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Identification of Damage in Offshore Jacket Structure by Utilizing Artificial Neural Networks

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Abstract:- Over the past few years with industrialization has necessitated humans to consider offshore resources of natural gas and oil. Fixed offshore jacket structures constitute an important part of offshore rigs. These structures are prone to damage due to their long term exposure to the saline environment which causes corrosion. Hence the health of these structures have to be overseen periodically to comprehend the extent of damage which in turn helps to decide a suitable course of action for the maintenance of the structure. Recently a lot of study had been carried out on the use of Artificial Neural Networks (ANN) in monitoring the health of a structure. ANN are a branch of machine learning and works by imitating the human brain. For this study, an offshore jacket was modelled in a finite element based software in order to create the training set. Damage was represented in the structure by two different methods separately. First method was by representing the damage through reduction of the area of cross section of the main tubes and second method was by using the reduction in elastic modulus to represent the damage. Three different neural networks were prepared for each method of damage representation with different input parameter cases namely modal frequency, modal frequency and eight nodal displacements, modal frequency and twelve nodal displacements. The optimum number of neurons in the hidden layer was obtained for the respective case. Each network was tested using a test set and output of the networks were compared with the true value of the damage. The results of the two methods of damage representation were compared.

Keywords: *Artificial Neural Networks; Damage; Elastic Modulus; Modal Frequency; Offshore Jacket; Structural Health Monitoring.*

I. INTRODUCTION

Over the past few decades with increasing industrialization has led humans to look for offshore resources of oil and natural gas to meet the ever increasing demand for fuel. In order to explore the offshore resources the drilling platforms were constructed. Fixed jacket structure are an important component of the offshore platforms [8]. Since they are always exposed to the harsh marine environment they are prone to damage due to corrosion and can experience fatigue [1]. Apart from that the jacket structure may also experience damage due to natural calamities such as cyclones and earthquakes. For carrying out the operations smoothly offshore jacket structures have to be maintained from time to time. For this purpose the structure have to be monitored for their health to determine the extent of damage and the necessary repair measures if required. In this past this was done through visual inspection with the aid from divers. This methods however has its shortcomings. There is a lack of trained professionals to carry out the job. The bad weather can hamper inspection work. Apart from this marine organism growth, low visibility and some hazardous condition also make the task difficult. To overcome these problems newer methods for structural health monitoring have been suggested.

The dawn of machine learning has opened new avenues to ease cumbersome tasks in various fields including those of engineering. Research has been done on the application of Artificial Neural Networks (ANN), which is a branch of machine learning, for various civil engineering related tasks. As the name suggests ANN are inspired by the nervous system of living organisms [2]. They consist of layers of neurons (nodes) with each layer containing one or multiple nodes. The first layer is titled as input layer which is followed by the hidden layer and output layer. ANNs can be used to establish the nonlinear relationship between input parameters and the desired output.

An offshore jacket structure is a space frame consisting of steel tubes. Tubes are preferred as they are more resistant to the wave forces [6]. Studies have shown that the damage in a structure effects the natural frequencies of the structure. This change in frequency hence can be used to monitor the health of the structure. The following paper proposes the use of natural frequency and nodal displacements as parameters to determine the percentage of damage in an offshore jacket structure. The training samples are obtained using finite element analysis of a jacket structure model. The damage is represented by two methods one is by change in the cross sectional area of the structural member and other is by reducing the elastic modulus of the structure.

II. LITERATURE REVIEW

J. T. Kim and N. Stubbs- Damage detection in offshore jacket structure from limited modal information: [1] In this paper an algorithm for the location and estimation of the damage in a jacket structure in case few post damage modal parameters are available was presented and a theory using changes in mode shape was formulated for the same. Using a numerical example the feasibility of the algorithm was demonstrated.

S. A Mourad, A. W. Sadek and A. F. Batisha- Structural health monitoring of offshore structure: [2] in this paper the authors proposed two neural networks for determining the integrity of a fixed jacket offshore platform. In the first network structural integrity is determined with the natural frequencies which are monitored. The second network accounts for deck drift which represents the structural response due to environmental loading. A finite element software was used to generate the training samples.

Ch Efstathiades, C.C. Baniotopoulo, P. Nazaro, L. Ziemiansk and G.E. Stavroulakis - Application of neural networks for structural health monitoring in curtain wall systems:[3] The use of artificial neural network for structural health monitoring of curtain walls by identifying the imperfections present was proposed in this paper. Finite element model was created to generate the training samples. Failure in such structure which usually occurs due damage of the connection with the bearing is represented by loss of rigidity in the connection and the column deflection is noted. It was concluded that ANN can be used efficiently used to identify and locate the damage in curtain walls.

Y. Lee, S. Lee and H. K. Bae -Design of jetty piles using artificial neural networks: [4] In this paper the use of artificial neural network was proposed to overcome the difficulties that arose during the design of jetty piles due to the interaction of the design parameters. To obtain the training sample for the ANN finite element analysis was carried out for different design cases. The training algorithm was optimised by using the Levenberg–Marquardt method of back propagation.

N. Gulgec, M Takac and S. Pakzad - Structural damage detection using convolutional neural networks: [5] In this paper the authors proposed the use of CNN (Convolution Neural Network) for identification of damage in structures. The CNN was used to classify the cases modelled using finite element program as damaged and healthy. The strain distribution for different cracking and loading scenarios were considered. The accuracy of the CNN was assessed using a cracked steel gusset connection model.

J. Guo, J. Wu, J. Guo and Z. Jiang - A damage identification approach for offshore jacket platforms using partial modal results and artificial neural networks: [7] This paper presented the use of artificial neural networks for the damage identification in offshore jacket platform. Combination of six modal results and natural frequency were proposed as the indices for damage identification. Training samples were generated using a finite element model and the damage in the structure was represented by reducing the structural elastic model. It was found that the prediction error was larger in case the damaged members were located deeper.

➢ *Model*

A four storey offshore jacket structure is modelled in a finite element software. Each storey is 10 m high with total height of the jacket structure being 40m.[9] It consists of four main steel tubes of cross section φ 1200 × 50 mm connected horizontally by pipe members and diagonally using braces of dimensions φ 780 × 40 mm and φ 510 × 40 mm respectively. Beam element with six degrees of freedom are used to represent each member. The material properties of the steel are listed in table I. The four corners at the base of the structure are assumed to be fixed. Twelve nodes are selected as shown in the fig.1 [9].

Table 1 Material Properties of Steel

Material	Properties of Material		
	Elastic modulus E	***Density ρ***	***Poisson's Ratio μ***
Steel	2×10^{11} Pa	7850 kg/m3	0.3

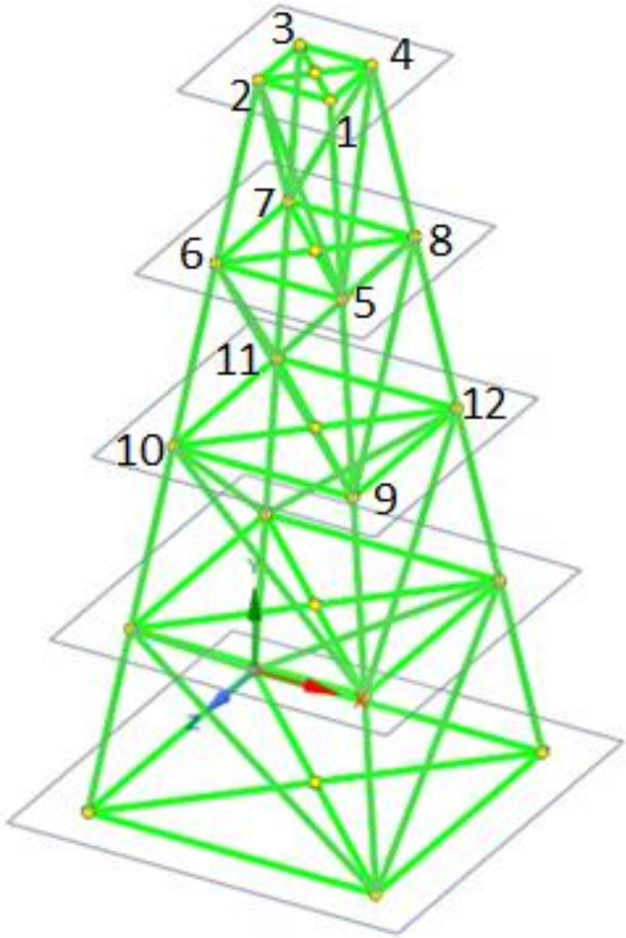

Fig 1 Offshore Jacket Model with Nodes

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III. METHODOLOGY

➢ *Modelling and Data Collection:*

For training the neural network first the data sets for training the network have to be obtained. This is done with the help of a finite element analysis software. The offshore jacket structure is modelled in the software according to the specification listed in the previous section. Modal analysis is carried out for the undamaged structure by considering six modes. The modal frequencies and the displacement at the twelve nodes are noted.

For the first method damage is represented by reducing the cross sectional area of the main tubes by different percentages namely 10%, 15%, 20%, 25%, 30%, 35%, 40%, 45% and 50%. The cross sectional area of the selected members are reduced and modal analysis of the structure is executed. The resulting modal frequencies and nodal displacements in x, y and z-direction are noted for each damage case.

For the second method damage is induced by reducing the elastic modulus of the selected main tubes. The elastic modulus is reduced by 10%, 15%, 20%, 25%, 30%, 35%, 40%, 45% and 50% to represent different damage conditions. Modal analysis is carried out for each damage condition and the respective modal frequencies and the displacement at the nodes in x, y and z-direction is noted.

The modal parameters serve as indices to measure damage. Guo J[6] proposed the following equation to reduce and simplify the damage indices for the ANN.

$$\Delta\varnothing_i = \sum_{j=1}^{\beta} \Delta\varphi x_i^j + \sum_{j=1}^{\beta} \Delta\varphi y_i^j + \sum_{j=1}^{\beta} \Delta\varphi z_i^j$$

Source: Guo J et al

Fig 2 Equation to Simplify the Damage Indices

In the (1) $\Delta\varnothing$ represents the damage index. i represents the mode. $\Delta\varphi x$, $\Delta\varphi y$, $\Delta\varphi z$ represents the modal difference between the damaged and undamaged structure in the x, y and z directions respectively.[6] β represents the order of modal results. The above equation is used to reduce the nodal displacement at each of the selected node points.

➢ *Training the Neural Network:*

For each method of damage representation neural networks with the following cases of input parameters were created:

- ANN to identify damage from modal frequencies
- ANN to identify damage from modal frequencies and 8 nodal displacements
- ANN to identify damage from modal frequencies and 12 nodal displacements

Hence a total of six ANNs were trained.

A neural network was created for each case, in a software for identifying the percentage of damage consisting of an input layer, a single hidden layer and a single output which gives the percentage of damage. The number of input neurons for each case of input parameters varies. For the ANN using only modal frequencies for identification six input neurons were required. In case of the ANN identifying damage from modal frequencies and 8 nodal displacements fourteen input neurons were required while 18 input neurons were required for the ANN identifying damage from modal frequencies and 12 nodal displacements.

The training data for each ANN consisted of 2000 data sets which were divided into training set, validation set and test set. Initially the number hidden neurons was set to 1 and the network was trained using the training set. During the training the software adjusts the weights during the back propagation process which uses the Lavenberg-Marquardt algorithm, such that there was minimum error. The root mean square error (RMSE) between the output of the network and the known damage is calculated and noted as the training RMSE value. The validation set was used to further optimize the network and the RMSE value obtained was noted as the validation set RMSE value. Similarly the network was trained and optimized while varying the number of nodes in hidden layer from 1 to 30. The RMSE values of the training set and validation set for each instance of number of hidden layer neurons were noted. A plot of variation of RMSE values of training sets and validation sets over the number of neurons in the hidden layer was drafted. The optimum number of neurons in the hidden layer was obtained such that the errors were minimum.

The process of training was carried out for each case and respective value of optimum number of hidden neurons were obtained.

The number neurons in the hidden layer was then set to the optimum number for the respective networks. Each ANN was again trained and tested using the test set and the obtained values of the output were noted separately. A graph was plotted between the obtained output and the target output for each network. The results of the two methods of damage representation were compared.

IV. OBSERVATION AND RESULTS

➢ *Damage represented by Change in Area of Cross section:*

- *Case 1-Damage Identification using Modal Frequencies:*

Fig. 3, shows the plot of training RMSE and the validation RMSE for various number of neurons in the hidden layer. The x-axis represents number of neurons and the y-axis represents RMSE value. The optimum number of neurons is observed to be 20 for this case. Hence the number of neurons in the hidden layer in the network is specified as 20. The RMSE value of the training set was found to be 0.6310 while the validation RMSE was found to be 1.657. The network was tested and the plot of target output and obtained output is plotted as shown in fig. 4.

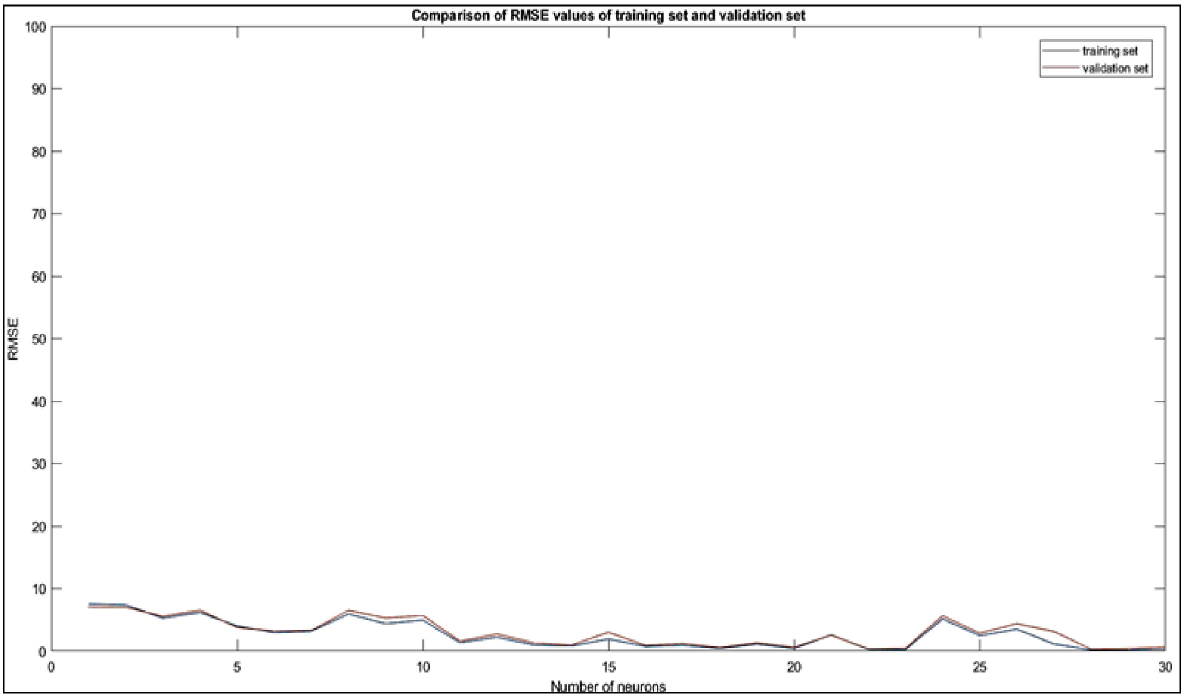

Fig 3 Evaluation of Varying Hidden Layer Neurons for 2000 Data Sets

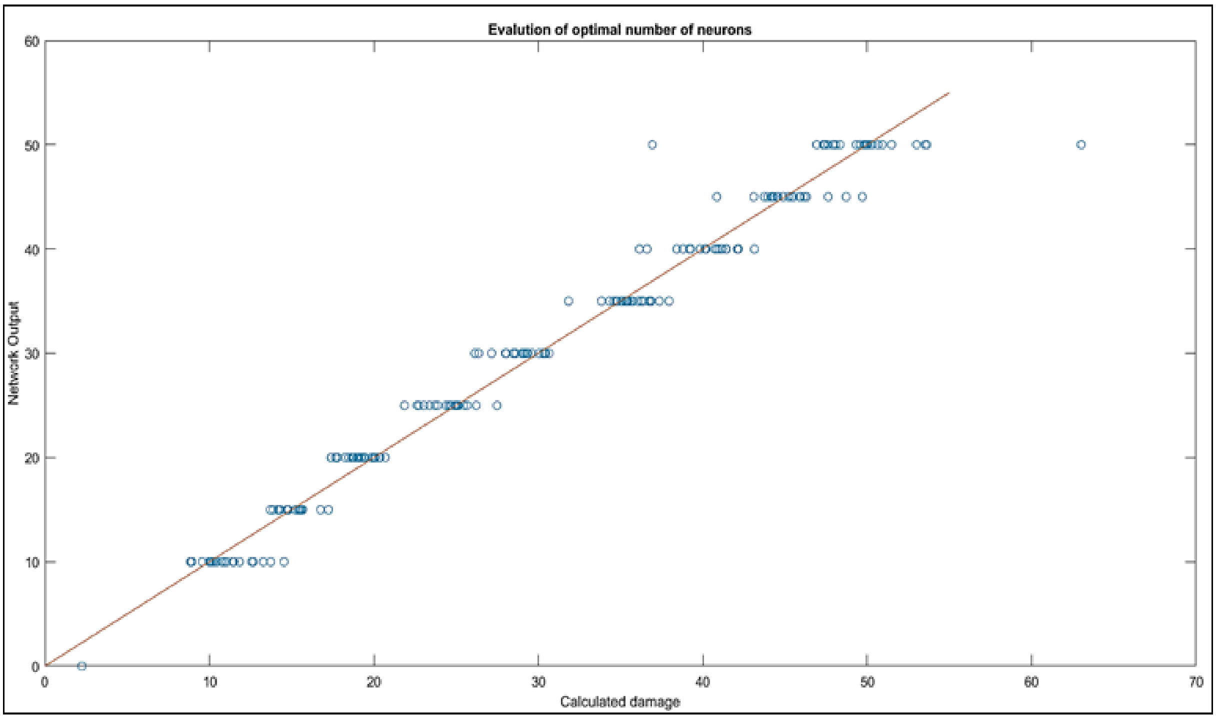

Fig 4 Assessment of Optimum Number of Hidden Neurons for 2000 Data Sets

- *Case 2-Damage Identification using Modal Frequencies and Displacement at 8 Nodes:*

Fig. 5, shows the training set RMSE and RMSE of the validation for different number of neurons when modal frequencies and 8 nodal parameters are used as input parameters. The y-axis represents RMSE value and the x-axis represents number of hidden neurons. The optimum number of neurons is found to be 16 for this case. Hence the number of neurons in the hidden layer in the network is fixed as 16. The training set RMSE was 0.4030 and that of the validation set was 0.7900. The network was tested and the plot of target output and obtained output is plotted as shown in fig. 6. It is observed that as compared to the case where only natural frequency is used as a parameter the case using nodal displacement aid in identifying the percentage to a better extent.

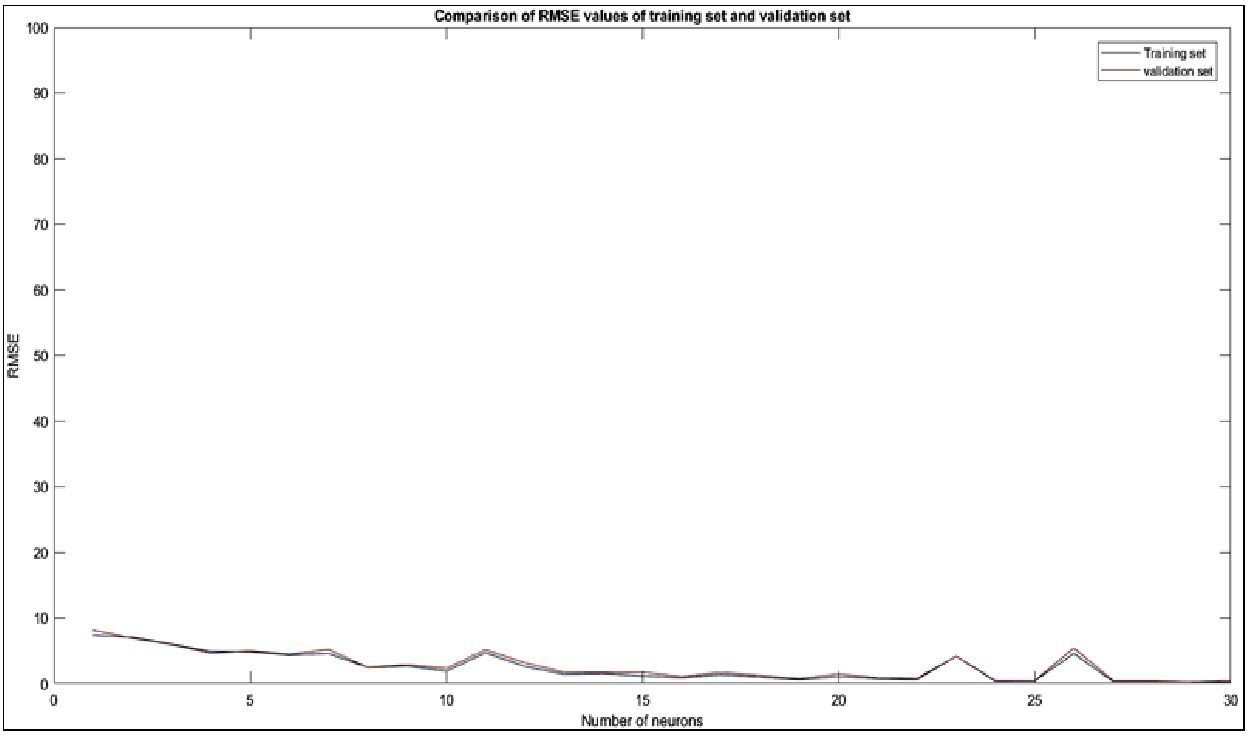

Fig 5 Evaluation of Varying Hidden Layer Neurons for ANN using Modal Frequencies and 8 Nodal Displacements

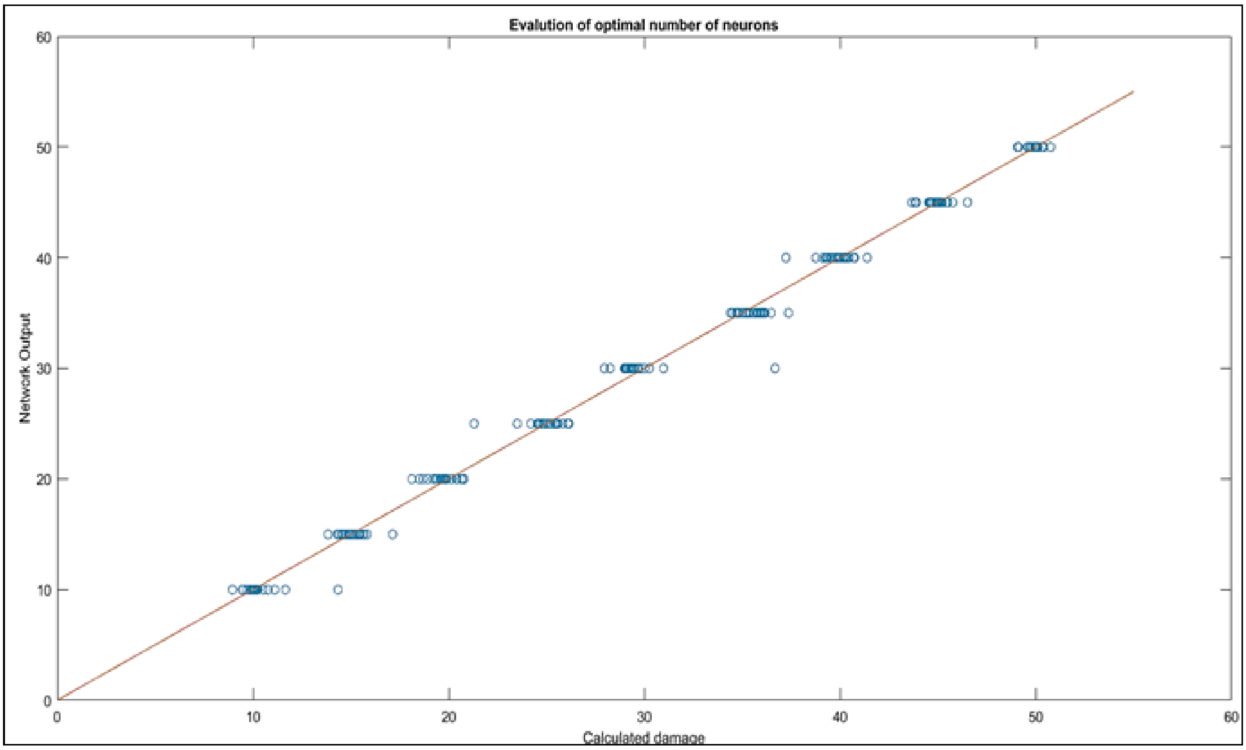

Fig 6 Assessment of Optimum number of Hidden Neurons for ANN using Modal Frequencies and 8 Nodal Displacements

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- *Case 3-Damage Identification using Modal Frequencies and Displacement at 12 Nodes:*

Fig 7, shows the RMSE of training set and RMSE of the validation set for different number of neurons in the case where input parameters were modal frequencies and 12 nodal displacements. The x-axis represented number of neurons and the y-axis represented RMSE value. The optimum number of hidden neurons is found to be 27 for this case. Hence the number of neurons in the hidden layer in the network is adjusted as 27. The training set RMSE was 0.5038 and that of the validation set was 0.4213. The network was tested and the target output is plotted against the obtained output as shown in fig. 8. It is observed that the use of 12 nodal displacement aid in identifying the percentage to a much better extent as compared to the case where only natural frequency is used as a parameter and the case where modal frequencies and 8 nodal displacements are used.

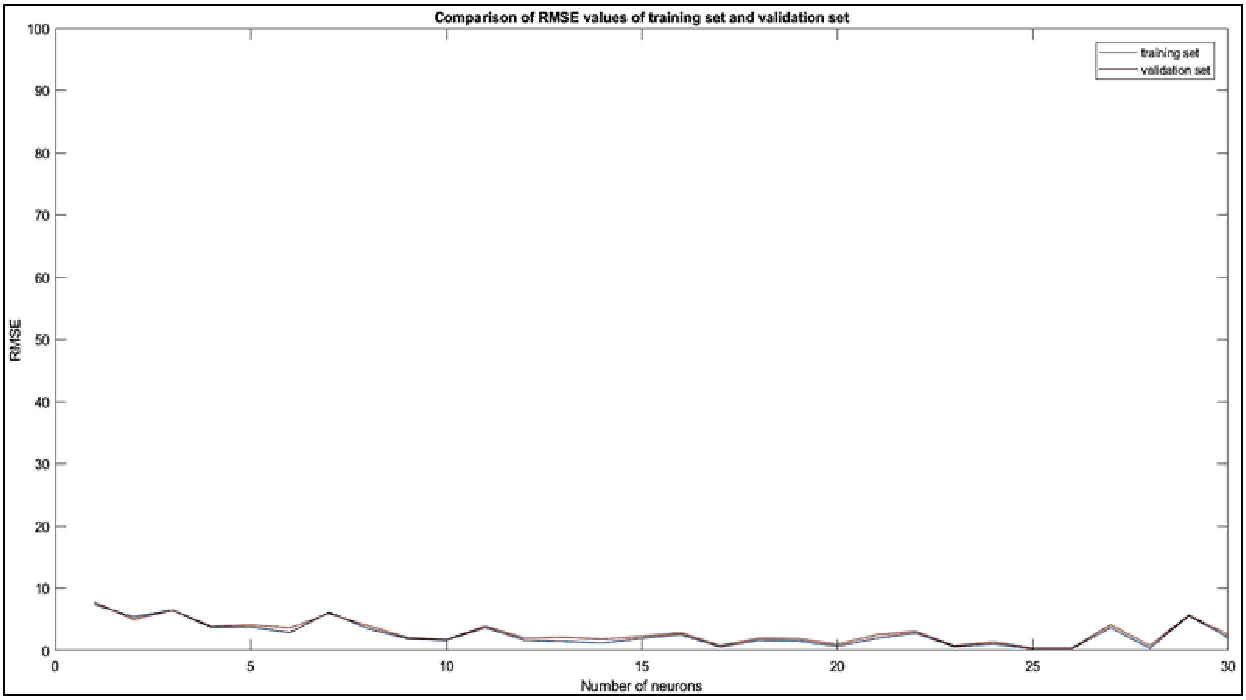

Fig 7 Evaluation of Varying Hidden Layer Neurons for ANN using Modal Frequencies and 12 Nodal Displacements

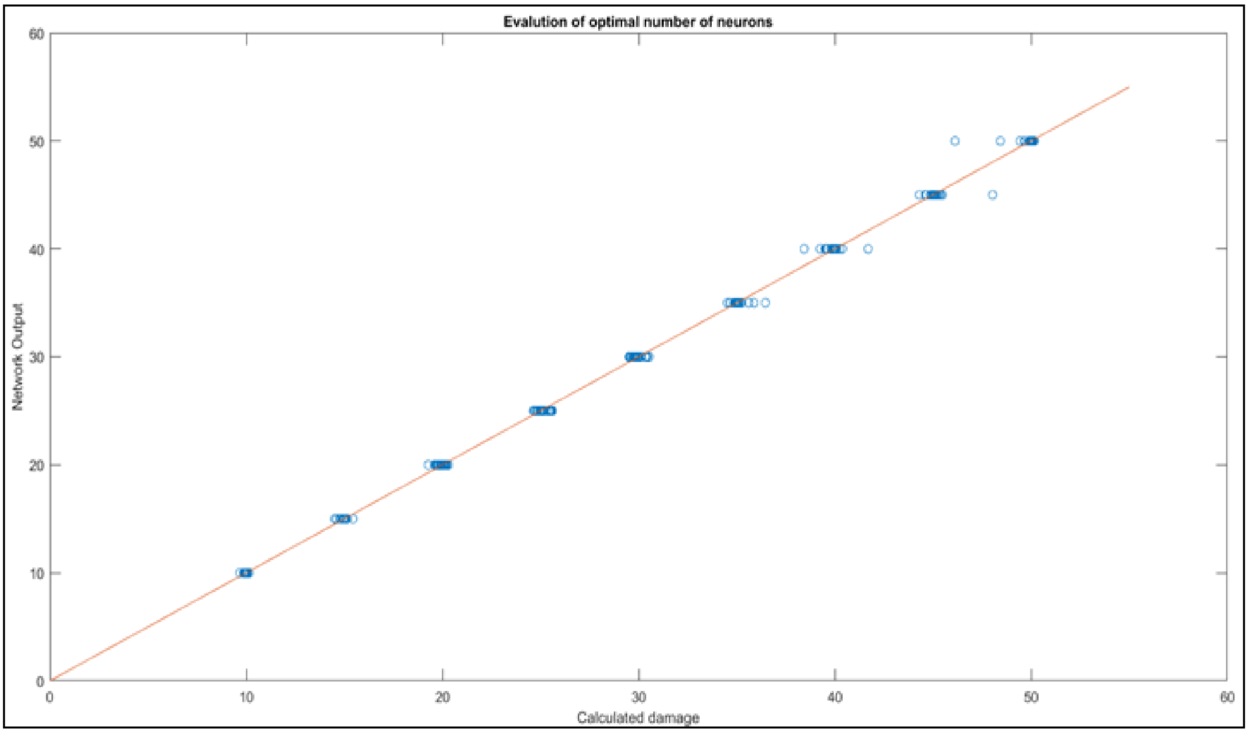

Fig 8 Assessment of Optimum number of Hidden Neurons for ANN using Modal Frequencies and 12 Nodal Displacements

Table 2 Comparison of Training RMSE and Validation when Damage in Represented by Change in Cross Sectional Area

Input Parameter	training set RMSE	validation set RMSE
Modal frequency	0.6310	1.2270
Modal frequency and 8 nodal displacements	0.4030	0.7900
Modal frequency and 12 nodal displacements	0.5038	0.4213

- *Damage Represented by Change in Elastic Modulus:*

- *Case 1-Damage Identification using Modal Frequencies:*

Fig. 9 shows the plot of training RMSE and the validation RMSE for various number of neurons in the hidden layer when the input parameters were only the six modal frequencies. The x-axis represented number of neurons and the y-axis represented RMSE value. The optimum number of neurons is observed to be 20 for this case. Hence the number of neurons in the hidden layer in the network is fixed as 20. The RMSE value of training was found to be 0.4129 while RMSE of validation set was found to be 2.7073. The network was tested and the plot of target output and obtained output is plotted as shown in fig. 10. We can observe that majority of the outputs from the network vary from the calculated values.

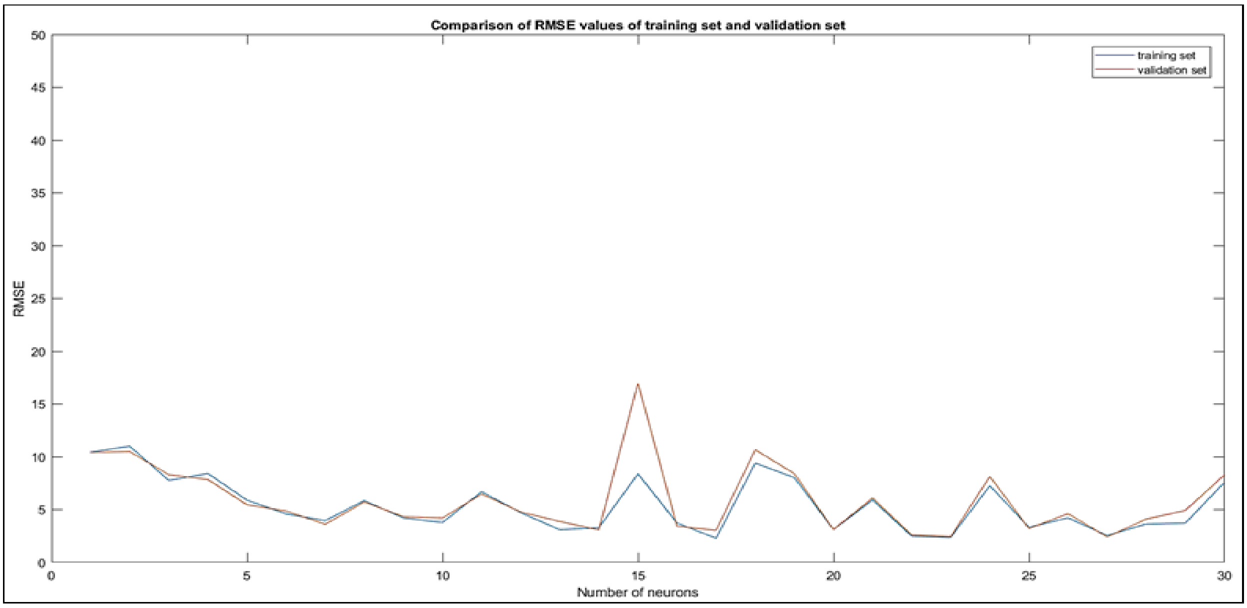

Fig 9 Evaluation of Varying Hidden Layer Neurons for ANN using Modal Frequencies

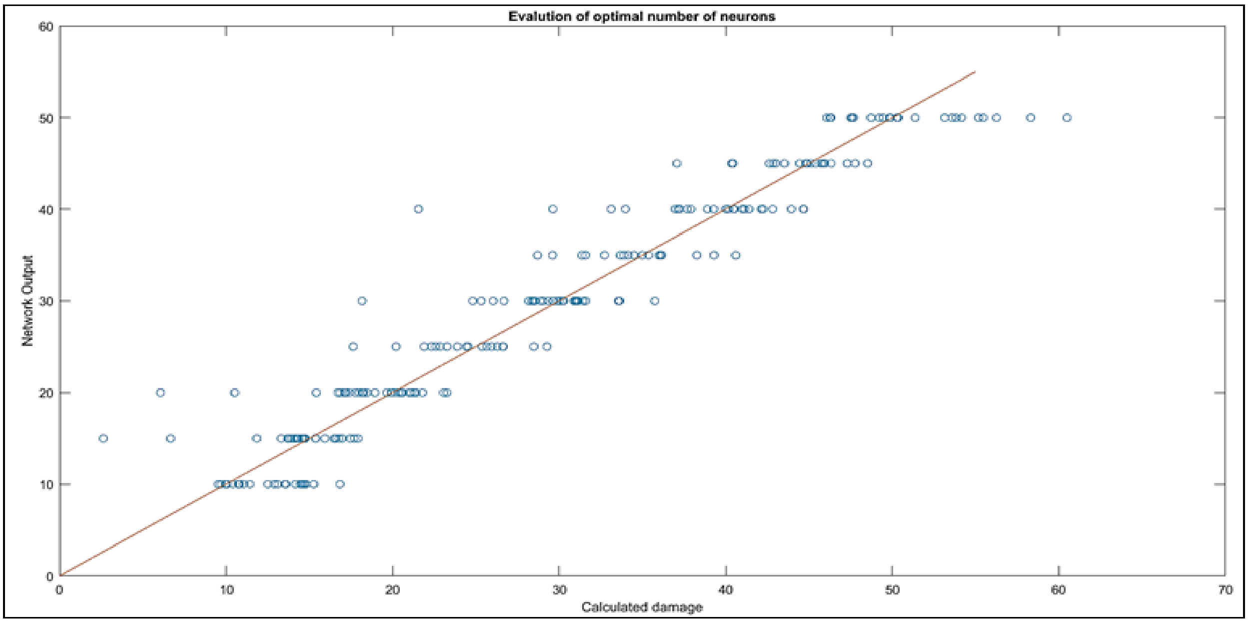

Fig 10 Assessment of Optimum number of Hidden Neurons for ANN using Modal Frequencies

- *Case 2-Damage Identification using Modal Frequencies and Displacement at 8 Nodes:*

Fig. 11, shows the RMSE of the training and RMSE of the validation set for different number of neurons. The x-axis represented number of hidden neurons and the y-axis represented RMSE value. The optimum number of neurons is found to be 24 for this case. Hence the number of neurons in the hidden layer in the network is adjusted to 24. The training set RMSE was 0.1649 and that of the validation set was 2.1994. The network was tested and the plot of target output and obtained output is plotted as shown in fig.12. It is observed that as compared to the case where only natural frequency is used as a parameter the case using nodal displacement aid in identifying the percentage to a better extent.

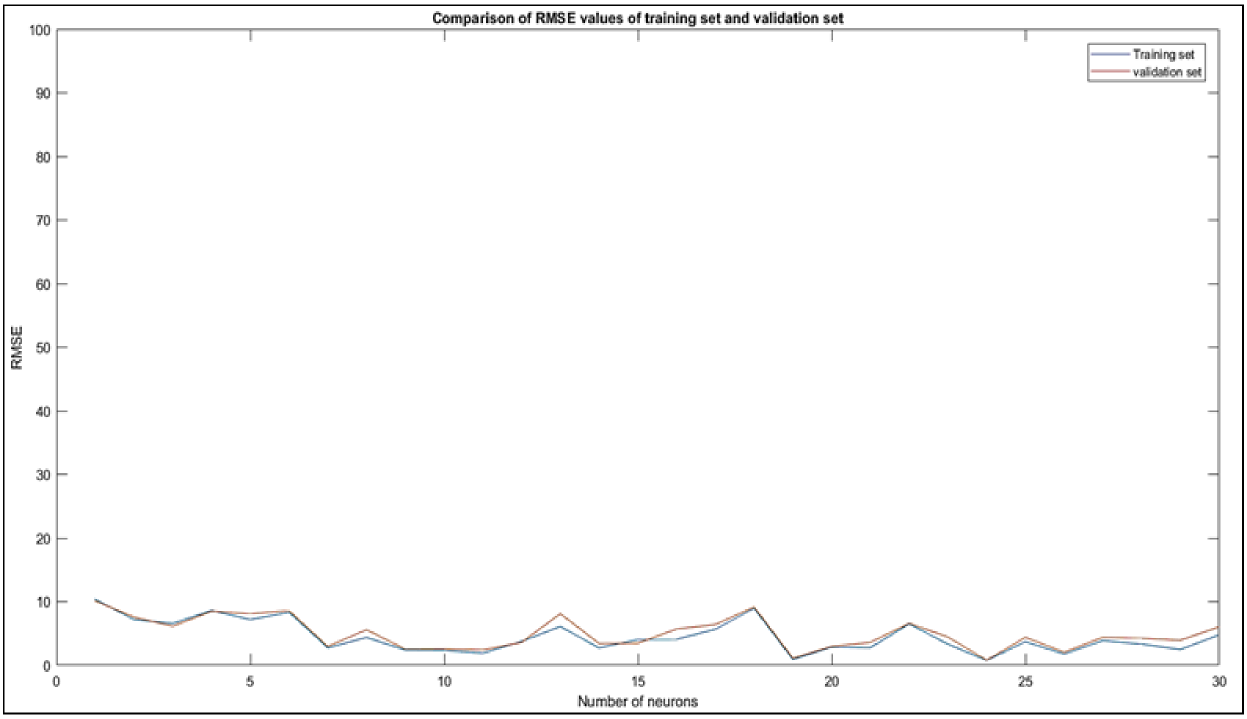

Fig 11 Evaluation of Varying Hidden Layer Neurons for ANN using Modal Frequencies and 8 Nodal Displacements

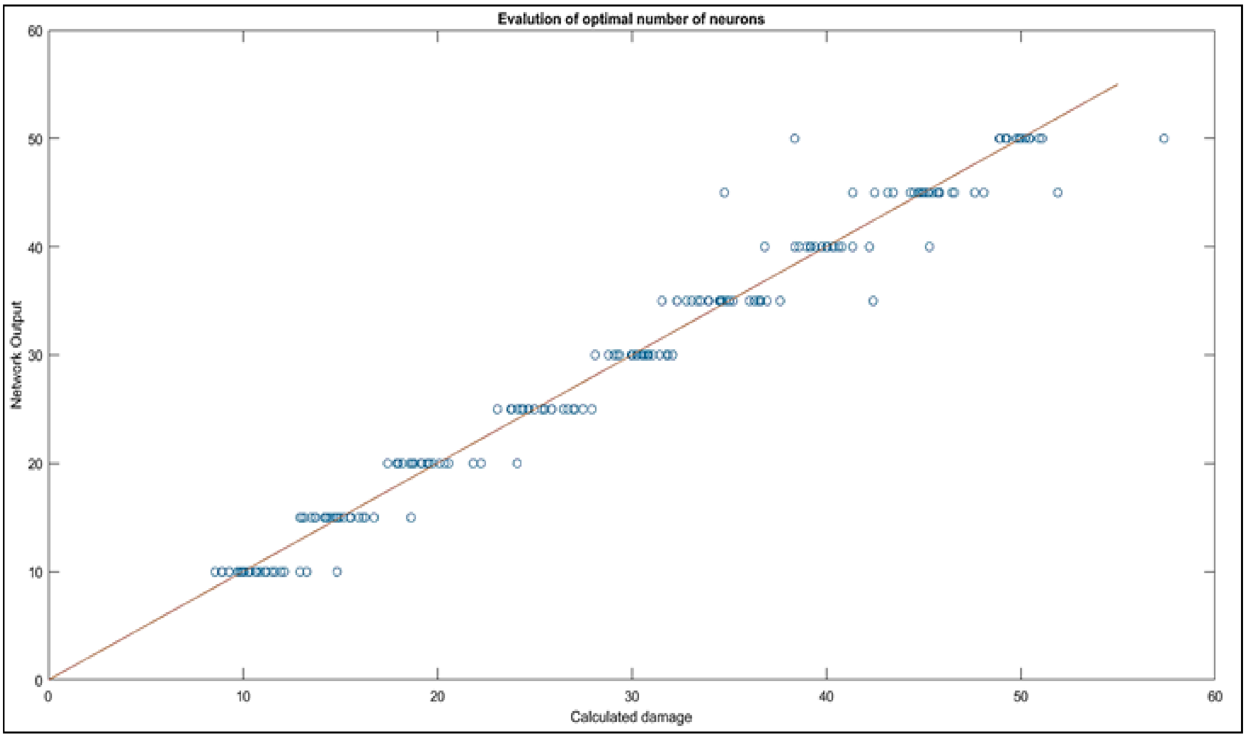

Fig 12 Assessment of Optimum number of Hidden Neurons for ANN using Modal Frequencies and 8 Nodal Displacements

- *Case 3-Damage Identification using Modal Frequencies and Displacement at 12 Nodes:*

Fig. 13, shows the RMSE of training and RMSE of the validation for different number of neurons. The y-axis represented RMSE value and the x-axis represented number of neurons. The optimum number of neurons is found to be 20 for this case. Hence the number of neurons in the hidden layer in the network is chosen as 20. The training set RMSE was 0.0510 and that of the validation set was 1.3194. The network was tested and the target output is plotted against the obtained output as shown in fig. 14. It is observed that the use of 12 nodal displacement aid in identifying the percentage to a much better extent as compared to the case where only natural frequency is used as a parameter and the case where modal frequencies and 8 nodal displacements are used.

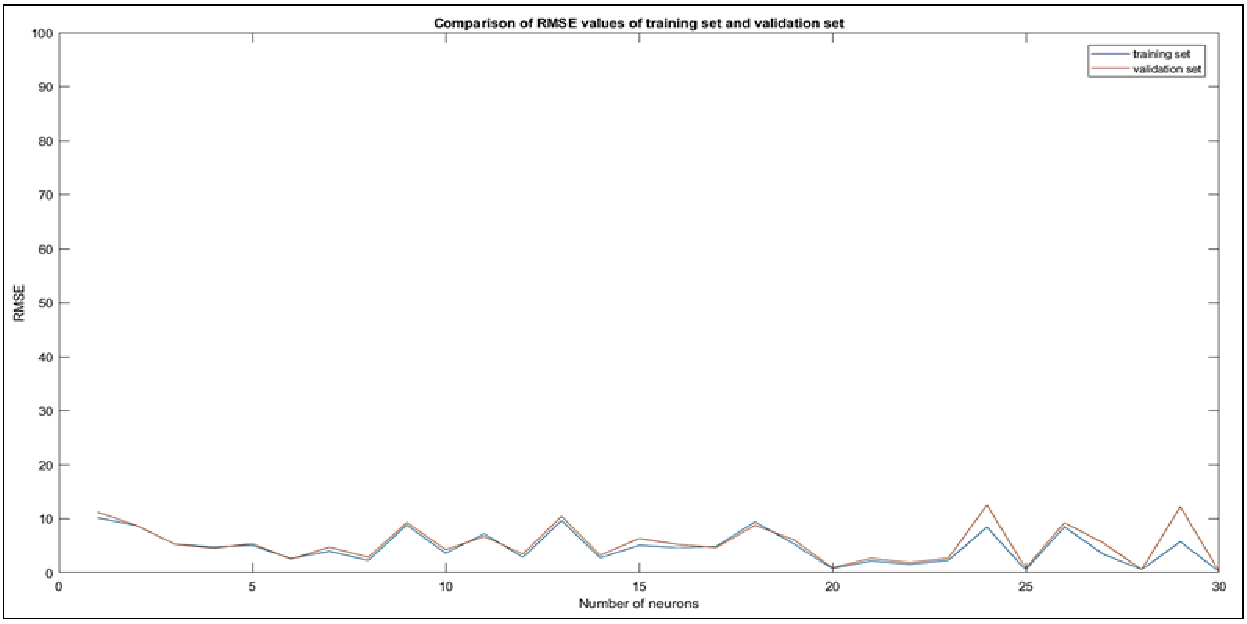

Fig 13 Evaluation of Varying Hidden Layer Neurons for ANN using Modal Frequencies and 12 Nodal Displacements

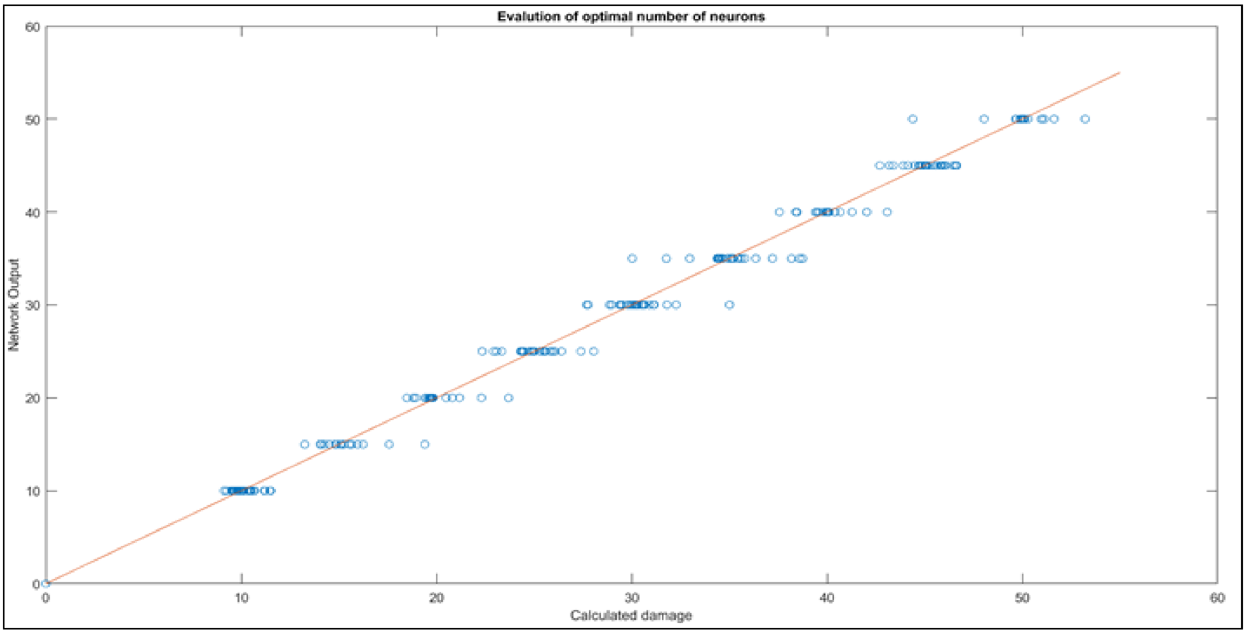

Fig 14 Assessment of Optimum number of Hidden Neurons for ANN using Modal Frequencies and 12 Nodal Displacements

Table 3 Comparison of Training RMSE and Validation RMSE when Damage in Represented by Change in Elastic Modulus

Input Parameter	training set RMSE	validation set RMSE
Modal frequency	0.4129	2.7073
Modal frequency and 8 nodal displacements	0.1649	2.1994
Modal frequency and 12 nodal displacements	0.051	1.3194

V. CONCLUSION

In this study artificial neural networks were developed to identify the percentage of damage in an offshore jacket structure.

➢ *The Following Conclusions were Drawn:*

- An Artificial neural network was proposed for the identification of damage in an offshore jacket structure. The damage in the structure was simulated by two different conditions. First was by reducing the area of cross section and second was by reducing the elastic modulus.
- Mainly three different parameters were suggested for the damage identification namely

✓ Using modal frequency as an identifier.
✓ Using modal frequency and the total nodal displacement at 8 nodes.
✓ Using modal frequency and the total nodal displacement at 12 nodes.

- Individual neural networks were created for each case while varying the number of neutrons in the hidden layer. The optimum number of neurons was found for each case.
- The networks were then trained with the optimum number of hidden neurons. They were tested using a test set and a plot of the target output and output generated by the network in all three cases.
- From the aforementioned three cases, from the plots of the test set it was observed that while with the use of modal frequencies the percentage of damage can be identified the inclusion of total nodal displacement helps in getting more accurate results
- From the graphs it was noted that, when same number of data sets were used there were more errors in predicting the damage in case of the ANNs which made use of the data set obtained by analyzing the offshore jacket structure where damage is represented by reducing the elastic modulus. The ANNs trained using the data set generated by reducing the cross sectional area gave lesser errors while predicting damage.

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