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ANALYSIS FOR THE REINFORCED BEAM-COLUMN JOINT SUBJECTED TO CYCLIC LOADING USING ABAQUS AND DEEP LEARNING WITH PYTHON

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ABSTRACT

Beam - column connection is a critical part of frame structure where it has to deal with different types of loads and transmit them. The beam-column connection effects on strength and serviceability of the structure should be taken into consideration throughout the design process. The beam-column connection has major roles in resisting lateral loads like earthquake, wind and blast. Undoubtedly, keeping joints sustain through these loads performing on a structure will protect human lives. For this specific reason, this research was carried out to investigate the beam-column connection by gathering the results from previous experimental researches. These researches have conducted an experimental trial on beam-column joint with different strengthen technique; such as ferrocement and carbon Fiber Reinforced Polymer, or using different types of stirrups like rectangle confining or spiral confining concrete. Theoretical analysis was operated using the finite element software, which is formulated considering the cyclic loading effects. The structural behavior under cyclic loading such as; energy dissipation capacity, stiffness degradation scalar, stress, good self-cantering, good ductility, compressive damage, tensile damage, displacements, equivalent plastic strain and plastic dissipation energy density were demonstrated. Comparisons with experimental results are performed to make sure that the finite element analysis is accurate. The parametric study in the next step will depend on evaluate parameters by calculating errors, accuracy, and predict its behavior by deep learning which considered to be advanced technology procedure of neural networks. In the end, the correlations between these parameters were presented as a prediction equation for parameters, and the best reinforcing details with minimum errors were proposed. For best details reinforcement from unconventional strengthen method was sample DCM- DOUBLE then DCM- SINGLE respectively, both show good handling for Damage dissipation energy density (DMENER), Magnitude of Plastic Strain (PEMAG) and Plastic Dissipation Energy Density (PENER), while for low Scaler Stiffness Degradation (SDEG) value samples (ND-T1 and ND-T2). Deep learning can be used to build equation connect all parameters with minimum error which improved by this research.

Keywords: beam- column, joint, python, cyclic load, earthquake, finite element, ABAQUS.

1. INTRODUCTION

1.1 Reinforced Concrete Beam- Column Joint

Transmission load between structural members is recognized as being one of the most critical design steps that designers should take into consideration. Loads transit from slab to beam then to the columns to deliver loads to the foundation, and in turn the foundation will transmit it to the soil or rock. In some cases, the assemblage of beam-column-slab transmit loads to foundations, at this point we need to answer the aim of design requirements, where the answer is "to produce members able to resist the specified gravity loads beside anticipated levels of an earthquake".

A beam-column joint has defined as the part of the deepest depth of the beam cross to the column, Figure-1 shows a beam-column joint location in the frame, figure-2 shows beam-column joints parts and figure- 3 beam-column joint connections types. Beam-column joint are also classified into two categories according to ACI352R-02 [Bonacci, *et al*. 2002].

- Type 1 connection is composed of members designed to satisfy ACI 318-02.
- Type 2 connection, frame members are designed to have sustained strength under deformation reversals into the inelastic range which this research focuses on studying.

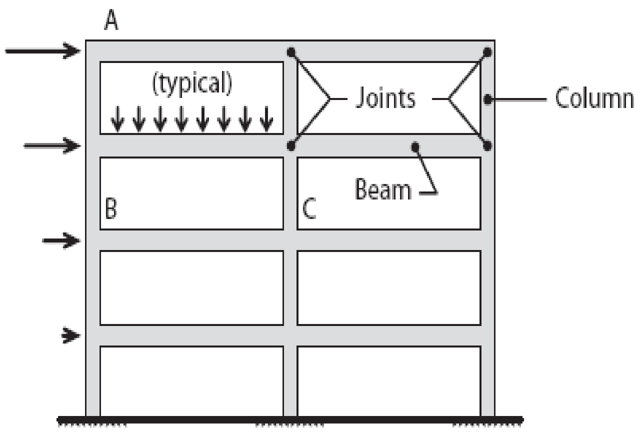

Figure-1. Beam-column joint location in the frame.

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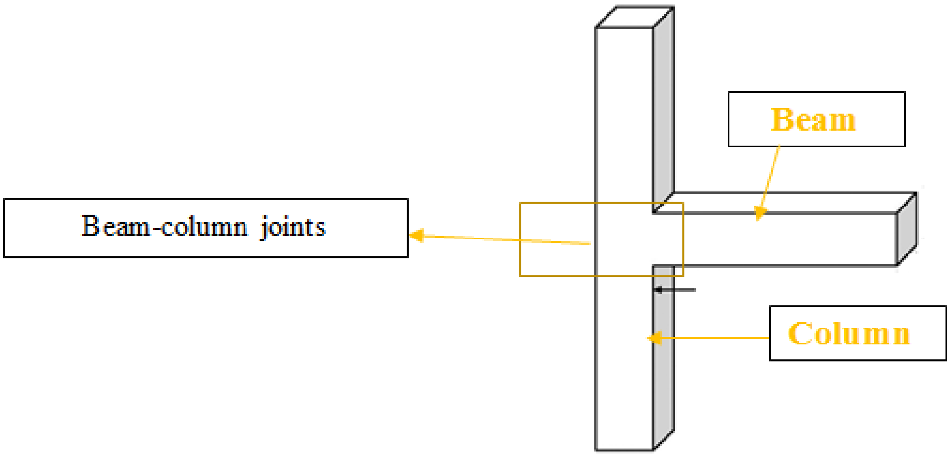

Figure-2. Beam-column joints parts.

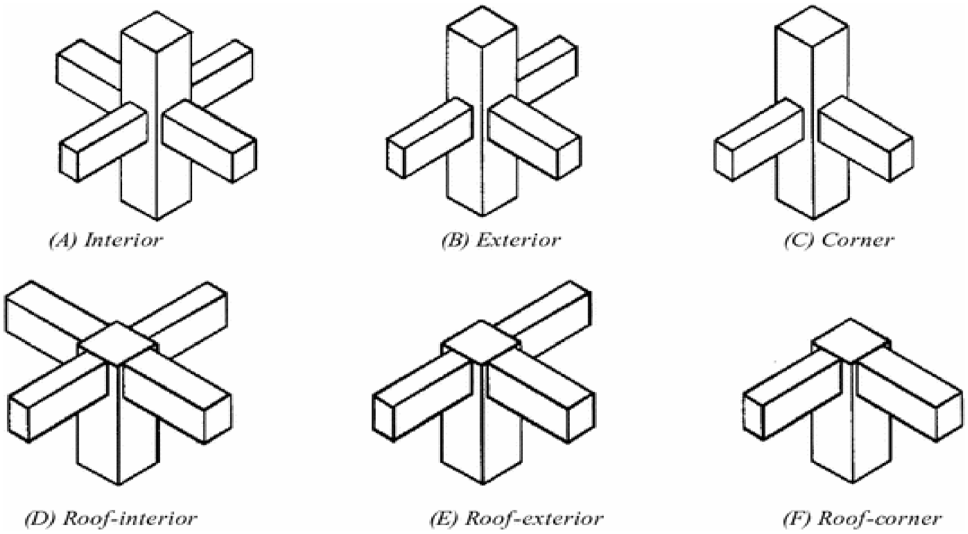

Figure-3. Beam column joint connections types.

The previous definition for type 2 leads us to generate considerable interest to prevent beam-column joints type 2 from failure under Severe reverse cyclic loading especially lateral load such as seismic, blast and wind. Through achieving good ductility, good energy dissipation, and good self-cantering capacity of the structure, where energy dissipation capacity is considered the key parameter in resisting lateral loading. To prevent the structure from failure, two elements of structure capacity need to be achieved:

a) Minimum stiffness, K.

b) Minimum strength, fy.

Beam-column joint dissipates energy through reversals of deformation in the inelastic range. Thus, it controls the achievement of good structure energy dissipation. Moreover, structure shouldn't exceed ultimate capacity due to lateral load or the structure will fail. Being designers, our primary aim is to save people's lives when a random earthquake or blast happens, and to ensure important facilities like (hospital and fire department) work when these disasters happen.

There are two main design philosophies:

a) Elastic design: In the lifetime of the structure remains elastic so if the load is removed on the member it will back to its original state. Besides, there is uniqueness relation between stress-strain design whether its linear or non-linear relationship.

b) Plastic design philosophy: where there is no uniqueness between stress-strain or load with displacement also there is no energy dissipation has taken place, which makes permanent deformation. This philosophy states that resisting force depends on both material properties and loading history.

Comparing both philosophies, elastic design philosophy needs high strength to achieve. Subsequently, that requires high cost which is not considered good economically. In contrast, the plastic design achieves the same high strength that elastic design requires with less cost. Furthermore, there are two important characters of inelastic design are ductility and yielding, which can help design less than elastic design demand.

2. LITRATURE REVIEW

Some studies tried to find numerical models that can help us understand the behavior of B-C joints under dynamic loads. Other studies try to use an analysis program to draw hysteretic loops to get results about best-detailing can resist dynamic loads and compare it with lab results. This section will review some of these studies.

[Venkatesan, *et al*. 2016] studied the seismic effect on exterior B-C joints strengthened with unconventional reinforcement detailing. Unconventional reinforcement refers to putting one to two layers of Ferrocement on joints and had done experimentally by putting a cyclic load on samples and register results such as displacement, stiffness and cumulative energy dissipation. At the same time, an analytical study was carried out by finite element models using the ANSYS program, where results show that Ferrocement samples have more energy dissipation capacity than needed for reinforced beam-column joints in seismic regions.

[Ercan, *et al*. 2019] Studied using fiber-reinforced plastics strengthening techniques. This research focuses on studying Carbon fiber-reinforced plastic (CFRP). Placing these CFRP sheets internally and externally on various locations on joints or whole sample. These Experimental tests were held by putting axial pressure on the column and the hydraulic jack made displacement at the tip of the beam to get Joint failure load, displacement, beam failure, moment Rigidity until first crack and Energy absorption capacity. The most notable factor is that this research proves that strengthen joints may increase ductility, not capacity.

[Azimi, *et al.* 2015] studied different types of confining such as common closed stirrups (DCM-CONVEN), rectangular spiral reinforcement (DCM-SINGLE) and twisted opposing rectangular spiral (DCM-DOUBLE). Experimental and Analytical analysis were conducted. Analytical analysis was performed by ANSYS. This research seeks to get hysteresis response, Energy dissipation capacity, load-drift envelops, beam deflection, crack opening, Damage index and tensile stresses in the joint rejoin. Results refer to the failure mode of RC beam-column connections, which is significantly affected by the angle between the shear reinforcement and shear cracks. DCM- DOUBLE and DCM - SINGLE specimens developing the higher capacity of the connected beam was observed. Rectangular spiral reinforcement gave a higher seismic performance. in the end, the DCM- DOUBLE specimen shows a higher energy dissipation capacity.

[Cao, *et al.* 2020] used experimental results to predict moment in beam-column connection by Extreme Learning Machine (ELM). Researchers studied whether applying soft computing methods of the proposed beam to column connection in concrete frames can gain high nonlinearity. ELM proves itself as a good static tool to predict moment in beam-column connection in concrete by getting the same results as the experimental one.

As it can be noted, all previous studies aim to study new methods without comparing previous studies together, which is the aim of this study. By using experimental results, finite element analysis and deep learning as statical tools to compute between different parameters. One last note that deep learning and ELM are different where deep learning depends on studying all hidden layers but ELM focuses on one hidden layer.

3. METHODOLOGY

This research will depend on obtaining experimental data from previous researches for various specimens for different joints having different details and influenced by cycle loading. Consequently, these experimental data will be inserted into the finite element analysis program. Finite Element Analysis results will be compared with the experimental results to control the margin of error between the two methods. Afterward, those results (parameters) will be applied to the Jupyter notebook which is considered as a host environment for the Python programming language. Furthermore, a conclusion will be built based on results from deep learning and propose updates on design details.

3.1 Collection of Data

The total number of Specimens is 15, divided into three main categories:

a) First category are 6 specimens (Non-Ductile ND-1, Ductile DD-1, Non-Ductile ND-T1, Non-Ductile-T2, Ductile-T1, Ductile-T2). The difference between ductile DD and noun ductile ND in specimens is spacing between strips in beam-column connection. Also, T1, T2 refer to numbers of layers of Weldmesh and Woven mesh in Ferrocement laminates at the beam-column connection [Venkatesan, et al. 2016]. See (Figure-4 and Figure-5).
b) The second category is 6 specimens (Target, Control, Sample 1, Sample 2, Sample 3, Sample 4), where target and control specimens have no CFRP on joints or members. Otherwise, samples 1,3,4 have CFRP on beam-column joints or on member-only, while sample 2 has diagonal bars on beam-column joints with no CFRP at all. [Ercan, *et al*. 2019]. See (Figure-6 to Figure-7).
c) The third category is composed of 3 specimens different in stirrups (common closed stirrups DCM-CONVEN, rectangular spiral reinforcement DCM-SINGLE, twisted opposing rectangular spiral DCM-DOUBLE) [Azimi, *et al.* 2015]. See (Figure-8 and Figure-9).

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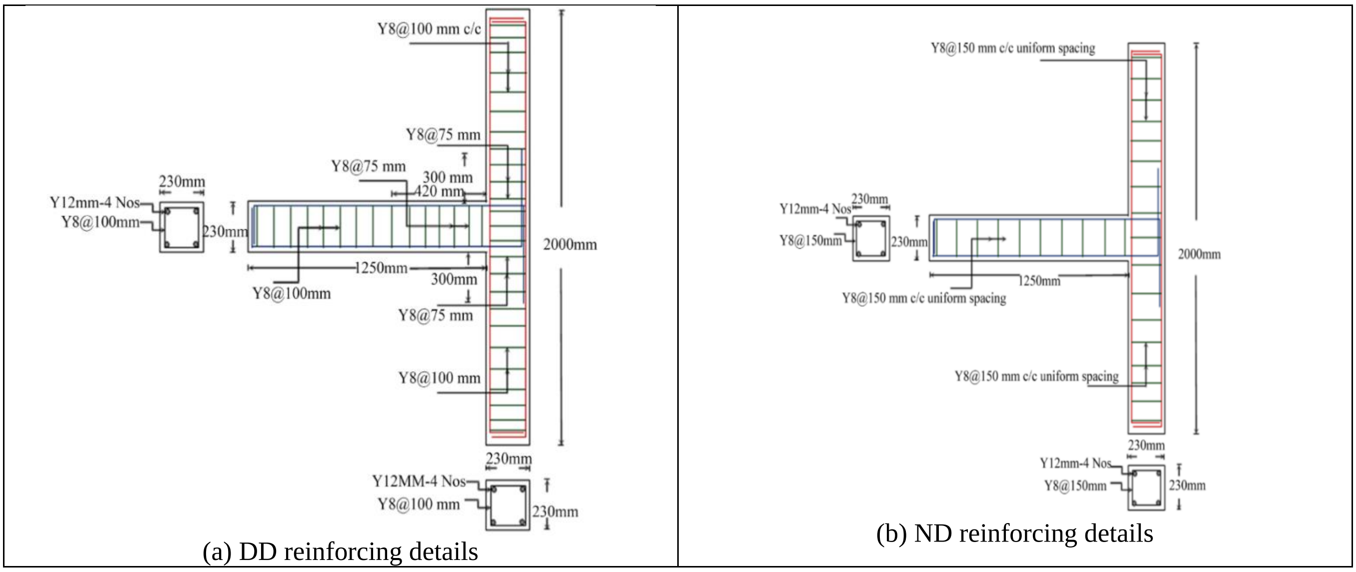

Figure-4. Reinforcing details for category number 1.

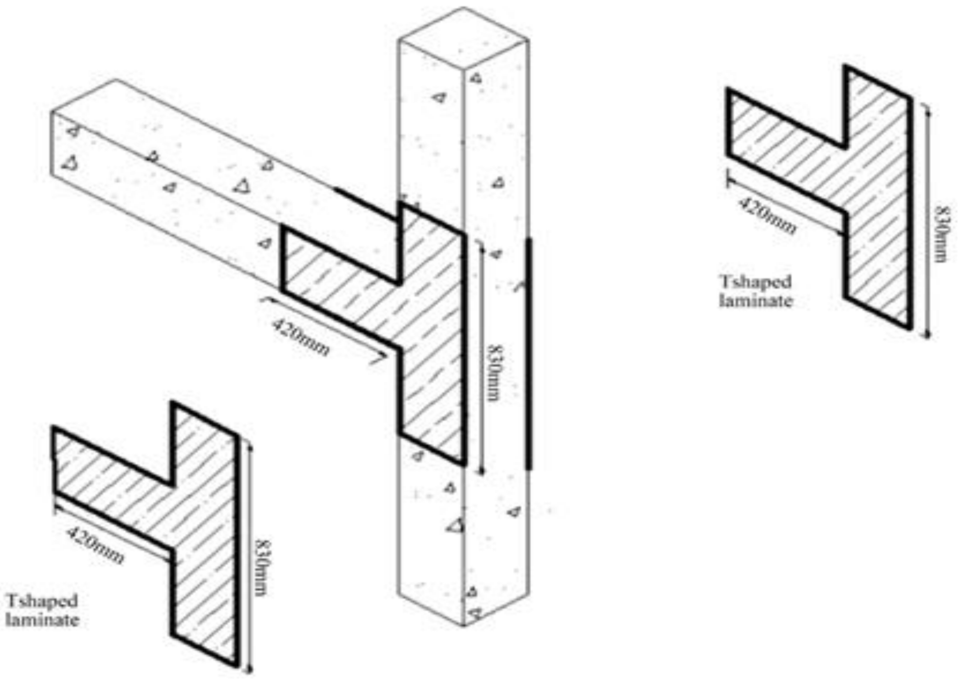

Figure-5. The detail of the Ferrocement laminates wrapping method.

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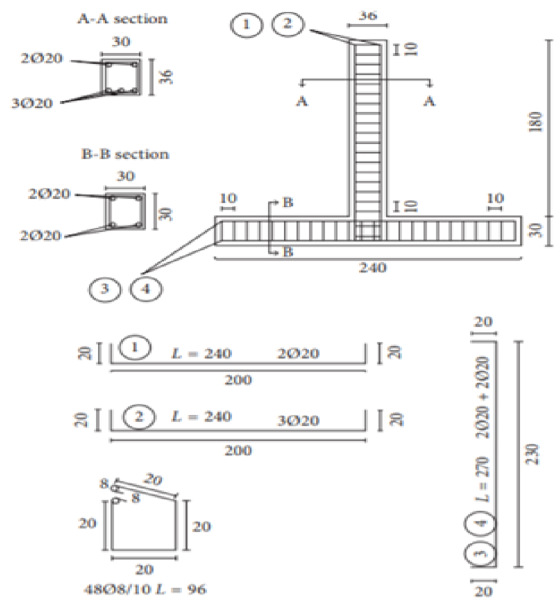
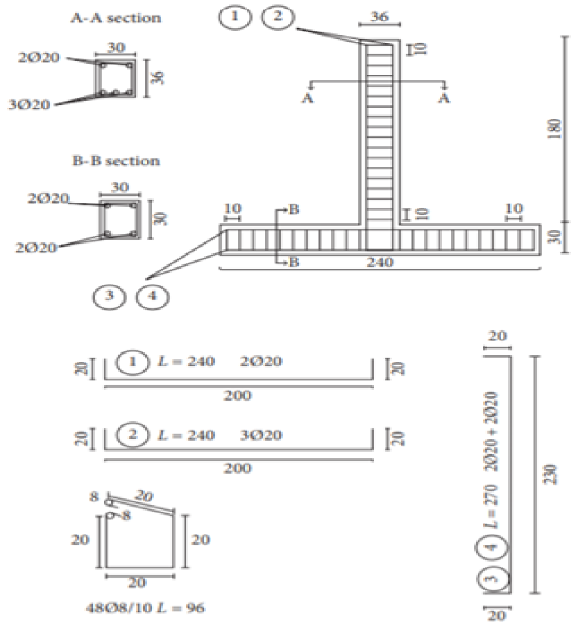
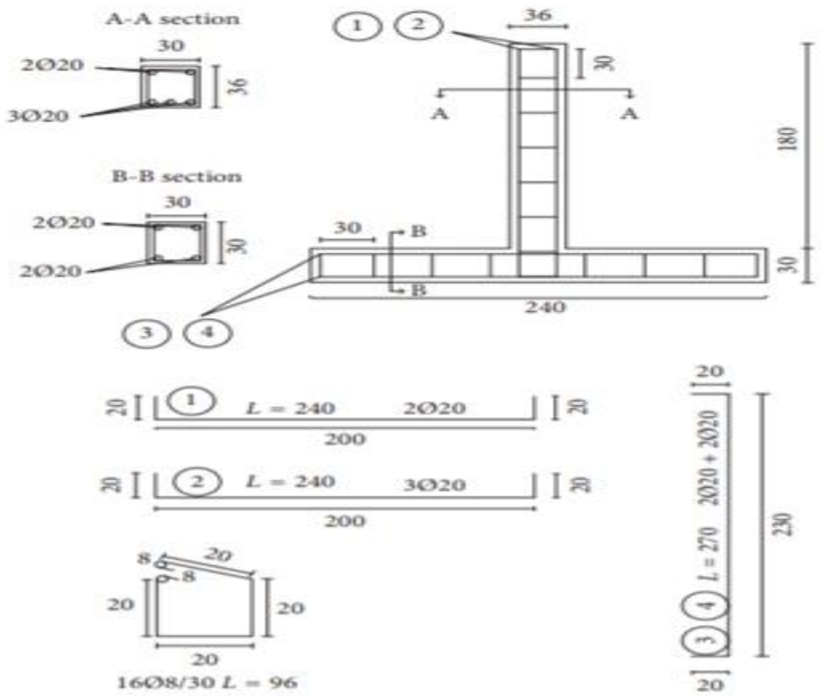


(a) Target sample reinforcing details



(b) Control sample reinforcing details



(c) Sample (1 to 4) reinforcing details

Figure-6. Reinforcing details category number 2.

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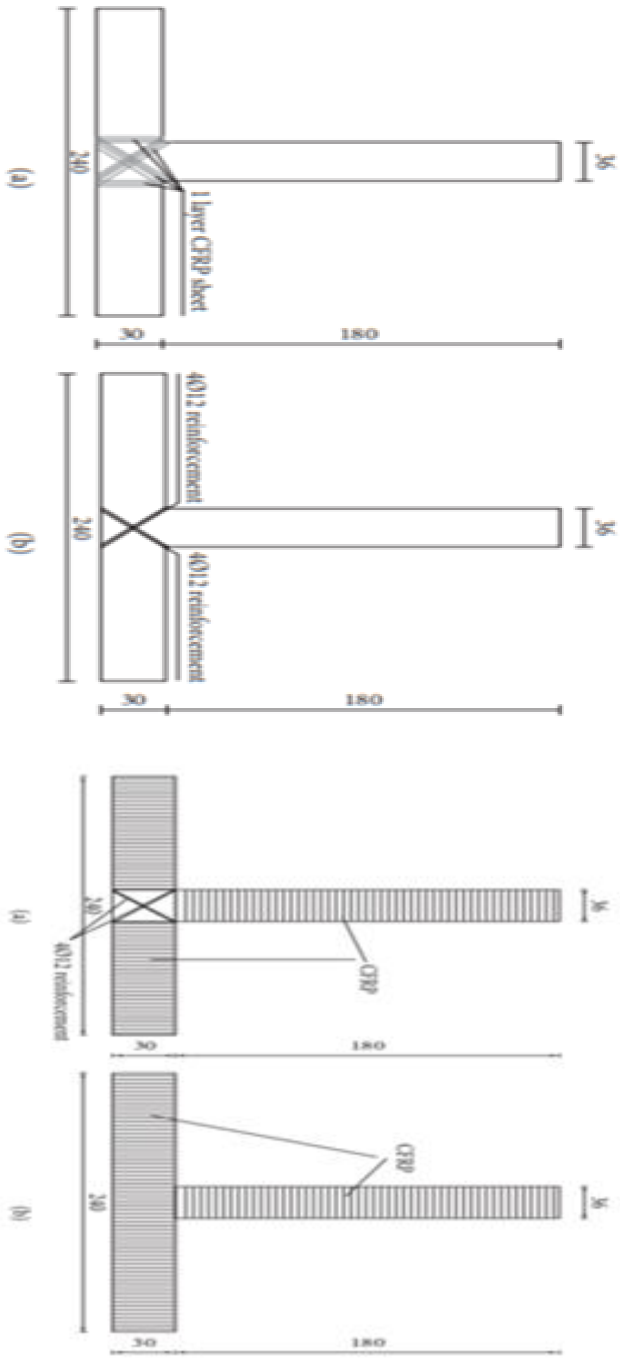

Figure-7. Schematic presentation of strengthening techniques: (a) Sample 1, (b) Sample 2, (c) Sample 3, (d) Sample 4.

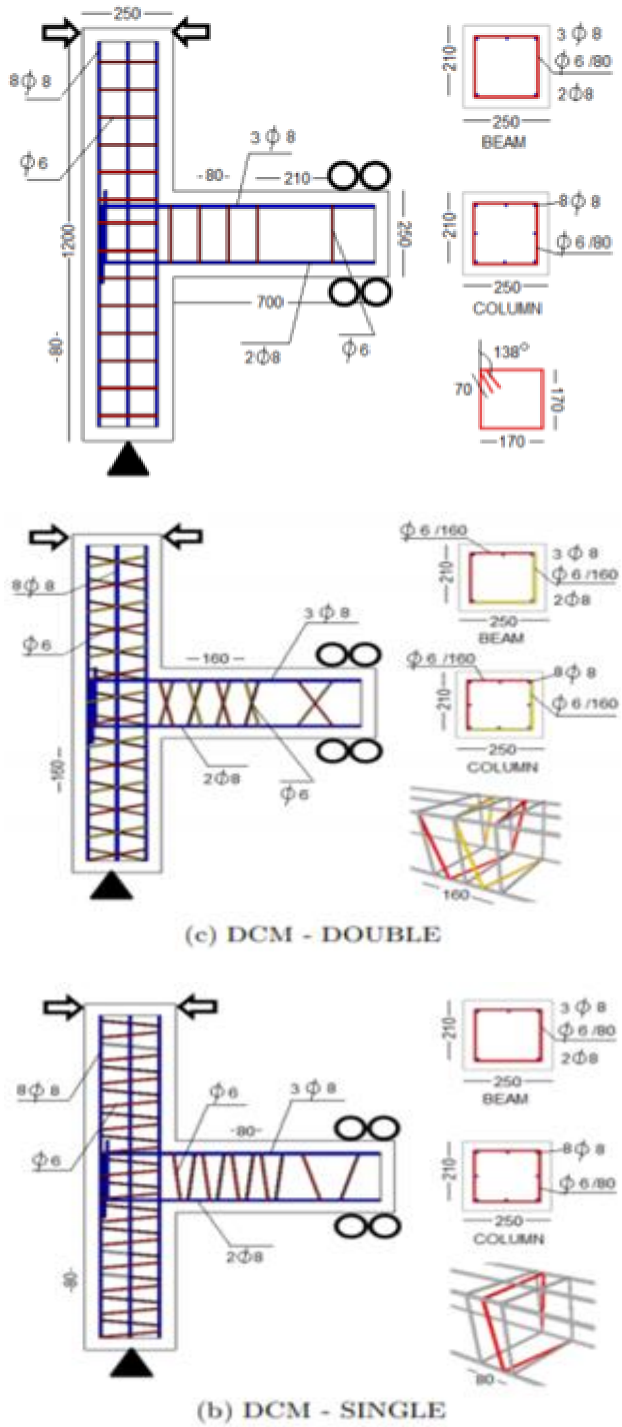

Figure-8. Reinforcing details for category (3).

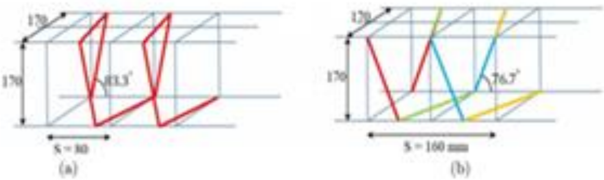

Figure-9. Application of (a) Single and (b) Twisted opposing rectangular spiral reinforcement in RC elements.

As long as this thesis focuses on reinforced concrete (R.C), the main material is concrete and steel. For material data for concrete are compressive strength (fc) and modulus of elasticity (Ec). On the other hand, steel data are: modulus of elasticity (Es) and yield stress both longitudinal and transverse steel as illustrated in Table-1.

Unconventional strengthening methods for beam-column joints used in researches depend on adding CFRP and ferrocement laminates. A 2mm thickness bonding is provided for Ferrocement laminates on beam-column joints. For CFRP sheets study providing following data:

- yielding strength(fy) = 3900 MPa
- ultimate strength (fu) = 4100 Mpa
- modulus of elasticity (E) = 230 GPa
- A 0.166 mm CFRP sheets thick type SikaWrap 300C.

Table-1. Material properties.

Material properties	Concrete		longitudinal Steel		transverse steel	
	F_c (MPa)	E_c (MPa)	E_s (MPa)	F_y (MPa)	E_s (MPa)	F_y (MPa)
Category 1	29.250	25419	200000	448	200000	448
Category 2	30	25742	200000	420	200000	420
Category 3	35	27805	200000	450	200000	450

After collecting reinforcement details and material properties, the next step is collecting loading protocol data where loading protocol refers to a chart that links load values with a number of cycles or displacement values with the number of cycles. This is shown in the following graphs (Figure-10 and Figure-11) for categories 2 and 3.

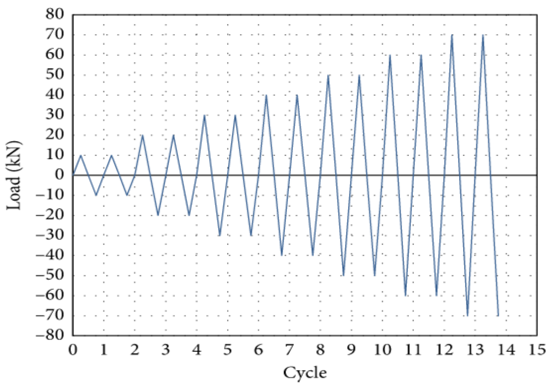

Figure-10. Loading protocol category 2.

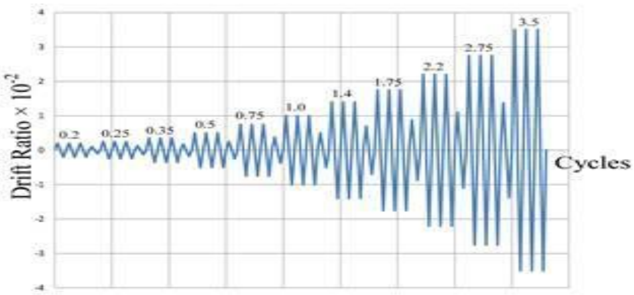

Figure-11. Loading protocol category 3

In the column, an axial load acts as the center. Axial load value was different from one category to another. A hydraulic jack is applied on the tip of the beam to make displacement as shown in Table-2.

Table-2. Hydraulic jack loads.

Category / Loads (KN)	1	2	3
Axial load	100	250	490.33
Hydraulic load	500	500	250

3.2 Analysis of Data

For analysis input data there were two programs suitable to use in an analytical step, which are ANSYS and ABAQUS. In this research used ABAQUS for samples modeling and analysis shown Figure-12.

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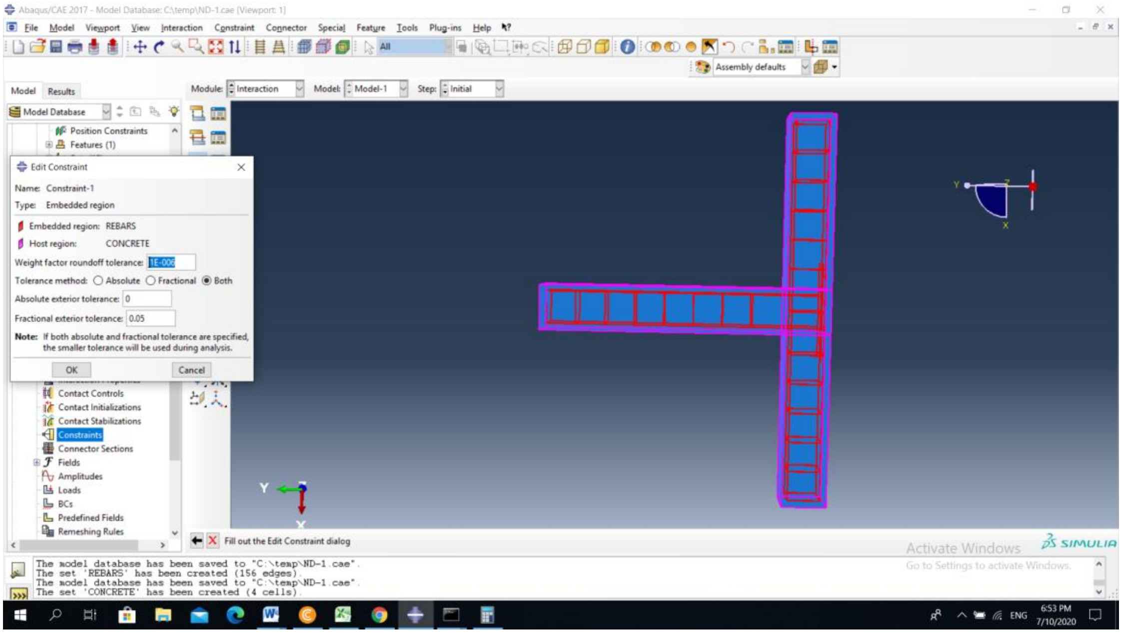

Figure-12. Beam- Column sample modeling on ABAQUS.

The material definition of the finite Analysis program input data ABAQUS is showing in Table-3:

Table-3. Material definition on finite analysis program ABAQUS.

	ABAQUS
Concrete	solid [plane stress/strain]
Tension member	wire [truss]

Some values for material and members behavior [Compressive behavior concrete, tension behavior concrete and Plastic behavior concrete] need to input on ABAQUS before started analysis as values input showing in below tables [Table-4, Table-5 and Table-6]. Finite element analysis program calculates the damage for reinforced concrete depending on Hashin's theory that's why we need defining [Compressive damage concrete and tension damage] as values input showing in Table-7, Table-8.

Table-4. Values of Compressive behavior concrete.

	Yield Stress	Inelastic Strain
2	20.1978	7.47E-05
3	30.00061	9.88E-05
4	40.30378	0.000154
5	50.00769	0.000762
6	40.23609	0.002558
7	20.23609	0.005675
8	5.257557	0.011733

* Compressive behavior concrete

Table-5. Values of tension behavior concrete.

	Yield Stress	Cracking Strain
1	1.99893	0
2	2.842	3.33E-05
3	1.86981	0.00016
4	0.862723	0.00028
5	0.226254	0.000685
6	0.056576	0.001087

* tension behavior concrete

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Table-6. Values of plastic concrete.

	Dilation Angle	Eccentricity	fb0/fc0	K	Viscosit Paramet
1	38	1	1.12	0.67	0.01

*Plastic concrete:

Table-7. Values of compressive damage concrete.

	Damage Parameter	Inelastic Strain
1	0	0
2	0	7.47E-05
3	0	9.88E-05
4	0	0.000154
5	0	0.000762
6	0.195402	0.002558
7	0.596382	0.005675
8	0.894865	0.011733

*Compressive damage concrete

Table-8. Values of tension damage concrete.

	Damage Parameter	Cracking Strain
1	0	0
2	0	3.33E-05
3	0.406411	0.00016
4	0.69638	0.00028
5	0.920389	0.000685
6	0.980093	0.001087

* tension damage concrete

Infinite analysis program must define boundary conditions and increment time. Where the matrix works depends on time as much as how accurate you are at this step and time to fit your model with no errors. There are three steps to program work on, step one is initial where there are no loads just to assign displacement as the boundary condition. Step two put an axial load on top of the column. Step three is the displacement at the tip of the column, see Figure-13 [Najafgholipour, *et al*. 2017].

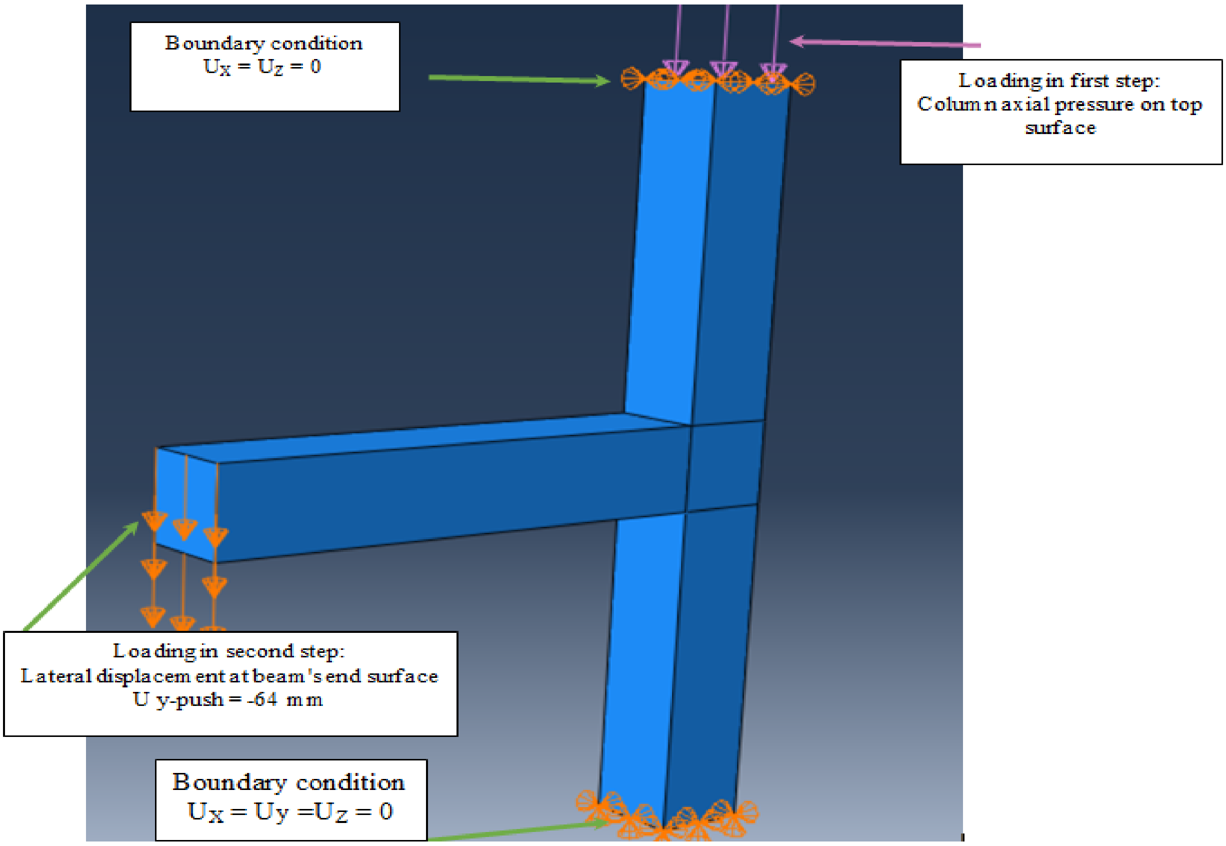

Figure-13. Simulated boundary conditions and loading of the specimen for exterior beam - column joint.

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After getting results from the finite analysis program ABAQUS, we need an unconventional method to study these results to make a final conclusion. At this time focusing on deep learning in research has increased. It started with artificial intelligence (AI) that began with making computers "think" like playing chess. The next level was machine learning. It was computing between machinery and intelligence.

Every method needs sets to work. For deep learning, a regression model, which needs Python Anaconda, Juypter Notebooks and TensorFlow. Where Juypter Notebooks is an environment that makes it easy to combine Python, Graphics, and Text. A Jupiter Notebooks needs to download google library where it can call mathematics functions. In addition, a high-level neural networks API (application programming interface) like Keras needed to complete sets for deep learning correctly.

4. RESULTS AND DISCUSSIONS

4.1 Damaged Reading

Table-9 shows the results of Tensile damage (DAMAGET), Compressive damage (DAMAGEC), Damage dissipation energy density (DMENER) from finite element analysis.

Table-9. Finite element analysis results damaged index.

Sample	DAMAGEC (READING)	DAMAGEC (ULTMATE)	DAMAGET (READING)	DAMAGET (ULTMATE)	DMENER (READING)	DMENER (ULTMATE)
ND-1	0.000719	0.000719	0.98	0.98	0.0067	0.0067
DD-1	0	0	0.98	0.98	0.00551	0.00551
ND-T1	0	0.809	0.98	0.98	0.00035	0.00769
ND-T2	0.05117	0.614	0.98	0.98	0.00033	0.006852
DD-T1	0	0	0.98	0.98	0.00551	0.00551
DD-T2	0	0	0.98	0.98	0.00551	0.00551
target	0.07457	0.89	0.98	0.98	0.0054	0.0054
control	0	0	0.98	0.98	0.0036	0.0036
sample 1	0	0	0.98	0.98	0.0011	0.001188
sample 2	0.024	0.024	0.98	0.98	0.0035	0.00358
sample 3	0	0	0.98	0.98	0.000403	0.000403
sample 4	0	0	0.98	0.98	0.00044	0.00044
DCM-CONVEN	0.127	0.5655	0.98	0.98	0.0106	0.0106
DCM-SINGLE	0.89	0.89	0.98	0.98	0.1142	0.1713
DCM-DOUBLE	0.8949	0.8949	0.98	0.98	0.2512	0.4307

Note: all parameters are unitless and these parameters are indicators values from zero to 1.

a) Tensile damage (DAMAGET) for all samples in Table-13 reached its' ultimate values and that expected hence concrete known as weak handling tensile stress.

b) Compressive damage (DAMAGEC) indicates that all samples have not been damaged except these samples (DCM- SINGLE, DCM-DOUBLE, sample 2).

c) Damage dissipation energy density (DMENER) indicates that all samples have reached its' ultimate value except (ND-T2, DCM - SINGLE, DCM - DOUBLE) where these three samples were good at handling damage.

4.2 Scaler Stiffness Degradation (SDEG), Displacement, Stress (S) Reading

Table-10 shows the results of Scaler Stiffness Degradation (SDEG), displacement, stress (S, miss) from finite element analysis.

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Table-10. Finite element analysis results (SDEG), displacement, (S).

Sample	SDEG READING	SDEG ULTMATE	Displacement READING (mm)	Displacement ULTAMATE (mm)	S, miss READING (N/mm^2)	S, miss ULTAMATE (N/mm^2)
ND-1	0.98	0.98	29	91.6	10.1337	448
DD-1	0.98	0.98	39	89.18	7.36	448
ND-T1	0.158	0.993	39.9	143.7	4.63	448
ND-T2	0.13	0.9923	46	110.06	12.33	448
DD-T1	0.98	0.98	44	89.19	9.91	447.3
DD-T2	0.98	0.98	44.5	89.1	9.91	447.3
target	0.98	0.98	21.8	78.15	4.99	431
control	0.98	0.98	17.5	69.4	8.65	435.6
sample 1	0.98	0.98	40.93	69	10.82	370.1
sample 2	0.98	0.98	30	70	7.77	428.7
sample 3	0.9796	0.9796	47	70	5.19	171.6
sample 4	0.979	0.9796	42	70	5.233	169.7
DCM-CONVEN	0.98	0.9844	36.15	144.6	8.33	448
DCM-SINGLE	0.9	0.9	29.66	178	28.79	448
DCM-DOUBLE	0.8982	0.8982	35.2	210.1	40.35	448

Note: SDEG is unit less parameter which indicates values from zero to 1.

a) All sample values for Scaler Stiffness Degradation (SDEG) have reached its’ ultimate except (ND-T1, ND-T2).

b) Lowest displacement value shown for sample (control) and higher value shown for sample (ND-T2).

c) Both ultimate displacement and ultimate stress values have not been reached by any of the samples.

4.3 Magnitude of Plastic Strain (PEMAG), Plastic Dissipation Energy Density (PENER) Reading

Table-11 shows the results of Magnitude of Plastic Strain (PEMAG), Plastic Dissipation Energy Density (PENER) from finite element analysis.

Table-11. Finite element analysis results PEMAG, PENER.

Sample	PEMAG (READING)	PEMAG (ULTAMTE)	PENER READING (N.mm)	PENER ULTMATE (N.mm)
ND-1	0.3134	0.3134	10.3	124.3
DD-1	0.2948	0.2948	9.99	119.9
ND-T1	0.00453	0.543	23.34	280.1
ND-T2	0.03986	0.4783	20.75	249
DD-T1	0.2948	0.2948	9.995	119.9
DD-T2	0.2948	0.2948	9.995	119.9
target	0.226	0.226	7.298	87.47
control	0.221	0.221	6.983	83.8
sample 1	0.03187	0.03187	0.7442	8.931
sample 2	0.2532	0.2532	7.271	87.25
sample 3	0.001342	0.001342	0.001282	0.001282
sample 4	0.001338	0.001338	0.001278	0.001278
DCM- CONVEN	0.3641	0.3641	17.8	213.7
DCM- SINGLE	0.072378	0.5976	25.3	304.5
DCM- DOUBLE	0.05	0.7445	31.62	379.4

Note: PEMAG is unit less parameter.

a) Samples (ND-T1, ND-T2, DCM- SINGLE, DCM- DOUBLE) have not reached its' ultimate values for Magnitude of Plastic Strain (PEMAG).

b) Plastic Dissipation Energy Density (PENER) for sample (DCM- DOUBLE) has reached the highest value (31.62) while the lowest value where for samples (sample 3, sample 4) (0.001278, 0.001278) respectively also its' ultimate values. it must be noted that a high Plastic Dissipation Energy Density (PENER) value refers to good sample handling energy.

4.4 Difference between Finite Element Analysis and Experimental Test

Table-12 shows the results of a comparison of the previous experiment from a literate review between displacement from the Experimental test and finite element analysis. Error percentage has not exceeded the 10% which is accepted in the civil engineering research field (earthquake and structural engineering). [Hashemi, *et al.* 2016]

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Table-12. Finite element analysis results vs experimental test for displacement.

Sample	Displacement-experimental (mm)*	Displacement-finite analysis (mm)	Error percentage %
ND-1	30	29	3.448275862
DD-1	40	39	2.564102564
ND-T1	40	39.9	0.250626566
ND-T2	45	46	2.173913043
DD-T1	45	44	2.272727273
DD-T2	45	44.5	1.123595506
target	22.38	21.8	2.974359
control	17.66	17.5	0.914285714
sample 1	40.1	40.93	-2.027852431
sample 2	32.4	30	0.8
sample 3	47.85	47	1.808510638
sample 4	43.44	42	3.428571429
DCM- CONVEN	-	36.15	_
DCM- SINGLE	-	29.66	_
DCM- DOUBLE	-	35.2	_

*Displacement- experimental values from [Ercan, et al. 2019] and [Venkatesan, et al. 2016] experimental results.

Same for Energy Dissipation capacity in table-13 shown below that shows the difference between Experimental test and finite element analysis where has not exceeded the 10% which is accepted in civil engineering research field (earthquake and structural engineering). [Hashemi, *et al*. 2016]

Table-13. Finite element analysis results vs experimental results for energy dissipation capacity.

Sample	Energy Dissipation capacity – experimental (N.mm) *	Energy Dissipation capacity - finite analysis (N.mm)	Error percentage %
ND-1	1031.67	1000	3.167
DD-1	989.34	980	0.953061224
ND-T1	2897.48	2900	0.086896552
ND-T2	2733.67	2700	1.247037037
DD-T1	2733.67	2700	1.247037037
DD-T2	3947.47	3500	12.78485714
target	37668.83	37000	1.807648649
control	11322.43	11000	2.931181818
sample 1	23696.6	23000	3.028695652
sample 2	15092.03	15000	0.613533333
sample 3	11882.27	11500	3.324086957
sample 4	1031.67	1000	3.167
DCM- CON	10000	10100	0.99009901
DCM- SINGLE	26100	25500	2.352941176

*Energy Dissipation capacity - experimental values from [Ercan, *et al*. 2019], [Venkatesan, *et al*. 2016], [Azimi, *et al*. 2015] experimental results.

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4.5 Results from Python

This section tried to train the model for finding the relation between parameters and errors for each parameter by converting data (input) to Z-table [see table-14] to minimize errors. After that python takes value from samples parameters Z-table, where this value is called X_test. Then it tries to build equation its' result gave as same as a possible value near x_test value this value called X_train. For example, in energy Dissipation capacity section in Table-15, the first value for X_train (0.31388673) and for X_test (0.62639225) with error percentage (99.5%). However, in next trial to train model error, the percentage went down to (21.18%). in this research "displacement" input data gave the lowest error when trial build equation collect all parameters where Final score Mean Square Error (MSE) = 0.00079506 (0.079%) and Final score Root Mean Square Error (RMSE) = 0.028196 (2.81%). to prove this in below section, will show the deep learning results for two parameters displacement and energy dissipation represent y in the main equation and compare the error percentage results in Table-17.

Table-14. Input data after convert it to z-table.

	DAMAGEC	DMENER	SD	Dis	stress	PEM	PENER	En
0	-0.458584	-0.317847	0.434970	-0.791075	-0.156943	1.130131	0.114826	-1.059612
1	-0.460995	-0.335924	0.434970	0.335385	-0.448563	0.989217	0.080906	-1.061313
2	-0.460995	-0.414309	-2.487423	0.436766	-0.735587	-1.209874	1.541685	-0.898017
3	-0.289426	-0.414613	-2.586969	1.123907	0.073970	-0.942213	1.258283	-0.915027
4	-0.460995	-0.335924	0.434970	0.898615	-0.180463	0.989217	0.081453	-0.915027
5	-0.460995	-0.335924	0.434970	0.954938	-0.180463	0.989217	0.081453	-0.846987
6	-0.210968	-0.337595	0.434970	-1.861212	-0.697738	0.467987	-0.213657	2.002195
7	-0.460995	-0.364939	0.434970	-2.086504	-0.312936	0.430107	-0.248125	-0.209110
8	-0.460995	-0.402916	0.434970	0.552791	-0.084788	-1.002746	-0.930785	0.811492
9	-0.380525	-0.366458	0.434970	-0.678429	-0.405456	0.674054	-0.216612	0.131091
10	-0.460995	-0.413504	0.433548	1.236553	-0.676711	-1.234026	-1.012076	-0.166585
11	-0.460995	-0.412942	0.431414	0.673323	-0.672190	-1.234057	-1.012077	0.556342
12	-0.035174	-0.258603	0.434970	0.014344	-0.346579	1.514235	-0.999086	-0.285655
13	2.523102	1.315174	0.150552	-0.716729	1.804529	-0.695856	-0.973883	1.024118
14	2.539531	3.396326	0.144152	-0.092670	3.019917	-0.865392	2.447696	1.832095

*SD= Scaler Stiffness Degradation
*dis= displacement
*PEM= Magnitude of Plastic Strain
*EN= Energy Dissipation capacity

- **Before training model:**

A - Main Equation form
$y=m_1x_1+m_2x_2+m_3x_3+\ldots+m_nx_n+b$
Energy Dissipation capacity = (5688.298*DAMAGEC) + (170098.127*DMENER) + (10139.194*SD) - (530.492*Displacement) - (787.858*stress) - (42851.714*PEM) -(237.812*PENER) + 36789.04103

- After training model:

A - Main Equation form
$y=mx_1+mx_2+mx_3+\ldots+mx_n+b$

4.5.1 Energy dissipation capacity as y representative

A - Main Equation Energy Dissipation capacity represent (y)
Energy Dissipation capacity = (m_1*DAMAGEC) +(m_2*DMENER) + (m_3*SD) + (m_4*Dis) + (m_3*stress) + (m_4*PEM) + (m_5*PENER) + b
Energy Dissipation capacity = (0.14428955*DAMAGEC) + (0.95233888*DMENER) + (0.24255598*SD) - (0.40053325*Dis) - (0.63733321 *stress) - (0.48106364 *PEM) - (0.18484448 *PENER) + (1.9849165485262278e*10^-16)

B - From the main equation trying to predict Energy Dissipation capacity value from main equation at these certain value
PENER =0.114826, PEM= 1.130131, stress= -0.156943, Dis = -0.791075, SD= 0.434970, DMENER= -0.317847, DAMAGEC = -0.458584
Is equal = - 0.41137541.

C- Training value and test value example were in first trial error percentage was 99.5% but in the

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next trial to train model error percentage went down 21.18% all show in Table-15.

Table-15. Training values examples.

Training model trial	X_train	X_test	Error percentage
First trial	0.31388673	0.62639225	99.5%
Second trial	-1.0220089	0.8054521	21.18%

D - Degree of error (Loss)
loss: 0.1066, val_loss: 0.0211

E - Final score Mean Square Error (MSE) = 0.02188 (2.188%)

F - Final score Root Mean Square Error (RMSE) = 0.14794 (14.7%)

G - The following Figure-14 shows two lines one represents predict values and the other Shows expected value after training model.

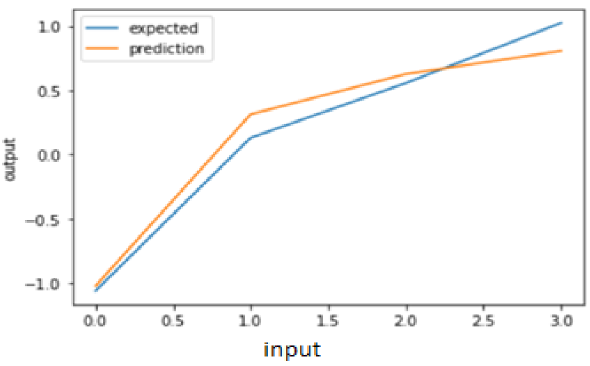

Figure-14. The differences between predict values and expected.

4.5.2. Finding displacement as y representative

A - Main Equation displacement represent (y)
Displacement = (m_1*DAMAGEC) + (m_2*DMENER) + (m_3*SD) + (m_4*En) + (m_3*stress) + (m_4*PEM) + (m_5*PENER)
Displacement = (-1.68347617*DAMAGEC) + (1.99301209*DMENER) + (0.60372591*SD) - (0.69159869*En) + (0.31516317*stress) - (0.32346632*PEM) – (1.01870836*PENER) + (-3.4433235646925584e-17)

B - From main equation trying to predict Displacement value from main equation at these certain value
PENER =0.114826, PEM= 1.130131, stress= -0.156943, En =-1.059612, SD= 0.434970, DMENER= -0.317847, DAMAGEC = -0.458584
is equal = 0.07676977

C - Training value and test value examples where final Error percentage is 4.64692 where first trying was enough to get equation collect all parameters with Error percentage equal 0.262861 all shows in Table-16.

Table-16. Training values examples.

Training model trial	X_train	X_test	Error percentage %
First trial	-0.68581384	0.6840111	0.262861
Second trial	-0.7378104	-0.70352495	4.64692

D - Degree of error (Loss)
loss: 0.0799, val_loss: 5.4023e-04

E - Final score Mean Square Error (MSE) = 0.00079506 (0.079%)

F - Final score Root Mean Square Error (RMSE) = 0.028196(2.81%)

G - The following chart shows two lines one represents predict values and other Shows expected value after training model.

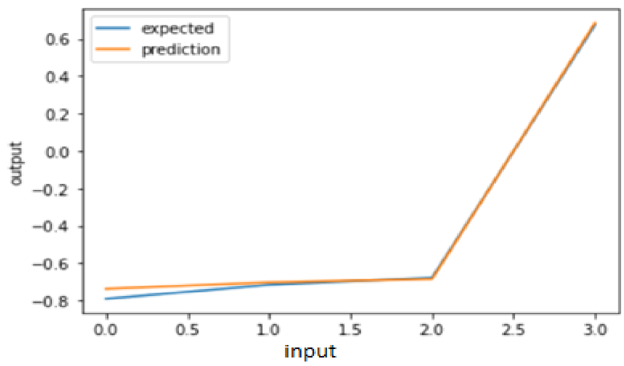

Figure-15. The differences between predict values and expected.

Comparison between Energy Dissipation capacity and displacement error percentage values when training model to be each one represent-y in the main equation:

Tabel-17. Comparison between energy dissipation capacity and displacement error percentage.

y- representative	Final score Mean Square Error (MSE)	Final score Root Mean Square Error (RMSE)
Energy Dissipation capacity	2.188%	14.7%
displacement	0.079%	2.81%

4.5.3. Displacement and ultimate displacement

To find the relation between ultimate Displacement and displacement same as before first input data as shown in Table-18. Then convert it to Z-table as shown in Table-19.

Table-18. Input data in Python.

	DisplacementREADING	DisplacementULTAMATE
0	29.00	91.60
1	39.00	89.18
2	39.90	143.70
3	46.00	110.06
4	44.00	89.19
5	44.50	89.10
6	19.50	78.15
7	17.50	69.40
8	40.93	69.00
9	30.00	70.00
10	47.00	70.00
11	42.00	70.00
12	36.15	144.60
13	29.66	178.00
14	35.20	210.10

Table-19. Input data after convert it to z-table.

	DisplacementREADING	DisplacementULTAMATE
0	-0.791075	-0.309211
1	0.335385	-0.365877
2	0.436766	0.910742
3	1.123907	0.123041
4	0.898615	-0.365642
5	0.954938	-0.367750
6	-1.861212	-0.624151
7	-2.086504	-0.829037
8	0.552791	-0.838403
9	-0.678429	-0.814988
10	1.236553	-0.814988
11	0.673323	-0.814988
12	0.014344	0.931816
13	-0.716729	1.713897
14	-0.092670	2.465537

A - Main Equation
Ultimate Displacement = (m_1*Displacement) + b
Ultimate Displacement = -0.00272* Displacement + 1.48309e^{-16}

B - Degree of error (Loss)
loss: 0.0084, val_loss: 0.0044

C - Final score Mean Square Error (MSE) = 0.005204 (0.5204%)

D - Final score Root Mean Square Error (RMSE) = 0.0721 (7.21%)

E - The following Figure-16 shows two lines one represents predict values and other Shows expected value after training model

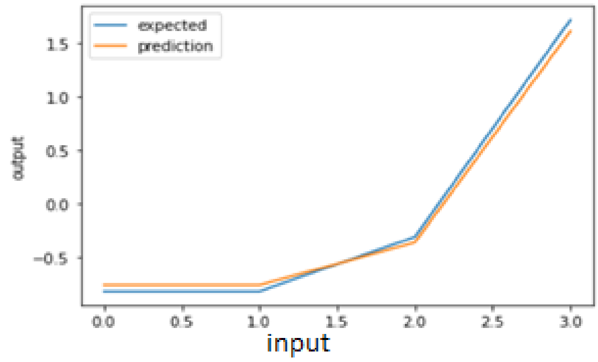

Figure-16. The differences between predict values and expected.

4.5.4 Displacement and Plastic Dissipation Energy Density (PENER)

To find the relation between Plastic Dissipation Energy Density (PENER) and displacement same as before first input data as shown in Table-20. Then convert it to a z-table as shown in Table-21.

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Table-20. Input data in Python.

	PENER	Dis
0	10.300000	29.00
1	9.990000	39.00
2	23.340000	39.90
3	20.750000	46.00
4	9.995000	44.00
5	9.995000	44.50
6	7.298000	19.50
7	6.983000	17.50
8	0.744200	40.93
9	7.271000	30.00
10	0.001282	47.00
11	0.001278	42.00
12	0.120000	36.15
13	0.350325	29.66
14	31.620000	35.20

Table-21. Input data after convert it to z-table.

	PENER	Dis
0	0.114826	-0.791075
1	0.080906	0.335385
2	1.541685	0.436766
3	1.258283	1.123907
4	0.081453	0.898615
5	0.081453	0.954938
6	-0.213657	-1.861212
7	-0.248125	-2.086504
8	-0.930785	0.552791
9	-0.216612	-0.678429
10	-1.012076	1.236553
11	-1.012077	0.673323
12	-0.999086	0.014344
13	-0.973883	-0.716729
14	2.447696	-0.092670

A - Main Equation
Dissipation Energy Density (PENER) = (m_1*Displacement) + b
Dissipation Energy Density (PENER) = 0.0831* Displacement + $1.1e^{-16}$

B - Degree of error (Loss)
loss: 0.8223, val_loss: 0.0011

C - Final score Mean Square Error (MSE) = 0.00164 (0.164%)

D - Final score Root Mean Square Error (RMSE) = 0.0405 (4.05%)

E - The following figure-17 shows two lines one represents predict values and other shows expected value after training model

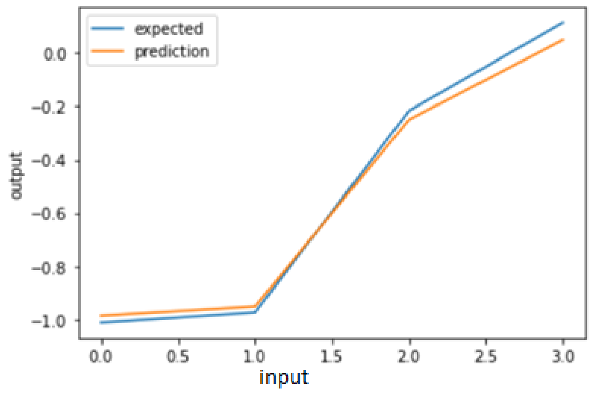

Figure-17. The differences between predict values and expected.

5. CONCLUSION AND FUTURE DIRECTS

5.1 Conclusion and Recommendations

1 - Errors percentage between Experimental test and finite element analysis for displacement and Energy Dissipation capacity did not exceed 10 %, which is accepted in the civil engineering research field (earthquake and structural engineering).

2 - For strengthen method sample DCM- DOUBLE then DCM- SINGLE respectively, they showed good handling for Damage dissipation energy density (DMENER), Magnitude of Plastic Strain (PEMAG) and Plastic Dissipation Energy Density (PENER). However, it gave highest stress values, where that agree with [Azimi, *et al.* 2015] research that the DCM- DOUBLE sample then DCM- SINGLE sample resist effectively to cyclic loading.

3 - For low Scaler Stiffness Degradation (SDEG) value samples (ND-T1, ND-T2) are suitable to achieve that by their strengthen technique but be aware that ND-T2 has the largest displacement with 46 mm.

4 - The control sample shows the lowest sample displacement with 17 mm.

5 - As per the [Ercan, *et al.* 2019] research, Sample 4 exhibits better strength and ductility among samples used in their research, but in this research this sample where poor handling Scaler Stiffness Degradation (SDEG), Magnitude of Plastic Strain (PEMAG), Plastic Dissipation Energy Density (PENER) were reached its' ultimate values.

6 - The [Venkatesan, *et al.* 2016] research mentions that "initial stiffness and energy dissipation for ductile and non-ductile detailed beam-column joints DD-1 and ND-1 showed higher strengths" among samples used in their research these samples detailed in this research in the first category [DD-1, DD-T1, DD-T2, ND-1, ND-T1, ND-T2]. On another hand, in this research non-ductile, ND-1 was good at handling Damage

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dissipation energy density (DMENER) and gave the lowest value for Scaler Stiffness Degradation (SDEG), stress and Magnitude of Plastic Strain (PEMAG) but ductile

DD-1 did not handle these parameters well.

7 - This research agrees with [Venkatesan, *et al*. 2016] research that the ferrocement for retrofitting increased the energy dissipation capacity and is more efficient for reinforced beam-column joints in seismic regions. Besides, the non-ductile reinforced beam-column joint can be vitalized by strengthening using ferrocement laminates but disagree that 'the non-ductile specimen ND-1, compared with the ferrocement-strengthened ND-T1 and ND-T2, showed increased strength, stiffness, and energy dissipation capacity' however, in this research ND-1 reached its' ultimate Magnitude of Plastic Strain (PEMAG) also lowest values in handling Plastic Dissipation Energy Density (PENER) and Scaler Stiffness Degradation (SDEG) that's among three samples so that's why in this research not recommended detailed used over ND-T2 and ND-T1.

8 - Using artificial intelligence (AI) by deep learning can help build an equation bind all parameters with min errors in our case displacement as y-representative collect all parameter together.

9 - after training (AI) model on displacement input data gave lowest score for Mean Square Error (MSE) = 0.00079506 (0.079%) and Root Mean Square Error (RMSE) = 0.028196(2.81%) where did not pass 4% so that accepted in civil engineering, beside (MSE) and (RMSE) low value is prefer than high values close to 1.

10 - The final equation for prediction displacement from deep learning is

Displacement = (-1.68347617*DAMAGEC) + (1.99301209*DMENER) + (0.60372591*SD) - (0.69159869*En) + (0.31516317*stress) - (0.32346632*PEM) – (1.01870836*PENER) + (-3.4433235646925584e-17)

To simplify the equation, we can use the minim value for the damage index which is 0, and the largest is 1.

IF Damage Index = 1 equation will be:

Displacement = -1.68347617 + 1.99301209 +0.60372591- (0.69159869*En) + (0.31516317*stress) – (0.32346632*PEM) - (1.01870836*PENER) + (-3.4433235646925584e-17).

Displacement = 0.913262- (0.69159869*En) + (0.31516317*stress) – (0.32346632*PEM) – (1.01870836*PENER) + (-3.4433235646925584e-17).

IF Damage Index = 0 equation will be:

Displacement = (0.69159869*En) + (0.31516317*stress) - (0.32346632*PEM) – (1.01870836*PENER) + (-3.4433235646925584e-17).

11 - For Ultimate Displacement prediction equation

Ultimate Displacement = -0.00272* Displacement + 1.48309e^{-16}

12 - For Dissipation Energy Density (PENER) prediction equation

Dissipation Energy Density (PENER) = 0.0831* Displacement + 1.1e^{-16}

5.2 For Future Work

For future work hoping to collect more data to build equations with zero errors where deep learning prediction equation deepened on large data input to minimize error so that will help to engineer using an equation to knows the performance of the designed structure and evaluate it. Same for the frame with collecting large data input and using the same method to get proper results also add more unconventional strengthen technique and compare it so engineer options would be more, this research proves that this method is possible to use [take lab data and input data to finite element program analysis then build a model using deep learning] where this research is the first one to do it.

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