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Prediction of Bolt Loosening Using Vibrational Analysis and Machine Learning

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Abstract:
Bolted connections are widely used in almost every structural system due to the added flexibility of assembly and disassembly of sub-systems for inspection, replacement, and routine maintenance. A bolted connection often constitutes the weakest link in the design; in many cases, the bolted connection can be responsible for determining the overall reliability and safety of an entire system. Preloading the bolt in a bolted connection would allow the transfer of various service loads through the clamped connection: either directly or through increased frictional resistance at the interface surfaces of the joint. Bolted joints possess a key advantage over other types of joint types such as riveted and welded joints, they can be dismantled. Although this is an important benefit, it can also cause potential problems if the bolt loosens as a result of operational conditions. Often this loosening occurs as a result of vibrational forces. The major causes of bolt loosening fall into the categories of spontaneous loosening (from vibration, shock, and dynamic loads), and slackening (from creep, settlement, and relaxation).Bolted joints are often designed and installed with proper analysis in advance to ensure they function optimally and for the long term without loosening or failure. Bolt testing and bolt loosening analysis are essential to ensure the reliability of bolted joints and prevent loosening in the field and further the failures.
Keywords: *Bolted Connections, Preload, frictional resistance, slackening, failure*

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I. Introduction:

Connections form an important part of any structure and are designed more conservatively than members. The connections provided in steel structures can be classified as riveted connections, bolted connections and welded connections. Among the three, Bolted joints are critical to the safe operation of many types of equipment in a wide range of applications, including power generation, manufacturing, mining, and transportation, and also in the structure which one subjected to dynamic forces. These bolted connections often suffer issues of accumulated damages due to continuous application of loads and deterioration from age or environmental factors.

Damage detection in overlapped beam components by loosening of bolts is a key step in determining the structure condition.Assessing the state of a structure can be identified by either manual inspection or experimental techniques such as NDT (Acoustic emission, ultrasonic check, and magnetic particle inspection). Which are used to avoid causing destruction or influences to structural operation. Vibration analysis is a process that monitors the levels and patterns of vibration signals within a component, machinery or structure, to detect abnormal vibration events and to evaluate the overall condition of the test object. The data collected from vibration analysis on beam components by loosening of bolts, are introduced in the Machine learning based algorithms for training and testing to predict the accuracy of the model.

Many researchers have done research on bolt-loosening monitoring framework using an image-based deep learning and graphical model**.** Hai Chein Pham et.at investigated a novel idea using synthetic data to train a deep learning model for bolt-loosening detection. Firstly, a bolt-loosening monitoring framework using an image-based deep learning model trained by computer graphics was presented. Secondly, the feasibility of the proposed idea was evaluated via the bolt-loosening monitoring of a lab-scaled bolted connection. Thirdly, for the in-situ applicability, the proposed idea was evaluated on a historical truss bridge in Danang, Vietnam which resulted in the conclusions that Both the laboratory and field tests showed that the deep learning model trained by the synthesized images can provide good bolt recognition and bolt angle estimation. The laboratory test demonstrated the feasibility of the proposed idea of training a deep learning model on graphical data for loosened bolt detection. The estimation error of bolt loosening increased along with the perspective angle; the error was ignorable for small perspective distortions and 1.25° ± 0.8° for the perspective angle of 40°. The number of pixels of the image of a single bolt should not be less than 22.9 K to ensure the accuracy of the bolt angle calculation. The field test results evidenced the practicality of the proposed framework using deep learning and a graphical model for large joint monitoring. The as-of-now bolt angles of the representative bolted joints were estimated with high accuracy. Lastly, the study also opened an alternative strategy to synthesize training databanks with saved times and costs. The graphic model can be easily reconfigured to generate additional high-quality images for a new training task. Besides, the results of this study further demonstrate the use of deep learning models trained on the graphical dataset to work with a real dataset. The presented methodology is promising to be integrated with the devices carrying digital cameras (e.g., drones, robotic cameras, and smartphone cameras) to carry out a vision-based bolt-loosening assessment on real-world structures.

Yang Zhang et.al studied machine vision-based structural health monitoring is gaining popularity due to the rich information one can extract from video and images. However, the extraction of characteristic parameters from images often requires manual intervention, thereby limiting its scalability and effectiveness. In contrast, deep learning overcomes the aforementioned shortcoming in that it can autonomously extract feature parameters (e.g. structural damage) from image datasets. Therefore, this study aims to validate the use of machine vision and deep learning for structural health monitoring by focusing on a particular application of detecting bolt loosening. First, a dataset that contains 300 images was collected. The dataset includes two bolt states, namely, tight and loosened. Second, a faster region-based convolutional neural network was trained and evaluated. The test results showed that the average precision of bolt damage detection is 0.9503. Thereafter, bolts were loosened to various screw heights, and images obtained from different angles, lighting conditions, and vibration conditions were identified separately. The trained model was then employed to validate that bolt loosening could be detected with sufficient accuracy using various types of images. Finally, the trained model was connected with a webcam to realize real time bolt loosening damage monitoring.

Prediction of bolt fastening state using structural vibration signals was carried out by Seong-Pil Jeong and Jung Woo Sohn for predicting the bolt fastening condition using time domain structural vibrational signals. They have made this experimental analysis in two ways, by using laser displacement sensor and piezoelectric film sensor for non-contact type and contact type respectively. After extracting the respective data for both conditions with different states of fastening, Mean Absolute Value of the measured vibration signal was calculated and K-NN classifier was adopted. The classification accuracy was identified based on the k value and distance function. They finally concluded that the classification accuracy was more for non-contact type and difference in classification accuracy can be reduced by using some other features like natural frequencies.

Gyungmin Toh et.al presented a novel method to measure clamping force by using the vibration of bolts. The resonance frequency of the bolt increases in line with the clamping force during the tightening process. These characteristics were measured and utilized in the k-means clustering algorithm. Bolt specimens were fastened to the load cell using a nut runner for verification of the proposed method. The precisely measured clamping force was labelled. The labelled data was used to predict the clamping force from the vibration responses. To use the proposed method in assembly of actual parts, an accelerometer was attached to the nut runner for vibration measurements. This enabled continuous monitoring of the clamping force without influence on the parts. The estimated clamping force was compared with those from the torque method. When the vibration of a bolt was transmitted through the nut runner, loss of high-frequency vibration energy occurred. The resonant frequency band vibrations of the bolt were preserved to determine the fastening force. The components in the low frequency band were excluded using a band-pass filter. The clamping force of the bolt used in the vehicle's lower arm and the link was also evaluated precisely. By using the proposed method, it is possible to continuously monitor variations of the clamping force during the manufacturing process.

II. Numerical study

2.1 Geometry:

A cantilever beam made up of two steel flats of the same size connected by a 4 bolted lap joint is considered for the present study.A beam is fixed at one sideto make it rigid and the other beam is connected to the fixed beam by using four bolts of size 5 mm. The beam is designed in ANSYS software and the bolts are tightened by applying pretension in static structural.

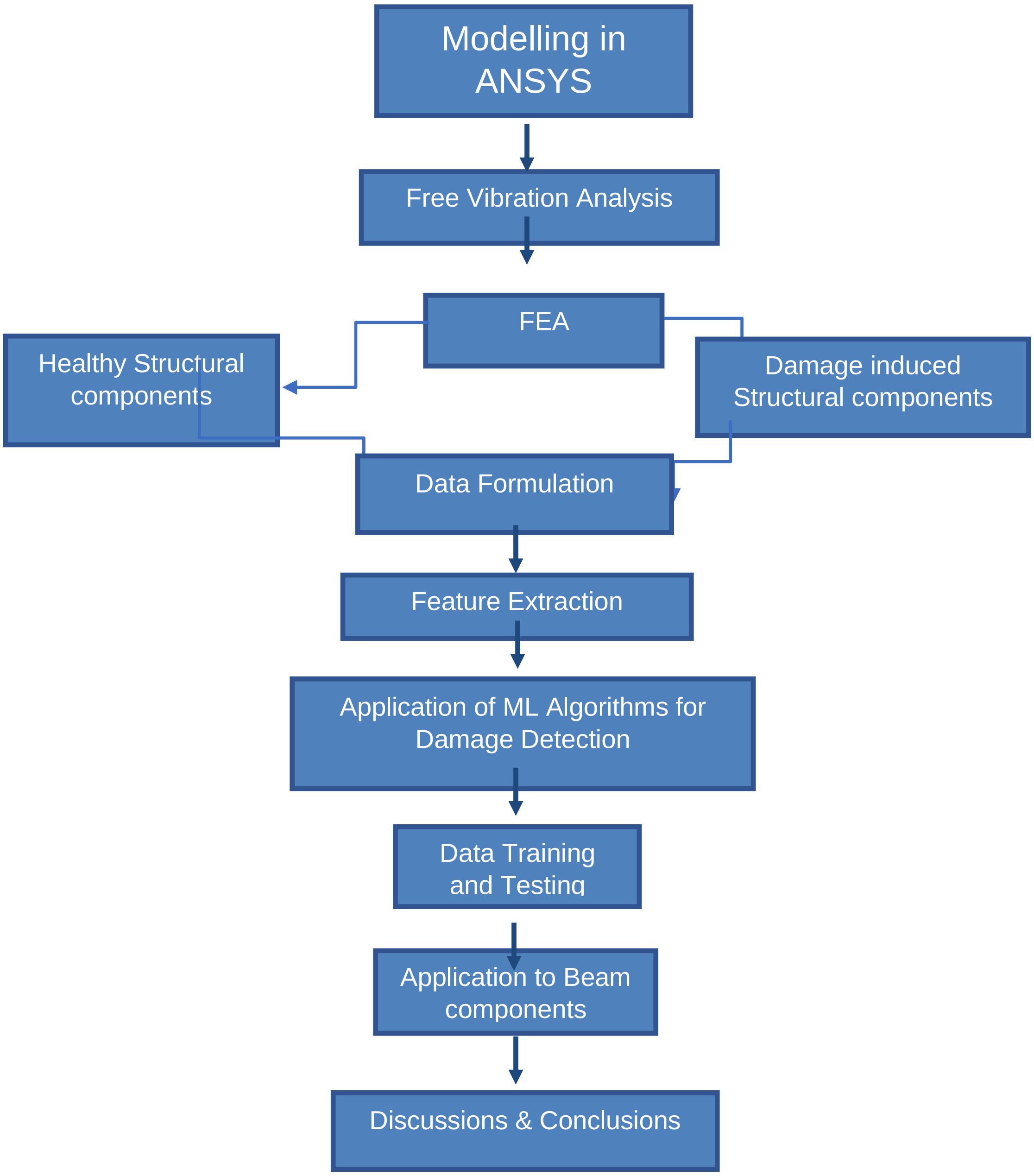
2.2 Connections:

Two steel flats of cross section 50mm X 2mm of lengths 150mm and 250mm are lap jointed using four bolts. Lap joint with an overlap of 50mm is made. The bolts are of 5mm diameter and of M5 8.8 grade.4 bolts are used in 2 rows with a pitch of 12.5 MM and a gauge of 7.5 mm.

2.3 Modelling and analysing using ANSYS:

The geometry of the bolts was modelled in ANSYS spaceclaim model, then the contact surfaces were given to plates, bolt head, shank, nut and washer with a friction coefficient of 0.2. Meshing is done with tetrahedral elements with 0.2 mm size . To make the bolts fully tighten a preload of 9 N is given for each bolt in static structure by splicing the shank at the nut. Then the developed model was imported to the modal analysis frame for extraction the natural frequencies from the initial modes.

2.4 Methodology:



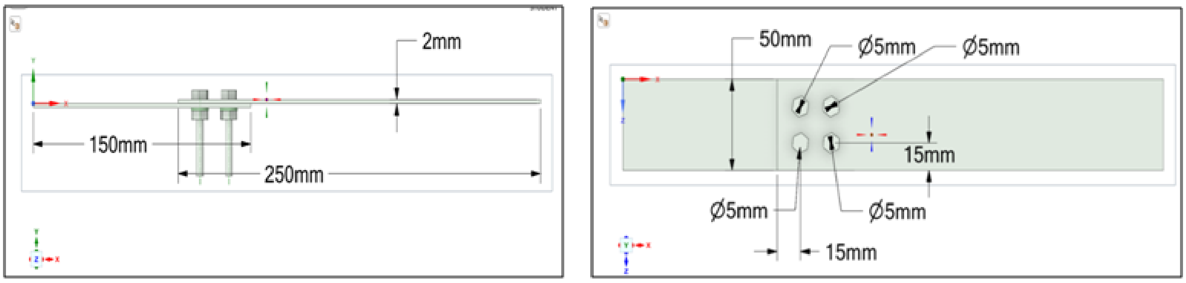


Figure 1: Geometry of the Beam

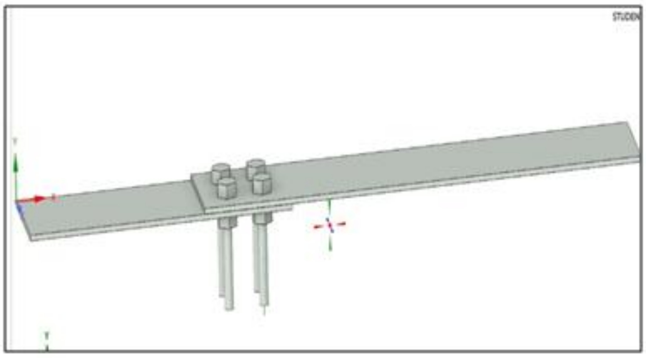


Figure 2: Geometry of the Beam modelled in ANSYS

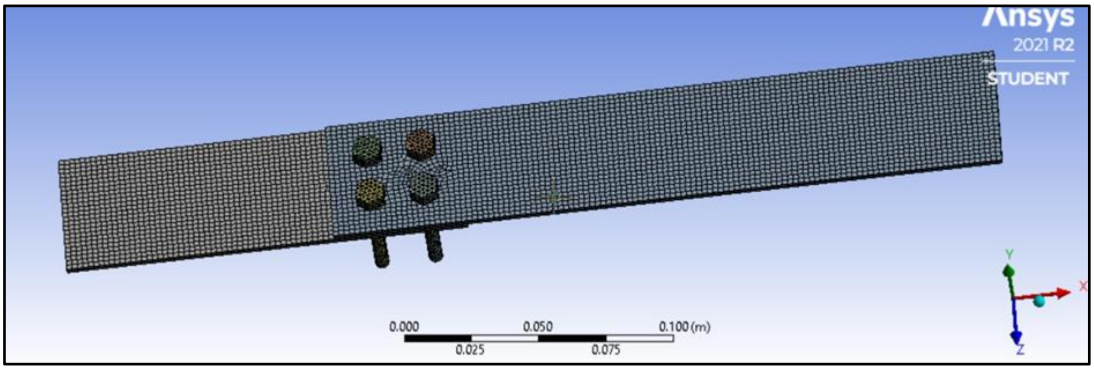


Figure 3: Discretized Model

2.5 Bolt preload:

In real world bolts are tightened by applying torque, where tightening of the bolt reduces its grip length and produces tensile preload. Giving threading, applying torque and rotating the nut in Ansys is computationally difficult and doesn't add any accuracy to the results. Instead, the shortening of the grip-length (which induces tensile preload) will result in simulations by slicing the bolt into two parts and applying calculated preload to both ends. It will make the bolt tighten and hold the two flats firmly. Insufficient bolt preload may cause the bolts to become loose, leading to failure of the machine assembly or separation end lateral moment of the mating parts. Since tightening of bolts produces tensile loads in the bolt, the bolt preload is also known as bolt pretension. The loosening condition of the bolt will be achieved by decreasing the bolt pretension. Bolt preload will be applied in static structure in Ansys workbench.

2.6 Free Vibration Analysis:

Modal analysis is performed and first 10 modes are extracted.Starting few modes (mostly 1-3) will contain the maximum weightage. The reaction of a structure is not equally influenced by all vibrational modes. Therefore, only those modalities with a greater participation factor are often taken into account. This presumption really aids in the problem's simplification. The remaining modes do not have higher participation factor but for getting more values, for more accuracy the first 10 modes natural frequency were taken.

For achieving the bolt loosening condition the pretension in the bolt was decreased by certain quantity. Here we considered 4 cases of bolt condition: Fully tighten (FT), Quarter turn (QT), Half turn (HT), Full loosen

(FL). These conditions are applied for the bolts in different ways like 1 bolt QT 3 bolts FT, 2 bolts FT 2 bolts QT, 3 bolts QT 1 bolt FT and so on… . Getting more data will be helpful for predicting more accurately.

2.7 Bolt pretension:

Table 1: Pretensions

BOLT STATE	PRETENSION (N-m)
FF - Fully Fastened	9
QT – Quarter Turn	6
HT – Half Turn	3
FT – Full Turn	-3

Table 2: Natural frequencies of first 10 modes for different bolt loosening conditions

mode	Fully tighten	3,4 QT	1,2,3,4 QT	1,2,3,4 HT	Fully loosen	1,2 QT 3,4 FT	1,2 FT 3,4 HT	3,4 FT 1,2 HT	1,2 FT 3,4 FL	1,2FL, 3,4 FT	1,2QT 3,4HT
1	13.46	13.454	13.45	13.446	13.441	13.453	13.443	13.447	13.437	13.448	13.441
2	71.053	71.013	70.996	70.973	70.94	71.008	70.953	70.985	70.915	70.991	70.942
3	174.31	174.28	174.2	174.03	173.86	174.2	173.93	174.15	173.64	174.19	173.85
4	209.66	209.47	209.36	209.22	209.05	209.43	209.12	209.26	208.94	209.3	209.07
5	308.32	308.15	308.1	307.94	307.85	307.85	307.5	307.67	306.67	307.86	307.06
6	419.72	419.74	419.66	419.5	419.44	419.63	419.41	419.58	419.29	419.59	419.39
7	425.22	425.03	424.94	424.8	424.64	425.02	424.73	424.9	424.61	424.91	424.71
8	711.01	710.53	710.46	710.31	710.09	710.5	710.03	710.46	709.7	710.49	709.94
9	935.92	935.99	935.71	935.58	935.66	935.52	935.29	935.47	934.96	935.5	935.18
10	1040.4	1037.5	1035.5	1032.6	1028.4	1037	1031.2	1034	1027.8	1034.3	1030.8

2.8Stiffness of the beam:

The natural frequency of a system/structure can be approximated by the basic formula Where, 'K' is the restoring force (Restoring Moment in case of rotational motion) and M is the mass of the moving system (for rotational motion we have to replace 'M' by 'I' the moment of inertia). Depending up on the system variants of formula can be arrived at. Here we are keeping the mass constant, and due to loosening of bolts the stiffness and frequencies will change. So frequencies and mass values are known values, by using them the unknown stiffness values are determined.

Natural frequency, $f = \frac{1}{2\pi}\sqrt{\frac{K}{M}}$

This Stiffness was used as target values for the ANN tool

2.9 Mass of beam:

Mass of the beam = volume of the beam * density of the beam
= (0.25*0.05*0.002) + (0.15*0.05*0.002)*7850
= 0.314 kg

Table 3: Stiffness for different bolt loosen states

mode	Fully tighten	3,4 QT	1,2,3,4 QT	1,2,3,4 HT	Fully loosen	1,2 QT 3,4 FT	1,2 FT 3,4 HT	3,4 FT 1,2 HT	1,2 FT 3,4 FL	1,2FL, 3,4 FT	1,2QT 3,4HT
1	2243.56 7061	2241.56 7299	2240.23 462	2238.90 2336	2237.23 7539	2241.23 409					
2	62519.2 5215	62448.8 8029	62418.9 8424	62378.5 4805	62320.5 5378	62440.0 866	62343.3 9679	19575.8 2659	62276.6 3669	62410.1 9265	62324.0 6782
3	376264. 7565	376135. 252	375790. 0154	375056. 914	374324. 5284	375790. 015	374626. 0123	117632. 5679	373377. 7978	375746. 872	374281. 4692
4	544352. 3454	543366. 1765	542795. 6453	542069. 9481	541189. 397	543158. 676	541551. 8902	170047. 2935	540620. 0101	542484. 5728	541292. 9541
5	1177205 .629	1175907 .823	1175526 .252	1174305 .639	1173619 .323	117361 9.32	1170952 .224	367678. 9983	1164639 .517	1173695 .571	1167603 .604

6	2181565.535	2181773.447	2180941.86	2179279.16	2178655.812	2180630.06	2178344.171	684000.0696	2177097.83	2180214.351	2178136.422
7	2239114.497	2237113.948	2236166.632	2234693.428	2233010.36	2237008.68	2233957.007	701462.5003	2232694.855	2235850.905	2233746.624
8	6260375.07	6251925.215	6250693.422	6248054.272	6244184.528	6251397.29	6243129.351	1960342.616	6237327.473	6251221.318	6241546.753
9	10847418.39	10849041.07	10842551.09	10839538.55	10841392.37	10838148.3	10832819.76	3401505.406	10825176.79	10837684.88	10830271.81
10	13404469.24	13329846.44	13278503.79	13204232.93	13097037.51	13317001.5	13168452.58	4134894.111	13081759.55	13247745.76	13158238.54

III. Artificial Neural Networks (ANN):

Artificial neural networks' major goal is to function similarly to the human brain. Artificial neurons are also interconnected to create neural networks, just like biological neurons are. The component of a computing system called an ANN is intended to stimulate how the human brain processes and analyses information. The benefit of ANN is that it does not need a mathematical equation to learn. Actually, all that is needed are the input and output data. Based on this information, ANN learns and comprehends the relationship between the input and output data through the training process. Without understanding the mathematical equation, the ANN can deliver the expected output for any input variable after the training is successfully finished. As a result, the data for ANN is required at the beginning. It is the main prerequisite for 27 implementing ANNs. Data can be gathered by running simulations and experiments in any software.

Layers of neurons make up neural networks; these neurons serve as the network's central processing nodes. The network has three layers: the input layer, which accepts input, the output layer, which predicts output, and the hidden layers, which carry out the majority of the network's computations. Channels link the neurons of one layer to the neurons of the subsequent layer. The inputs are multiplied by corresponding weights for each of these channels, and their sum is then supplied as input to the neurons in the hidden layer. Each of these channels is given a numerical value known as a weight. Each of these neurons has a bias value attached with it, which is added to the input sum and then sent via an activation function, which is a threshold function. The outcome of the activation function decides whether or not a certain neuron will be stimulated. Forward propagation is the process by which data travels across the network from an active neuron to the neurons in the next layer over the channels. 28 The neuron with the greatest value in the output layer determines the output. The values essentially represent a likelihood.

3.1 ANN using MATLAB:

Input:

10x15 double

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	13.4600	13.4540	13.4500	13.4460	13.4410	13.4530	13.4430	13.4470	13.4370	13.4480	13.4410	13.4380	13.4440	13.4400	13.4400
2	71.0530	71.0130	70.9960	70.9730	70.9400	71.0080	70.9530	70.9850	70.9150	70.9910	70.9420	70.9220	70.9660	70.9320	70.9370
3	174.3100	174.2800	174.2000	174.0300	173.8600	174.2000	173.9300	174.1500	173.6400	174.1900	173.8500	173.6900	174.0800	173.7700	173.8200
4	209.6600	209.4700	209.3600	209.2200	209.0500	209.4300	209.1200	209.2600	208.9400	209.3000	209.0700	208.9700	209.1500	209.0200	209.0600
5	308.3200	308.1500	308.1000	307.9400	307.8500	307.8500	307.5000	307.6700	306.6700	307.8600	307.0600	307.0300	307.6100	307.4500	306.9200
6	419.7200	419.7400	419.6600	419.5000	419.4400	419.6300	419.4100	419.5800	419.2900	419.5900	419.3900	419.3000	419.5500	419.3100	419.3600
7	425.2200	425.0300	424.9400	424.8000	424.6400	425.0200	424.7300	424.9000	424.6100	424.9100	424.7100	424.6200	424.7900	424.6300	424.6900
8	711.0100	710.5300	710.4600	710.3100	710.0900	710.5000	710.0300	710.4600	709.7000	710.4900	709.9400	709.7700	710.3200	709.8600	709.8000
9	935.9200	935.9900	935.7100	935.5800	935.6600	935.5200	935.2900	935.4700	934.9600	935.5000	935.1800	935.0700	935.3900	935.1400	935.0100
10	1.0404e+03	1.0375e+03	1.0355e+03	1.0326e+03	1.0284e+03	1037	1.0312e+03	1034	1.0278e+03	1.0343e+03	1.0308e+03	1028	1.0318e+03	1.0283e+03	1.0306e+03

Fig 4: Natural frequencies from ANSYS taken as an input

Target:

10x15 double

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	2.2436e+03	2.2416e+03	2.2402e+03	2.2389e+03	2.2372e+03	2.2412e+03	2.2379e+03	702.7017	2.2359e+03	2.2396e+03	2.2372e+03	2.2362e+03	2.2382e+03	2.2369e+03	2.2369e+03
2	6.2519e+04	6.2449e+04	6.2419e+04	6.2379e+04	6.2321e+04	6.2440e+04	6.2343e+04	1.9576e+04	6.2277e+04	6.2410e+04	6.2324e+04	6.2289e+04	6.2366e+04	6.2306e+04	6.2315e+04
3	3.7626e+05	3.7614e+05	3.7579e+05	3.7506e+05	3.7432e+05	3.7579e+05	3.7463e+05	1.1763e+05	3.7338e+05	3.7575e+05	3.7428e+05	3.7359e+05	3.7527e+05	3.7394e+05	3.7415e+05
4	5.4435e+05	5.4337e+05	5.4280e+05	5.4207e+05	5.4119e+05	5.4316e+05	5.4155e+05	1.7005e+05	5.4062e+05	5.4248e+05	5.4129e+05	5.4078e+05	5.4171e+05	5.4103e+05	5.4124e+05
5	1.1772e+06	1.1759e+06	1.1755e+06	1.1743e+06	1.1736e+06	1.1736e+06	1.1710e+06	3.6768e+05	1.1646e+06	1.1737e+06	1.1676e+06	1.1674e+06	1.1718e+06	1.1706e+06	1.1665e+06
6	2.1816e+06	2.1818e+06	2.1809e+06	2.1793e+06	2.1787e+06	2.1806e+06	2.1783e+06	6.8400e+05	2.1771e+06	2.1802e+06	2.1781e+06	2.1772e+06	2.1798e+06	2.1773e+06	2.1778e+06
7	2.2391e+06	2.2371e+06	2.2362e+06	2.2347e+06	2.2330e+06	2.2370e+06	2.2340e+06	7.0146e+05	2.2327e+06	2.2359e+06	2.2337e+06	2.2328e+06	2.2346e+06	2.2329e+06	2.2335e+06
8	6.2604e+06	6.2519e+06	6.2507e+06	6.2481e+06	6.2442e+06	6.2514e+06	6.2431e+06	1.9603e+06	6.2373e+06	6.2512e+06	6.2415e+06	6.2386e+06	6.2482e+06	6.2401e+06	6.2391e+06
9	1.0847e+07	1.0849e+07	1.0843e+07	1.0840e+07	1.0841e+07	1.0838e+07	1.0833e+07	3.4015e+06	1.0825e+07	1.0838e+07	1.0830e+07	1.0828e+07	1.0835e+07	1.0829e+07	1.0826e+07
10	1.3404e+07	1.3330e+07	1.3279e+07	1.3204e+07	1.3097e+07	1.3317e+07	1.3168e+07	4.1349e+06	1.3082e+07	1.3248e+07	1.3158e+07	1.3087e+07	1.3184e+07	1.3094e+07	1.3153e+07

Fig 5: Stiffness were taken as target values

Table 4: Actual and predicted stiffness values

Bolt state	**Actual Values**	**Predicted Values**
Fully tighten	2243.567061	2244.6565
3,4 QT	2241.567	2242.223
1,2,3,4 QT	2240.23	2239.46
1,2,3,4 HT	2238.902	2239.487
Fully loosen	2237.237539	2243.217
1,2 QT	2241.23	2239.49
1,2 FT 3,4 HT	2237.903383	2243.217
3,4 QT 1,2 HT	2244.7676	2243.217
1,2 FT 3,4 FL	2235.90615	2243.2169
1,2 FL 3,4 FT	2239.56843	2239.5368
1,2 QT 3,4 HT	2237.237539	2243.217
1,2 QT 3,4 FL	2236.23896	2243.217
1,2 HT 3,4 QT	2238.236342	2243.217
1,2 HT 3,4 FL	2236.904653	2243.217
1 FT 2 QT 3 HT 4 FL	2236.904653	2243.217

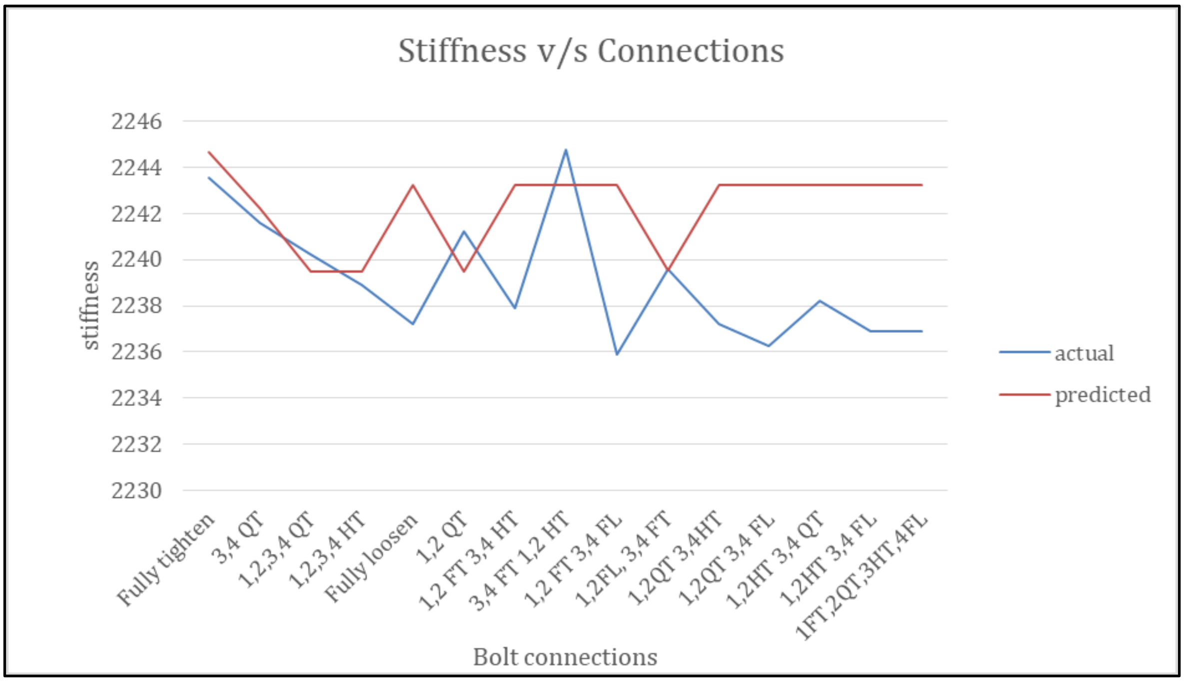


Fig 6:Stiffness vs Bolt connections

IV. Conclusions

- Since tightening of bolts produces tensile loads in the bolt, the bolt preload also known as bolt pretension is used to simulate various loosening conditions. The loosening condition of bolt is achieved by decreasing the bolt pretension.
- The bolt loosening situations for various preload conditions were studied by simulating various loosening conditions in finite element simulation tool ANSYS.
- It is observed that there is change in the stiffness of the lapped member as the bolts are loosened and hence there is change in the natural frequencies.
- The modal frequencies are decreased maximum for the case of fully loosened when compared to the fully tightened state.
- The present study proved that changes in the bolt loosening will affect the modal parameters like modal frequencies and mode shapes of the structural assembly.
- An ANN (Artificial Neural Networks) algorithm is proposed for predicting the changes in the stiffness in order to identify the bolt loosening.
- The application of ANN algorithm proved to be 96% efficient in predicting the damage case.
- Further studies can be done on the parameters affecting the stiffness changes in the connected beams.
- Other Machine learning algorithms can also be studied for the prediction of bolt loosening

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