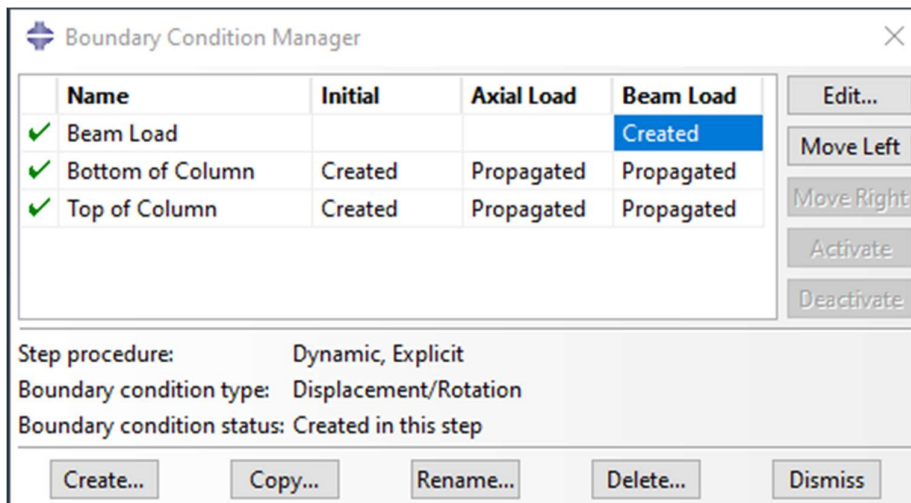


Load Module

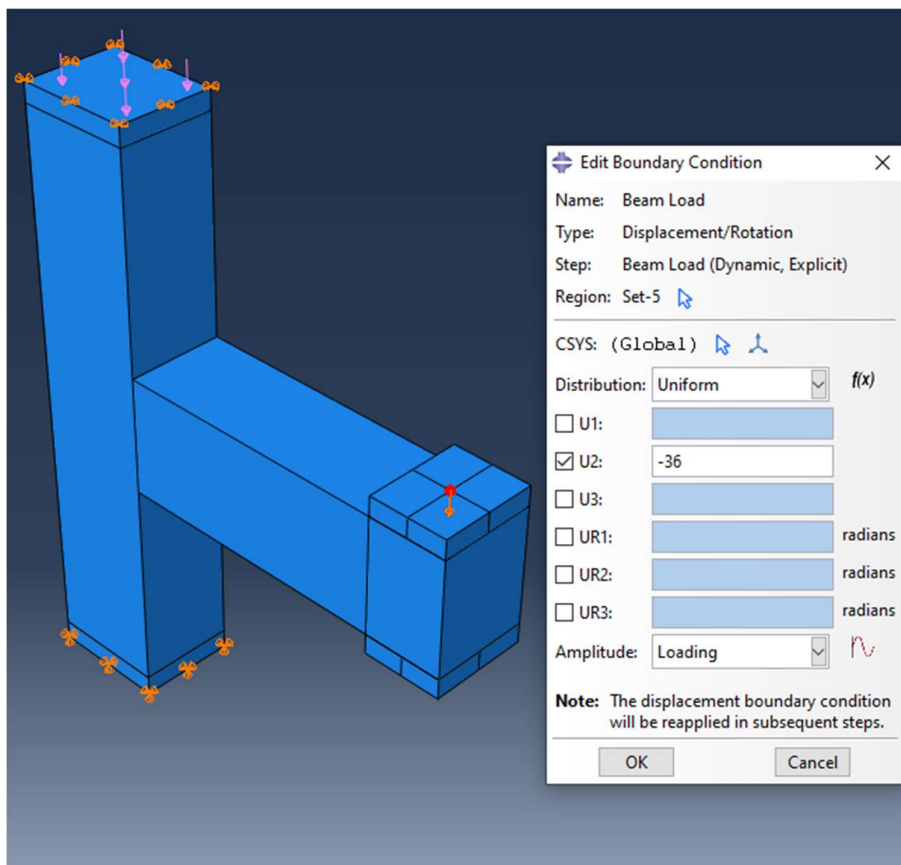
Applied Axial load on the top of the column:



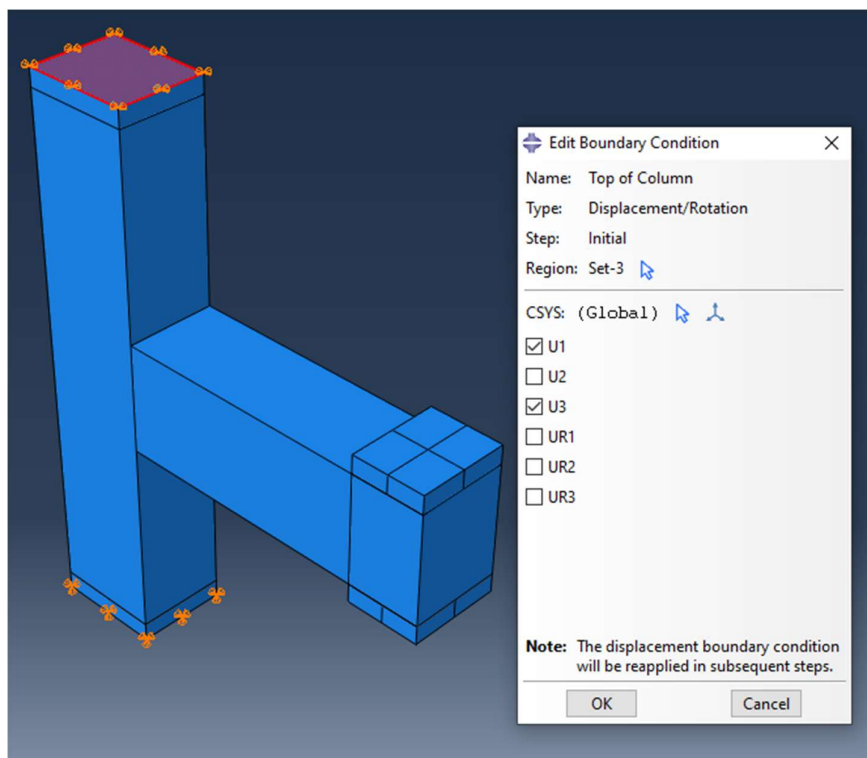
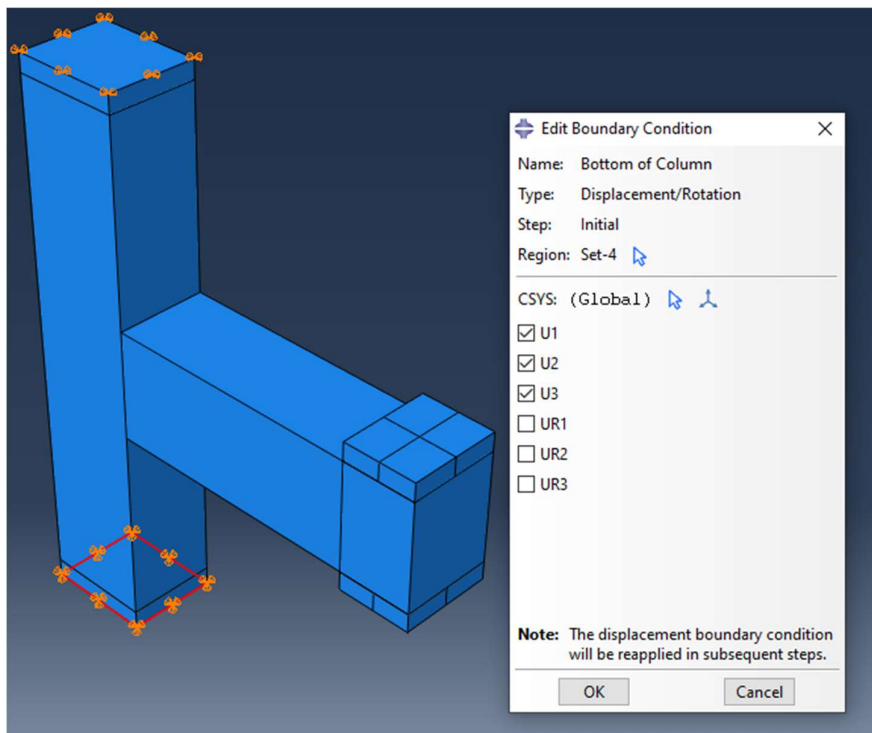
Boundary conditions were created in the load module as follow:



Beam loading as Boundary condition:



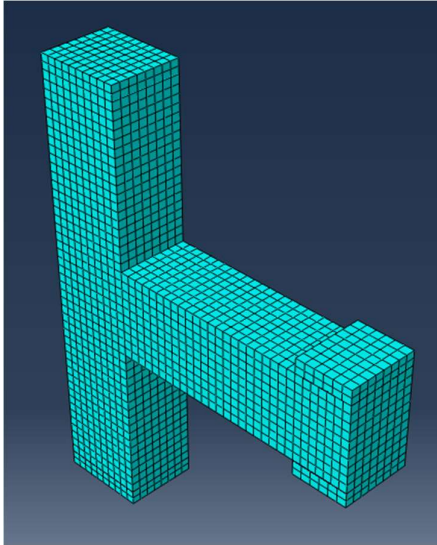
Bottom and top of column boundary condition:



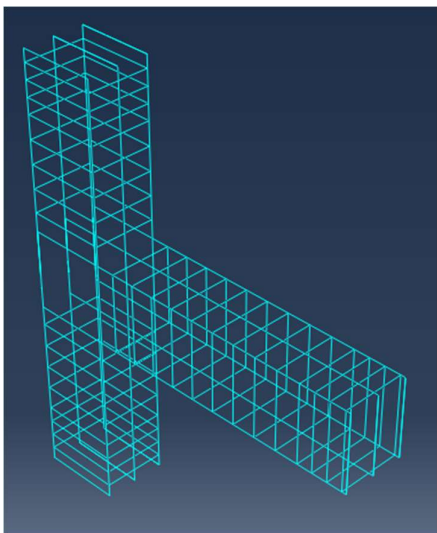
Mesh Module

The meshing of the simulated connection is done in the mesh module as shown in next figures, where the size of the meshing was mentioned in chapter 3 as 30 mm.

Concrete meshing:



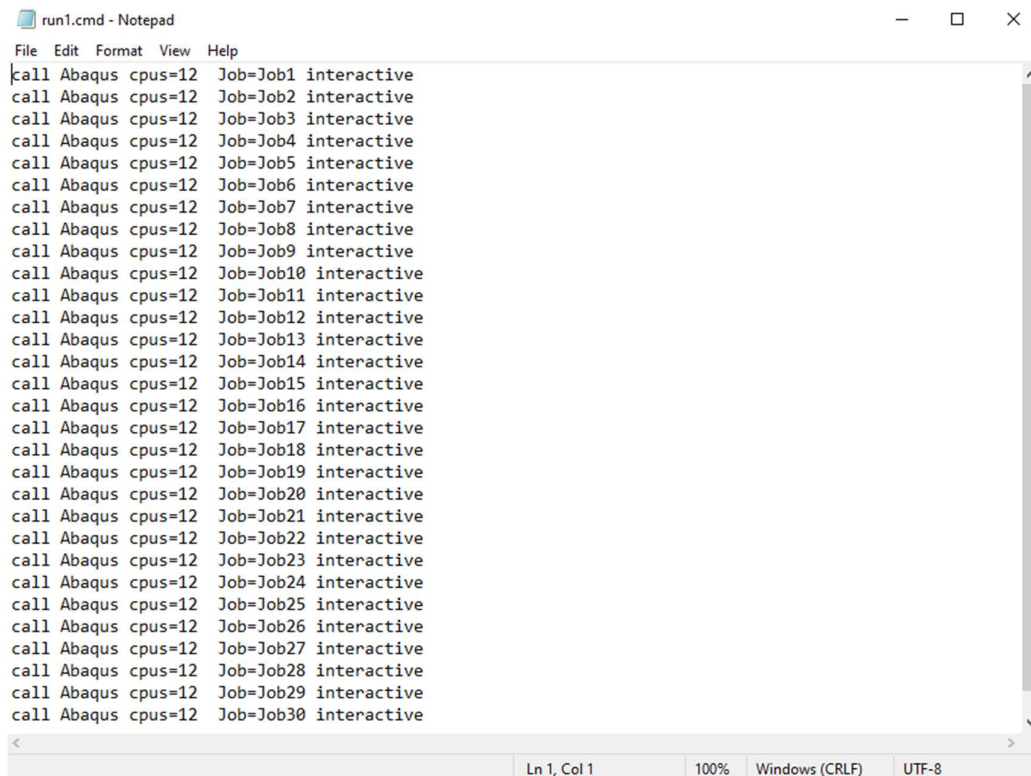
Reinforcement meshing:



Job Module

In this module, the job was created for all the samples within one cae file (.cae, for Abaqus modeling). This was applied using cmd file to run the analysis continuously for all the samples in one cae file, where each cae file was made of ninety 90 samples modelled each one differently. The next figure was taken from the used cmd file for running the analysis, where 12 CPU personal desktop was used for running a large number of samples (6480 total, 72 cae files, each with 90 samples). Each run takes about 5-6 minutes using the 12 CPU. A total of two months is needed to finish the 6480 samples modeling and running their analysis.

One sample of the written cmd file to be used for continuous running of the analysis:



```
run1.cmd - Notepad
File Edit Format View Help
call Abaqus cpus=12 Job=Job1 interactive
call Abaqus cpus=12 Job=Job2 interactive
call Abaqus cpus=12 Job=Job3 interactive
call Abaqus cpus=12 Job=Job4 interactive
call Abaqus cpus=12 Job=Job5 interactive
call Abaqus cpus=12 Job=Job6 interactive
call Abaqus cpus=12 Job=Job7 interactive
call Abaqus cpus=12 Job=Job8 interactive
call Abaqus cpus=12 Job=Job9 interactive
call Abaqus cpus=12 Job=Job10 interactive
call Abaqus cpus=12 Job=Job11 interactive
call Abaqus cpus=12 Job=Job12 interactive
call Abaqus cpus=12 Job=Job13 interactive
call Abaqus cpus=12 Job=Job14 interactive
call Abaqus cpus=12 Job=Job15 interactive
call Abaqus cpus=12 Job=Job16 interactive
call Abaqus cpus=12 Job=Job17 interactive
call Abaqus cpus=12 Job=Job18 interactive
call Abaqus cpus=12 Job=Job19 interactive
call Abaqus cpus=12 Job=Job20 interactive
call Abaqus cpus=12 Job=Job21 interactive
call Abaqus cpus=12 Job=Job22 interactive
call Abaqus cpus=12 Job=Job23 interactive
call Abaqus cpus=12 Job=Job24 interactive
call Abaqus cpus=12 Job=Job25 interactive
call Abaqus cpus=12 Job=Job26 interactive
call Abaqus cpus=12 Job=Job27 interactive
call Abaqus cpus=12 Job=Job28 interactive
call Abaqus cpus=12 Job=Job29 interactive
call Abaqus cpus=12 Job=Job30 interactive
Ln 1, Col 1 100% Windows (CRLF) UTF-8
```

Details of created job that used 12 CPU:

Edit Job

Name: Job1

Model: Model1

Analysis product: Abaqus/Explicit

Description:

Parallelization

☒ Use multiple processors 12

☐ Use GPGPU acceleration 1

Abaqus/Explicit

Number of domains: 12

Parallelization method: Domain

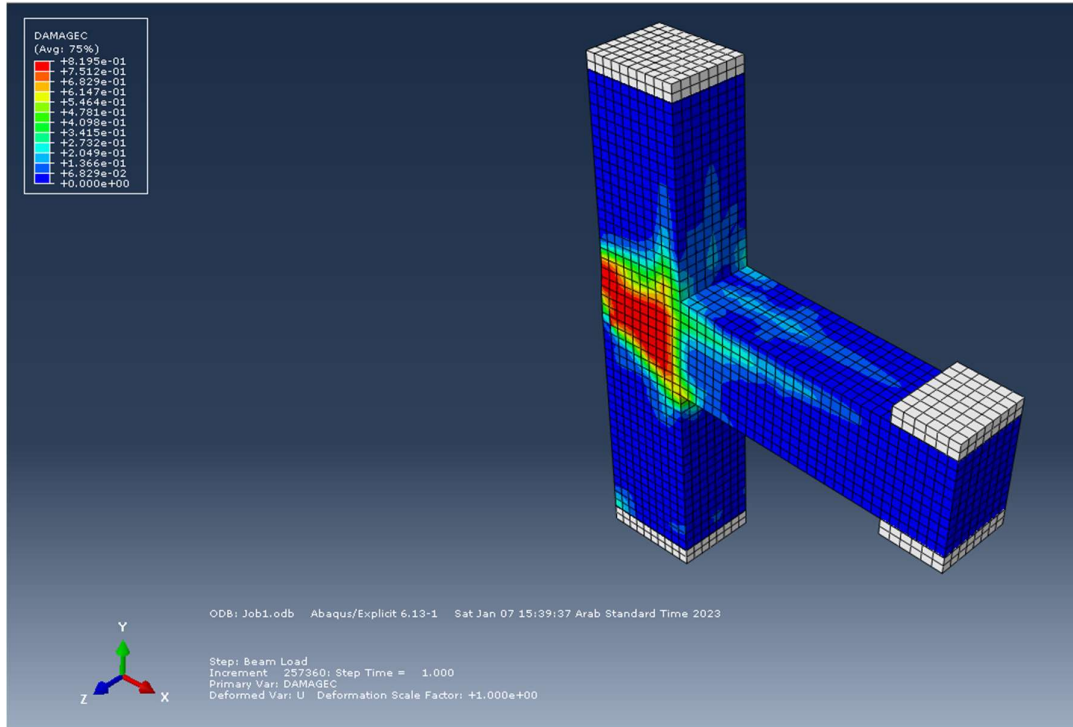
Multiprocessing mode: Default

OK Cancel

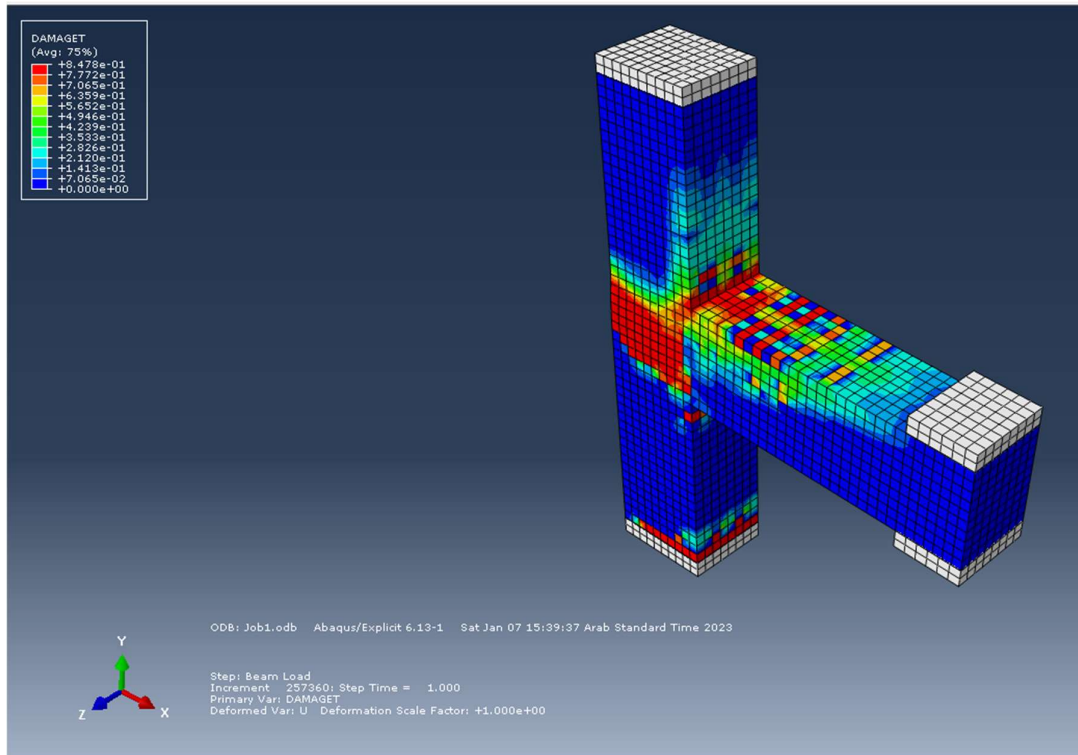
Visualization Module

This module presents the results of the analysis as requested in the field output in the step module. Following are some of the results that have been used for this research in the calculation of the shear strength of the reinforced concrete exterior beam-column joint area.

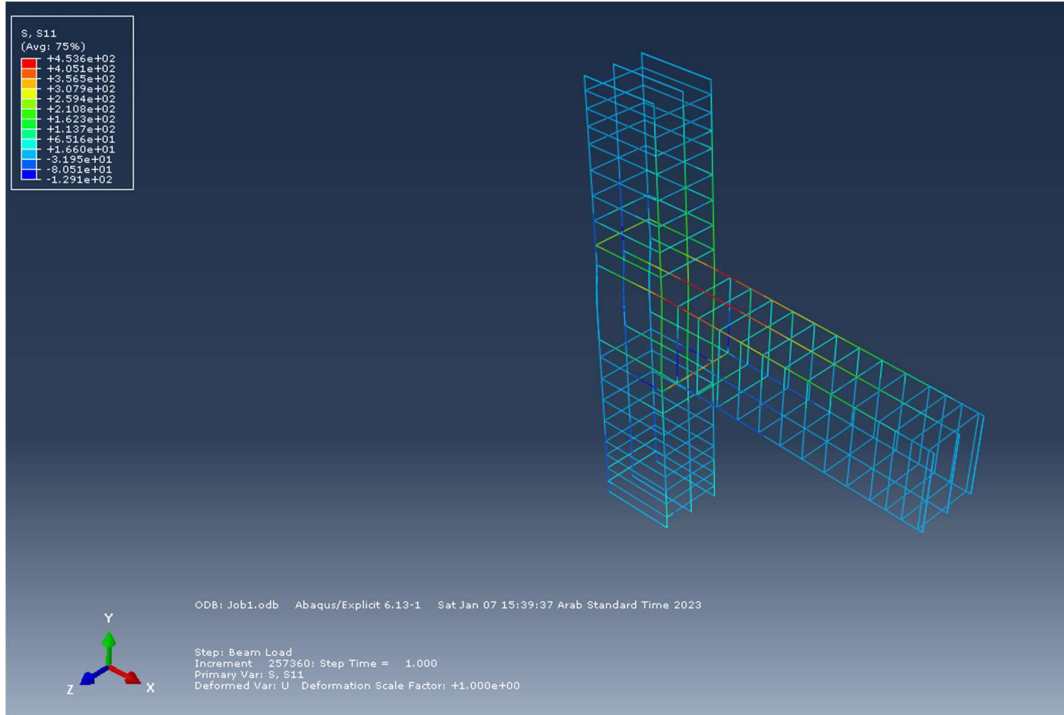
Damage of concrete in compression



Tension Damage of concrete



Reinforcement stress



Moreover, the load-displacement curve was extracted for each model from the field output in the XY data manager tool in this module, where a Python script was developed and used for each cae file to speed up the extracting procedure. Those collected files were as text files and so the MATLAB software was used to transfer the data to an Excel sheet for the 6480 samples.

Appendix (3) Part of the Data Used for Developing the Proposed ANN Model

This appendix presents part of the data used for training, validation, and testing the proposed ANN final model. The total sets of data are 4320, only 150 data points were presented in the following table to avoid heavy prints of thesis papers.

Input Data							Output Data
Column Depth	Beam Depth	Concrete compressive strength	Beam tension reinforcement total area	Beam tension reinforcement yield strength	Axial column load	Joint Area	BCJ shear strength
mm	mm	MPa	mm ²	MPa	Ratio	mm ²	MPa
300	200	30	603.186	660	0.15	75000	3.818
400	500	50	1472.622	660	0.1	100000	5.082
300	300	20	942.478	660	0.15	75000	3.561
300	300	45	942.478	460	0.15	75000	4.888
150	600	55	1472.622	460	0.15	37500	6.977
300	150	30	942.478	660	0.1	75000	5.195
500	600	45	942.478	660	0.05	125000	3.432
150	300	25	942.478	460	0.1	37500	4.817
300	500	25	942.478	660	0.05	75000	3.327
200	300	20	942.478	660	0.05	50000	3.884
200	600	55	942.478	460	0.1	50000	5.960
300	300	20	1472.622	460	0.05	75000	3.568
150	150	20	1472.622	660	0.1	37500	5.659
400	150	60	1472.622	660	0.05	100000	6.193
300	200	17	1472.622	460	0.1	75000	3.487
400	200	55	1472.622	660	0.1	100000	6.439
150	400	30	942.478	460	0.15	37500	3.333
200	600	35	1472.622	460	0.15	50000	2.330
400	200	55	942.478	660	0.1	100000	5.416
300	400	17	603.186	460	0.1	75000	2.932
150	500	30	942.478	460	0.15	37500	0.855
150	300	20	603.186	660	0.05	37500	3.825
400	400	30	1472.622	460	0.05	100000	4.173
150	500	35	1472.622	660	0.1	37500	3.604
500	600	35	942.478	660	0.1	125000	3.334
150	400	17	1472.622	660	0.1	37500	5.308
500	500	25	1472.622	460	0.15	125000	4.196
400	200	35	942.478	660	0.15	100000	4.277
200	200	60	1472.622	460	0.1	50000	5.205

600	500	60	1472.622	660	0.15	150000	4.694
400	500	55	1472.622	660	0.05	100000	4.815
150	500	40	942.478	660	0.1	37500	3.908
300	400	20	1472.622	460	0.15	75000	4.420
500	200	30	942.478	660	0.05	125000	3.651
200	150	17	942.478	460	0.05	50000	4.960
150	150	55	942.478	660	0.15	37500	8.393
200	500	17	1472.622	460	0.1	50000	3.026
150	300	35	1472.622	460	0.05	37500	5.900
200	300	25	1472.622	460	0.05	50000	3.994
150	150	50	942.478	660	0.1	37500	7.822
200	200	20	603.186	460	0.15	50000	3.087
500	200	20	1472.622	660	0.05	125000	3.455
300	150	50	1472.622	660	0.15	75000	7.310
500	300	35	942.478	660	0.1	125000	4.111
500	300	20	1472.622	660	0.1	125000	3.345
200	300	35	603.186	660	0.05	50000	4.803
200	150	55	1472.622	460	0.1	50000	8.365
150	200	20	603.186	460	0.05	37500	2.696
300	500	35	942.478	460	0.05	75000	3.937
150	200	25	1472.622	660	0.1	37500	3.075
200	300	30	1472.622	660	0.1	50000	5.313
500	600	40	1472.622	460	0.1	125000	3.770
150	500	40	942.478	660	0.15	37500	1.092
150	400	60	603.186	660	0.1	37500	6.453
400	600	60	942.478	660	0.05	100000	3.888
150	200	35	1472.622	660	0.1	37500	4.052
300	500	30	1472.622	460	0.05	75000	3.853
200	200	17	1472.622	460	0.1	50000	2.924
600	200	40	1472.622	660	0.05	150000	3.850
400	400	55	942.478	660	0.1	100000	4.873
150	150	17	942.478	660	0.15	37500	4.879
200	200	45	603.186	460	0.05	50000	4.611
400	400	55	1472.622	460	0.05	100000	5.111
150	300	17	942.478	460	0.05	37500	3.952
150	500	25	603.186	460	0.1	37500	2.566
200	150	25	942.478	660	0.05	50000	5.576
150	200	45	942.478	660	0.15	37500	4.196
300	150	40	603.186	660	0.15	75000	4.824
400	500	55	942.478	660	0.1	100000	4.652
150	200	45	603.186	660	0.1	37500	4.264
200	600	25	1472.622	660	0.1	50000	4.553
200	300	17	603.186	660	0.05	50000	2.860
300	600	50	942.478	660	0.15	75000	5.344
200	400	30	942.478	460	0.1	50000	4.994
300	300	20	1472.622	660	0.15	75000	3.631

150	500	50	942.478	460	0.1	37500	1.271
300	300	30	1472.622	660	0.05	75000	4.849
500	300	20	942.478	660	0.1	125000	3.157
600	150	35	1472.622	460	0.15	150000	3.685
300	400	40	942.478	460	0.1	75000	4.650
150	400	30	942.478	460	0.1	37500	4.455
300	300	45	942.478	660	0.1	75000	5.008
200	500	17	1472.622	660	0.1	50000	3.026
500	500	40	1472.622	460	0.15	125000	4.048
400	400	20	1472.622	660	0.05	100000	3.548
300	300	55	1472.622	660	0.1	75000	5.976
150	150	35	942.478	460	0.05	37500	6.759
500	200	50	1472.622	660	0.1	125000	5.262
300	600	30	942.478	460	0.05	75000	4.569
150	600	20	942.478	660	0.1	37500	3.321
150	150	35	603.186	460	0.05	37500	6.124
300	150	17	942.478	660	0.15	75000	4.248
150	150	35	942.478	660	0.15	37500	6.864
300	150	35	942.478	660	0.1	75000	5.684
300	400	50	1472.622	660	0.1	75000	5.863
300	500	50	942.478	460	0.1	75000	4.306
400	400	17	1472.622	660	0.15	100000	3.666
300	150	60	1472.622	660	0.15	75000	7.512
200	150	50	1472.622	460	0.15	50000	8.534
200	300	60	942.478	460	0.1	50000	5.892
150	400	30	942.478	660	0.05	37500	4.449
400	150	20	603.186	660	0.15	100000	3.466
150	300	45	603.186	460	0.15	37500	5.833
500	500	35	1472.622	460	0.05	125000	3.990
600	200	40	942.478	660	0.05	150000	3.640
300	300	40	1472.622	460	0.05	75000	5.554
200	400	45	603.186	660	0.1	50000	5.134
200	400	30	942.478	460	0.15	50000	5.309
150	600	50	942.478	660	0.1	37500	6.669
400	400	17	1472.622	460	0.15	100000	3.666
300	400	45	942.478	660	0.15	75000	5.152
300	300	40	942.478	460	0.1	75000	4.856
150	500	17	942.478	460	0.1	37500	2.101
200	200	50	603.186	460	0.05	50000	4.546
300	200	60	1472.622	660	0.15	75000	5.487
400	300	35	942.478	660	0.1	100000	4.461
200	200	17	942.478	660	0.15	50000	3.027
150	150	17	1472.622	660	0.05	37500	5.161
200	300	60	603.186	660	0.15	50000	5.955
200	300	30	942.478	660	0.1	50000	4.975
400	300	20	603.186	660	0.1	100000	3.160

150	300	25	1472.622	660	0.15	37500	5.289
200	600	60	1472.622	660	0.1	50000	5.264
500	300	20	1472.622	460	0.1	125000	3.363
600	300	17	1472.622	660	0.1	150000	2.908
200	400	25	603.186	460	0.1	50000	4.000
300	200	35	1472.622	460	0.05	75000	4.916
600	200	40	942.478	660	0.05	150000	3.640
200	150	40	1472.622	660	0.1	50000	7.509
300	150	35	942.478	660	0.05	75000	5.485
300	300	17	603.186	660	0.15	75000	3.025
300	400	50	1472.622	660	0.1	75000	5.863
150	600	40	603.186	460	0.05	37500	4.040
300	300	17	603.186	660	0.15	75000	3.025
150	150	55	603.186	660	0.1	37500	7.416
200	500	17	1472.622	660	0.05	50000	2.887
200	500	20	603.186	660	0.15	50000	3.313
300	400	25	1472.622	460	0.05	75000	4.178
600	200	45	1472.622	660	0.1	150000	4.252
400	200	40	942.478	660	0.1	100000	4.729
200	200	35	603.186	660	0.15	50000	4.325
400	500	20	603.186	660	0.1	100000	2.823
400	400	17	1472.622	460	0.05	100000	3.189
300	500	20	603.186	460	0.15	75000	2.332
300	200	35	1472.622	460	0.05	75000	4.916
200	600	45	942.478	660	0.15	50000	5.681
200	300	35	942.478	660	0.05	50000	4.518
400	150	40	942.478	660	0.15	100000	5.363
200	300	50	603.186	660	0.05	50000	5.763

Appendix (4) MATLAB code for Developing the Proposed ANN Model

MATLAB code for developing the proposed ANN model

Importing the Data

```
uiimport('C:\Users\ADMIN\Desktop\Thesis\Matlab Tut\Data10.txt',1)
```

Extracting Data from Matrix

```
x= Data10(:,1:7);  
y = Data10(:,8);
```

Normalization of Input and the target (real output) data

```
x2= x' ; % only as rows  
y2 =y';  
[x22,settingsx] = mapminmax(x2);  
[y22,settingsy] = mapminmax(y2);
```

Defining the Input & Output of the Model

```
input1 = x22;  
target1 = y22;
```

Using nftool for ANN

```
nftool
```

The final function was extracted and saved from the nftool with the name of
(FinalANN13NodesMaxMinReg.m)

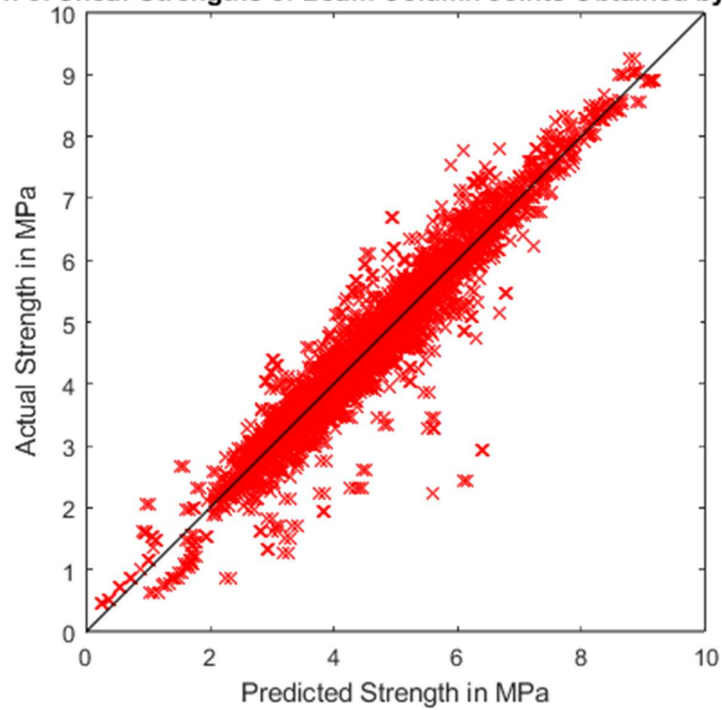
Finding the Model Prediction and reversing the normalization from the prediction value.

```
output1 = FinalANN13NodesMaxMinReg(input1);  
ynet = output1';  
y_Prediction = mapminmax.reverse(ynet,settingsy);  
final_prediction = y_Prediction;
```

ANN Performance Check

```
close all
figure(1);
hold all;
plot(final_prediction,y,'xr');
plot((0:10),(0:10),'-k')
axis square; box on;
ylabel('Actual Strength in MPa')
xlabel('Predicted Strength in MPa')
title("Comparison of Shear Strengths of Beam-Column Joints Obtained by Neural Network")
```

Comparison of Shear Strengths of Beam-Column Joints Obtained by Neural Netw



MATLAB Code used with future data points:

Testing the proposed model using literature data points

%Enter the unnormalized value and MATLAB will normalize the values:

```
MM= [200 300 35 314 500 0.14 40000
200 300 22 461.6 495 0.23 40000
200 300 35 307.7 495 0.14 40000
200 300 20 452.2 585 0.25 40000
406.4 406.4 33.1 2578.68993590121 458.5 0.1 165160.96
]';

for i = 1 :5

    pnew = MM(:,i);
    pnewn = mapminmax('apply',pnew,settingsx);
    pnewn_fornet = pnewn;
    anewn = FinalANN13NodesMaxMinReg(pnewn_fornet);
    anewn_forreverse = anewn';
    anew = mapminmax('reverse',anewn_forreverse,settingsy)
    RR(i) = anew;

end
RRRR=RR';
```

The original data will provide the parameters settingsx and settingsy.

Appendix (5) Weights and Biases of Final Proposed Model

The following matrices present the final weights and biases for the proposed ANN model for the hidden layer and the output layer.

Following is the hidden layer weights matrix $[w_1]$ 13×7 that connects the input parameters to the hidden layer nodes. The size of the matrix is 13×7 , where each column represents the weights related to one of the input parameters connected to each neuron in the hidden layer.

$$w_1 = \begin{bmatrix} -0.5185 & -1.2716 & -0.6639 & -2.4119 & -0.01598 & -0.01724 & -0.5546 \\ -0.3564 & -0.2010 & 0.1107 & 0.3688 & 0.01812 & 0.1010 & 0.04684 \\ 1.02148 & 1.5968 & 1.8751 & 0.1720 & -0.07108 & 0.1344 & 1.3570 \\ -1.1757 & -1.2049 & -0.6131 & -1.9716 & -0.004361 & 0.01057 & 0.2407 \\ -1.6588 & 1.9250 & -0.2070 & 0.3456 & 0.04525 & -0.01282 & -3.1511 \\ -0.1273 & 3.2528 & -0.1104 & -0.1829 & -8.99E-03 & -0.1661 & 1.4606 \\ -0.7594 & -6.5145 & 0.1309 & 0.1816 & 0.003089 & 0.1362 & -0.5558 \\ 1.1948 & 1.4796 & -0.5909 & -1.1049 & 0.02793 & -1.6679 & -0.4448 \\ -1.7703 & 1.02750 & -0.04094 & 0.6819 & 0.05208 & 0.6061 & -0.4093 \\ -1.7264 & 2.5915 & 0.1979 & 0.1240 & -0.002712 & 0.3527 & -1.1080 \\ -1.6888 & 1.5962 & -0.2815 & 0.3812 & 0.04438 & 0.06161 & -2.05322 \\ 0.7699 & 0.1931 & 0.6702 & -0.2095 & -0.01054 & 0.0003977 & -0.7588 \\ 1.8974 & -3.7958 & -0.2495 & -0.02304 & 0.009568 & -0.2515 & 0.6299 \end{bmatrix}$$

The following weight matrix $[w_2]$ 1×13 contains the weights connecting the hidden layer neurons to the output layer neuron, which is having a size of 1×13 .

$$w_2 =$$

$$[0.5997 \quad 0.6566 \quad -0.1274 \quad -0.6396 \quad 1.1219 \quad 1.9717 \quad 1.9659 \quad 0.02919 \quad 0.2192 \quad -2.3402 \quad -1.3293 \quad 0.5239 \quad -2.4671]$$

$[B1]$ 13×1 shows the biases values for the hidden layer while $[B2]$ 1×1 shows the bias value for the output layer. In $[B1]$ each element presents the connection for one of the hidden neurons, where the first element is bias for the first hidden neurons and so on. $[B2]$ is single bias for the output single neuron.

As mentioned in chapter 4, each input parameter is multiplied by its weight after applying the normalization, and the bias is added after the summation of that multiplication. Next is passing the total to a hyperbolic tangent sigmoid transfer activation function. The results now will be the values for the hidden layer nodes which will be considered as inputs to the output layer node. Therefore, each hidden layer neuron will be multiplied with its connection weight with the output neuron and finally summed and added to the output bias. The result from the last mentioned will go through purlin function (linear transfer function) that will give the final answer value of the prediction for the shear strength of beam-column joint after reversing the normalization.

$$B_1 = \begin{bmatrix} 1.3476 \\ -0.1554 \\ -0.9316 \\ 1.1729 \\ -3.8005 \\ 4.7283 \\ -7.8068 \\ 0.5165 \\ -2.238 \\ -5.0222 \\ -3.0808 \\ 0.8607 \\ 6.0085 \end{bmatrix}$$

$$B_2 = [-0.2427]$$

Appendix (6) Literature Data Collected for Comparison with the Proposed ANN Model

The following table presents the collected data from literature which have been used for comparison with the proposed ANN model.

												Average
												0.915
Source	Test Number	Serial Number	column depth (mm)	Beam Depth (mm)	Concrete Strength f_c (MPa)	top tension reinforcement of beam	f_y (MPa)	Column Axial loading ratio	Joint Area (mm ²)	Experimental Joint Shear Strength (MPa)	ANN Proposed model Prediction	ANN Prediction/ Actual
(Tsonos, 2005)	A1	1	200	300	35	314.000	500	0.14	40000	4.310	4.568	1.060
	E1	2	200	300	22	461.600	495	0.23	40000	5.800	4.385	0.756
	E2	3	200	300	35	307.700	495	0.14	40000	4.100	4.555	1.111
	G1	4	200	300	20	452.200	585	0.25	40000	5.560	4.408	0.793
(Pantelidis, Hansen, Nadauld, & Reaveley, 2002)	Unit 1	5	406	406	33	2578.690	459	0.10	165160	5.280	3.969	0.752
	Unit 2	6	406	406	30	2578.690	459	0.25	165160	5.044	5.369	1.065
	Unit 3	7	406	406	34	2578.690	459	0.10	165160	5.001	3.997	0.799
	Unit 4	8	406	406	32	2578.690	459	0.25	165160	5.613	5.409	0.964
	Unit 5	9	406	406	32	2578.690	459	0.10	165160	4.662	3.931	0.843
	Unit 6	10	406	406	31	2578.690	459	0.25	165160	5.153	5.391	1.046
(Chalioris, Favvata, & Karayannis, 2008)	JA-0	11	300	300	34	452.389	580	0.05	60000	4.100	3.952	0.964
	JA-s5	12	300	300	34	452.389	580	0.05	60000	4.100	3.952	0.964
	JA-X12	13	300	300	34	452.389	580	0.05	60000	4.100	3.952	0.964
	JA-X14	14	300	300	34	452.389	580	0.05	60000	4.100	3.952	0.964
	JB-0	15	300	300	32	471.239	580	0.05	60000	4.300	3.886	0.904
	JB-s1	16	300	300	32	471.239	580	0.05	60000	4.300	3.886	0.904
	JB-X10	17	300	300	32	471.239	580	0.05	60000	4.300	3.886	0.904
	JB-X12	18	300	300	32	471.239	580	0.05	60000	4.300	3.886	0.904
	JCa-0	19	200	200	21	157.080	470	0.10	20000	3.600	2.741	0.761
	JCa-X10	20	200	200	21	157.080	470	0.10	20000	3.600	2.741	0.761
	JCa-s1	21	200	200	21	157.080	470	0.10	20000	3.600	2.741	0.761
	JCa-s1-X10	22	200	200	21	157.080	470	0.10	20000	3.600	2.741	0.761
	JCa-s2	23	200	200	21	157.080	470	0.10	20000	3.600	2.741	0.761
	JCa-s2-X10	24	200	200	21	157.080	470	0.10	20000	3.600	2.741	0.761
(Karayannis,	B0	25	300	300	32	471.000	580	0.05	60000	3.317	3.885	1.171
	B1	26	300	300	32	471.000	580	0.05	60000	3.583	3.885	1.084

Chalioris, & Sirkelis, 2007)	C0	27	300	300	32	452.000	580	0.05	60000	3.483	3.863	1.109
	C2	28	300	300	32	452.000	580	0.05	60000	3.483	3.863	1.109
	C3	29	300	300	32	452.000	580	0.05	60000	3.700	3.863	1.044
	C5	30	300	300	32	452.000	580	0.05	60000	3.683	3.863	1.049
(Antonopoulos & Triantafillou, 2003)	C1	31	200	300	16	462.000	585	0.09	40000	2.900	3.706	1.278
	C2	32	200	300	19	462.000	585	0.07	40000	2.875	3.999	1.391
	S-C	33	200	300	15	462.000	585	0.09	40000	3.075	3.687	1.199
(Ghobarah & Said, 2002)	T1	34	400	400	31	1195.000	425	0.20	100000	5.270	4.883	0.927
	T2	35	400	400	31	1195.000	425	0.10	100000	5.020	4.480	0.892
(Shrestha, Smith, & Samali, 2009)	UM1	36	300	450	25	1809.000	532	0.08	90000	3.998	4.539	1.135
	UC1	37	300	450	26	1809.000	532	0.08	90000	3.250	4.559	1.403
(Park & Paulay, 1974)	S4	38	381	457	21	1282.000	296	0.00	125730	2.521	1.423	0.564
(Kaku & Asakusa, 1991)	No 1	39	220	220	31	531.000	391	0.17	48400	5.124	3.727	0.727
	No 2	40	220	220	42	531.000	391	0.10	48400	5.165	4.206	0.814
	No 3	41	220	220	42	531.000	391	0.00	48400	4.483	4.110	0.917
	No 4	42	220	220	45	531.000	391	0.17	48400	4.938	4.242	0.859
	No 5	43	220	220	37	531.000	391	0.09	48400	4.566	4.049	0.887
	No 6	44	220	220	40	531.000	391	0.00	48400	4.318	4.066	0.941
	No 7	45	220	220	32	531.000	391	0.12	48400	5.145	3.782	0.735
	No 8	46	220	220	41	531.000	391	0.08	48400	5.041	4.218	0.837
	No 9	47	220	220	41	531.000	391	0.00	48400	4.876	4.073	0.835
	No 10	48	220	220	44	531.000	391	0.17	48400	5.021	4.235	0.843
	No 11	49	220	220	42	531.000	391	0.08	48400	4.773	4.242	0.889
	No 12	50	220	220	35	531.000	391	0.00	48400	4.277	3.861	0.903
	No 13	51	220	220	46	531.000	391	-0.04	48400	4.318	4.145	0.960
	No 14	52	220	220	41	531.000	391	0.08	48400	4.669	4.211	0.902
	No 15	53	220	220	40	531.000	391	0.08	48400	4.752	4.166	0.877
	No 16	54	220	220	37	531.000	391	0.00	48400	5.186	3.954	0.763
(CHUN & KIM, 2004)	JC-2	55	500	500	60	3096.605	403	0.05	250000	5.364	3.610	0.673
	JM-2	56	500	500	60	3096.605	403	0.05	250000	5.364	3.610	0.673
(Paulay & Scarpas, 1981)	Unit 1	57	457	610	23	1885.000	296	0.05	208849	3.610	1.406	0.389
	Unit 2	58	457	610	23	2790.000	296	0.15	208849	4.740	4.350	0.918
	Unit 3	59	457	610	27	1885.000	296	0.05	208849	3.605	1.591	0.441
(Liu, 2006)	Unit RC-1	60	230	330	19	471.000	324	0.07	52900	2.647	3.242	1.225
	Unit RC-6	61	250	330	26	452.000	307	0.06	62500	2.832	3.440	1.215
	Unit NZ-7	62	250	330	30	452.000	307	0.05	62500	3.040	3.633	1.195
(Vatani-Oskouei, 2010)	Specimen 1	63	350	400	24	1018.000	417	0.00	122500	3.265	2.415	0.740
	Specimen 2	64	350	400	20	1018.000	417	0.00	122500	3.469	2.062	0.594
(Megget, 1974)	Unit A	65	380	460	22	1655.840	375	0.01	125400	4.362	3.099	0.711
(Clyde, Pantelides)	Test 2	66	457	406	46	2564.000	454	0.10	139385	6.794	5.457	0.803

, & Reaveley, 2000)	Test 4	67	457	406	41	2564.00 0	454	0.25	139385	7.045	6.714	0.953
	Test 5	68	457	406	37	2564.00 0	454	0.25	139385	6.751	6.438	0.954
	Test 6	69	457	406	40	2564.00 0	454	0.10	139385	6.651	5.019	0.755
(Hwang, Lee, Liao, Wang, & Tsai, 2005)	0T0	70	420	450	67	2040.00 0	430	0.02	176400	5.652	5.205	0.921
	3T44	71	420	450	77	2040.00 0	430	0.01	176400	6.037	5.787	0.958
	3T3	72	420	450	69	2040.00 0	430	0.02	176400	6.417	5.320	0.829
	2T4	73	420	450	71	2040.00 0	430	0.02	176400	6.122	5.450	0.890
	1T44	74	420	450	73	2040.00 0	430	0.02	176400	5.890	5.561	0.944
	3T4	75	420	450	75	2040.00 0	491	0.01	176400	6.293	5.715	0.908
	2T5	76	420	450	77	2040.00 0	491	0.01	176400	6.587	5.792	0.879
	1T55	77	420	450	70	2040.00 0	491	0.02	176400	6.383	5.380	0.843
(Ajmal, 2016)	BCJ - M	78	300	300	46	942.478	607	0.05	75000	5.057	5.133	1.015
	BCJ - RC	79	300	300	46	942.478	607	0.05	75000	4.239	5.133	1.211
	BCJ - CL	80	300	300	46	942.478	607	0.05	75000	3.955	5.133	1.298

الملخص

الزلازل المدمرة الأخيرة مثل زلزال وتسونامي المحيط الهندي (2004) في إندونيسيا، وزلزال وتسونامي سيتشوان (2008) في الصين، وزلزال وتسونامي توهوكو في اليابان (2011)، وزلزال وتسونامي جوركا في نيبال (2015)، والزلازل التي حدثت في تركيا وسوريا (2023) قد أظهرت أوجه قصور إنشائية في الهياكل حيث تسببت في خسائر كبيرة في الأرواح وأضرار اقتصادية. وكانت معظم هذه المباني تفتقر إلى التسليح الزلزالي وكانت تصاميمها الزلزالية ليست جيدة. يعتبر التسليح الزلزالي غير الكافي في العقد (BCJs) الموجودة في وصلات الأعمدة مع الجسور، الحوائط الحاملة، والأعمدة هم المصادر الرئيسية للضرر في الهياكل الخرسانية المسلحة خلال الحدث الزلزالي.

غالبية المباني الخرسانية المسلحة التي تم بناؤها في الثمانينيات لم تكن تحتوي على تسليح مرتبط بقوة الزلازل؛ بدلاً من ذلك، تم تصميمها لأحمال الجاذبية. وفي المناطق النشطة زلزالياً، يوجد العديد من هذه الأنواع من الهياكل على نطاق واسع في جميع أنحاء العالم. تشكل العقد في مناطق اتصال العمود مع الجسور دوراً مهماً في تكامل الأنظمة الإنشائية في الهياكل الخرسانية المسلحة. تعتبر العقد في مناطق اتصال العمود مع الجسور أجزاء مهمة في الهياكل الخرسانية المسلحة حيث تخضع لضغوط عالية أثناء النشاط الزلزالي. يجب التنبؤ بقوة القص لهذه العقد لضمان السلامة العامة للهياكل أثناء حدوث الزلازل.

إن أحد أهم الدوافع لهذه الدراسة هو التنبؤ بقوة القص لهذه العقد التي ليس لها تسليح زلزالي. لقد شهد استخدام التعلم الآلي (ML) بالتزامن مع طريقة تحليل العناصر المنتهية (FEA) مؤخراً اهتماماً كبيراً من مجتمع البحث. في هذه الدراسة، تم استخدام التعلم الآلي (ML) - الشبكة العصبونية الاصطناعية (ANN) للتنبؤ بقوة تحمل العقد في الهياكل الخرسانية المسلحة التي لا تحتوي على كانات تسليح في مناطق اتصال العمود مع الجسور. يحتاج تطوير نموذج شبكة عصبونية اصطناعية للتنبؤ بقوة تحمل القص إلى بيانات للتدريب والتحقق من صحة واختبار النموذج. وبالتالي، تعد البيانات أمراً ضرورياً لتقديم دقة أفضل في نموذج الشبكة العصبونية الاصطناعية. في هذه الدراسة، تم إنتاج مجموعات البيانات اللازمة لنموذج الشبكة العصبونية باستخدام برنامج العناصر المنتهية (ABAQUS). تمت محاكاة عدة عينات من وصلات الأعمدة مع الجسور في برنامج (ABAQUS) مع الأخذ في الاعتبار سبعة متغيرات متعلقة بتفاصيل التصميم حيث تم استخدامها كمدخلات لنموذج الشبكة العصبونية الاصطناعية (ANN). السبع مدخلات هي عمق العمود، وعمق الجسر، وقوة مقاومة الخرسانة للضغط، والمساحة الإجمالية لتسليح الشد في الجسر، وقوة مقاومة الشد لحديد التسليح في الجسر، وحمل العمود المحوري، ومساحة العقدة في وصلة العمود مع الجسر. العدد الإجمالي لعينات الوصلات الخارجية للعمود مع الجسر التي تمت محاكاتها هو 6480، ولكن قل العدد بعد إبعاد العينات ذات فشل الانحناء في الجسر وتم أخذ العينات ذات فشل القص في العقدة فقط. بلغ العدد الإجمالي للعينات ذات فشل القص في العقدة 4320 والتي

تم استخدامها لتطوير النموذج المقترح. تم تقسيم البيانات إلى عدة مجموعات كالتالي: (1) مجموعة تدريب 70% (3024 عينة)، (2) مجموعة اختبار 15% (648 عينة)، (3) ومجموعة التحقق 15% (648 عينة) والتي تم استخدامها لتطوير نموذج الشبكة العصبونية الاصطناعية (ANN) للتنبؤ بقوة القص في العقدة الموجودة في الهياكل الخرسانية المسلحة، حيث أن هذه القوة هي الناتج من استخدام النموذج المقترح. تم فحص دقة ناتج النموذج المقترح باستخدام بيانات الاختبار لمقارنة القيم الناتجة مع القيم المتوقعة لبيانات الاختبار المكونة من 648 عينة من الوصلات الخارجية والتي تمت مقارنة قوة القص في العقد الخاصة بها مع النتائج النهائية لنموذج الشبكة العصبونية الاصطناعية المقترح (ANN) لنفس البيانات. النموذج المقترح أظهر دقة عالية بلغت 95.6% في دقة التنبؤ بقوة القص لعقد العينات في بيانات الاختبار. بالإضافة إلى ذلك، تم استخدام بيانات الاختبار لمقارنة دقة النموذج المقترح في التنبؤ بقوة القص للعقد في الوصلات الخارجية للهياكل الخرسانية مع دقة معادلة (ACI) للتنبؤ بهذه القوة. لقد وجد أن النموذج المقترح دقيق في التنبؤ بقوة القص في العقد الموجودة في الوصلات الخارجية الموجودة في الهياكل الخرسانية المسلحة عند مقارنته مع معادلة (ACI). علاوة على ذلك، تم التنبؤ بقوة القص في عقد الوصلات الخارجية باستخدام نموذج الشبكة العصبونية الاصطناعية (ANN) المقترح لعينات 80 تم جمعها من الأبحاث العلمية. لقد وجد أن النموذج المقترح قادر على التنبؤ بقوة القص لهذه العقد بمتوسط دقة 91.5%.

جامعة البحرين

قسم الهندسة المدنية

كلية الهندسة



التنبؤ بقوة العقدة في نقطة اتصال العمود مع الجسر في الهياكل الخرسانية المسلحة باستخدام التعلم الآلي

أطروحة مقدمة كجزء من متطلبات الحصول على درجة الماجستير في
الهندسة المدنية

إعداد

رنيم وائل معتوق

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إشراف

د. محمد أجمل

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مملكة البحرين

فبراير، 2024