STRUCTURAL HEALTH MONITORING OF BRIDGES

M.Tech. Thesis

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STRUCTURAL HEALTH MONITORING OF BRIDGES

A THESIS

Submitted in partial fulfillment of the requirements for the award of the degree

of

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by

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the thesis entitled **STRUCTURAL HEALTH MONITORING OF BRIDGES** in the partial fulfillment of the requirements for the award of the degree of **MASTER OF TECHNOLOGY** and submitted in the **DEPARTMENT OF MECHANICAL ENGINEERING, Indian Institute of Technology Indore**, is an authentic record of my own work carried out during the time period from August 2020 to May 2022 under the supervision of **Dr. Pavan Kumar Kankar, Associate Professor, Department of Mechanical Engineering, Indian Institute of Technology** and **Prof. Sandeep Chaudhary, Professor, Department of Civil Engineering, Indian Institute of Technology.**

The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other institute.

30/05/2022
(Sushil Sukalal Bagle)

This is to certify that the above statement made by the candidate is correct to the best of our knowledge.

30/05/2022 | 30.05.2022
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Mr. Sushil Sukalal Bagle has successfully given his M.Tech. Oral Examination held on **May 24, 2022.**

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With Regards,

Sushil Sukalal Bagle

Dedicated to

My beloved parents

Sukalal Bagle and Sarita Bagle
for their unwavering support
throughout the journey

Abstract

Bridges are subjected to damage during their service life, severely affecting their safety and functionality. Thus, monitoring bridge structures for damage occurrence, location, and extent are essential. When damage occurs in a structure, the consequence changes its modal parameters, such as natural frequencies and mode shapes. This work presents a damage detection approach based on finite element modeling and machine learning techniques. Numerical modal analysis of concrete steel composite girder bridge was performed using ANSYS workbench software for healthy and damage scenarios. The required data for the machine learning algorithms in the form of natural frequencies were obtained from numerical modal analysis using ANSYS workbench software. The feasibility of an artificial neural network (ANN) and support vector regression (SVR) as powerful tools for damage severity prediction in a concrete-steel composite girder bridge model is evaluated.

This work also describes the deflection prediction of the beam using ANN and SVR algorithms. The performance of an ANN and the SVR is compared for deflection prediction, and the applicability of ANN and SVR as powerful tools for predicting beam deflection is investigated.

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ACRONYMS

SHM	Structural health monitoring
FE	Finite element
ML	Machine learning
ANN	Artificial neural network
SVM	Support vector machine
SVR	Support vector regression
NDT	Non-destructive testing

Chapter 1

Introduction

1.1 Overview

Railway and highway bridges are the essential components of transportation infrastructure. Bridges are expected to have higher levels of safety than other parts of the transportation system. Bridge failure might damage the structures and cause the loss of lives. Changes in loading conditions, environmental effects, and random actions can cause damage to bridges, which are constructed to last a long time. Deterioration in bridges may impact the operation, serviceability, and safety. Therefore, it is essential to ensure that bridges are always safe and efficient by monitoring their structural performance.

Introducing structural health monitoring techniques can save costs by enhancing the understanding and performance of the bridge structures and ensuring the safety and reliability of structures. Structural health monitoring is essential to see whether damage occurs, where it occurs, and how severe it is.

1.2 Structural health monitoring (SHM)

SHM is a valuable method for assuring the integrity and safety of structures, identifying the progression of damage, and measuring performance deterioration. Damage diagnosis in structural systems begins with recognizing the damage and determining its location, type, and severity. Primarily goal of structural health monitoring is to detect, locate, and quantify structural deterioration through the collection of data on the bridge. The SHM system may assess the structure's serviceability, reliability, and functionality.

SHM system is classified into four stages. The initial stage is damage detection. The SHM system notifies of a detected failure at this stage without specifying the failure's nature. The second stage consists of the localization of the identified damage. The third stage is the damage quantification stage. The SHM system automatically performs a diagnostic of the kind, extent, or severity of the damage in the third stage. The fourth stage is a prognosis of the structure's remaining service life[1]. Specific techniques are used for bridge SHM; they are as follows:

1.2.1 Non-destructive testing (NDT)

NDT methods are a collection of techniques for evaluating the qualities of a material or system without causing damage to it. This benefit is valuable for reviewing in-service bridges since the bridges may stay open to traffic during the assessment period, reducing the impact on the traveling public. Acoustic emission-based monitoring and electro-magnetic-based approaches are two of the most well-known NDT techniques for damage detection. This technique can only be applied to detect damage on a local and require access to specific structure components, leading to a time and cost-consuming process.

1.2.2 Vibration-based damage detection technique

Vibration-based damage detection approaches can be employed for a global assessment of the structure's health. It uses modal parameters to identify damage to the structure. Natural frequencies are the most crucial vibration parameter; therefore, this technique detects damage by directly measuring changes in natural frequency. These approaches involve monitoring and assessing the structure's dynamic behavior, which is frequently compared to behavior simulated by numerical models, such as finite element (FE) models.

1.2.3 Machine learning-based technique

Machine learning (ML) allows systems to learn and develop independently without having to be explicitly programmed to do so. ML is concerned with creating algorithms that can access data and utilize it to learn independently, i.e., it makes a prediction using past data. It utilizes data sets of feature signals acquired from a structure over time and soft computing algorithms to warn about damage and its features for damage detection in structures.

1.3 Significance and objectives of the study

The concerns regarding bridge structural maintenance and monitoring have become a significant challenge for engineers and researchers. In view of this, vibration-based monitoring and machine learning-based approach is utilized in this work for the bridge structure's damage detection and severity prediction. This work also focuses on deflection prediction in the beam of structure using ML techniques like artificial neural network (ANN) and support vector regression (SVR).

The following are the objectives of the present thesis work:

- To develop the finite element model of the girder bridge.
- To determine modal parameters of the bridge in damage and undamaged scenarios for damage detection.
- To train and test machine learning algorithms using natural frequencies to assess damage severity.
- To check the applicability of ML algorithms like ANN and SVR for deflection prediction in the beam.

The present work aims to provide significant contributions to structural health monitoring, damage identification, severity prediction, and structural deflection prediction.

1.4 Thesis organization

The thesis comprises five chapters. Each of them is described briefly to give a sound understanding about the contents covered in the thesis.

Chapter 1 introduces the structural health monitoring of bridges, the stages involved in SHM, and different techniques used for SHM. The significance and objectives of the work have been highlighted, along with the organization of the thesis.

Chapter 2 reviews the literature and past work that has been done on structural health monitoring bridges.

Chapter 3 explains vibration-based monitoring of concrete steel composite girder bridge in detail. The FE model of the girder bridge was created. The numerical modal analysis is performed on the bridge structure to identify damage. The machine learning approach is utilized for the damage severity prediction. The implementation and performance of an ANN and SVR have been discussed.

Chapter 4 describes the deflection prediction of the beam using an ANN and the SVR algorithms. It compares the effectiveness of an ANN and the SVR for the beam deflection prediction. Three ANN and SVR models have been created to predict inelastic midspan beam deflection of an interior span, a left exterior span, and a right exterior span.

Chapter 5 concludes and summarizes the research work and presents comprehensive discussions based on the results obtained. The scope of future work is also mentioned in this chapter

Chapter 2

Literature review

2.1 Overview

SHM techniques, which utilize mathematical and statistical approaches to identify and isolate damage, have become increasingly essential technology. This chapter contains a survey of the literature in the fields of SHM and damage detection methods. SHM methods are classified into model-based methods for damage detection and non-model-based, i.e., ML-based damage detection methods. The review focuses on a summary of damage detection techniques.

2.2 Model-based techniques for damage detection

A model-based damage detection approach compares the characteristics of a mathematical model describing the monitored bridge to assess the bridge's health. Finite Element (FE) modeling techniques are commonly used to develop mathematical models. The response obtained by sensors on an actual structure is used to prepare the FE model. Due to its computational and modeling capabilities, FE methods are used to evaluate and predict bridge performance. Some work on the FE model updating strategies have been reviewed.

[2] provided an approach for simultaneously estimating bridge stiffness and mass characteristics. The difference between analytical and measured displacements produced by non-destructive testing of bridge structure in the laboratory was defined as an objective error function that must be reduced. The updated FE model data and experimentally measured data have a good agreement. As a result, the authors suggest that if the measured data differ significantly from the predictions of the FE model, a failure may have occurred, which indicates that, for the damage detection process, the proposed updating technique can be suitable.

He et al. [3] monitored the bridge using approximately 150 sensors, and the FE model was created. A simple updating technique was presented by minimizing an objective function based on the numerical and measured natural frequencies difference. The collected data by the FE model and the data acquired by the sensors were found to be in good agreement. Hence presented approach can be used as a bridge health monitoring.

An update technique was proposed by Feng et al. [4] for the railway bridge FE model. The method was based on the difference between analytical and measured bridge displacements. According to the study, the actual bridge displacements and those estimated using the updated FE model were nearly identical.

A FE updating technique presented by Xia et al. [5] is based on optimizing an objective to minimize the differences in measured and numerical modal properties of the bridge. According to the results, the simulated and measured modal properties of the bridge are observed to be in good agreement.

2.3 Machine learning-based techniques for damage detection

Various fault detection techniques have been established in recent decades to determine the existence of failure in a bridge by relying just on bridge behavior analysis without constructing a structure model. ML approaches can provide a quick analysis without any computational work. Mehrjoo et al. [6] employed ANN to detect damage in truss joints in bridge structures. For damage identification, mode shapes and natural frequencies were employed as input features to the ANN. The ANN's applicability and effectiveness in determining the location of joint damage and the severity in truss bridges have been demonstrated. The location and damage severity in truss bridge joints were determined with high accuracy using the suggested method.

Park et al.[7] presented a sequential fault identification approach using an acceleration-based ANN (ABNN) and a modal parameter-based ANN (MBNN). The ABNN method uses acceleration as an input feature to detect the damage in the beams. Then using mode shapes and modal strain energies, an MBNN algorithm is developed to predict damage severity and the location in the beam. It concluded that the damage's location and severity are accurately detected using an ABNN and the MBNN sequentially.

Two different ANN approaches were analyzed by Al Rahmani et al. [8] to predict crack location and propagation in a simply supported beam in a FE model. FEA software was used to create damage databases for beams with various parameters. The results indicated that both ANNs were found to be able to accurately predict the propagation of the cracks, despite their differences in structure and input data.

Tan et al. [9] analyzed the approach for detecting damage in bridge structure using vibration characteristics and ANN. The damage index, based on modal strain energy, is used for locating and detecting the damage in beams. The relative modal flexibility change was used to detect and quantify bridge deck damage. The proposed method was found to be capable of detecting damage in single and multiple damage scenarios.

Lee et al. [10] proposed an ANN-based damage detection method using the modal features. ANN with three different input types, i.e., mode shapes, mode shape ratios before and after damage, and mode shape differences between before and after damage, are studied. The suggested method could detect the damages for all case studies using different input parameters. Results showed that the suggested technique was found to be capable of identifying damages in all case studies when different input parameters were used.

Pendharkar et al. [11] created neural networks to predict inelastic deflections for the composite beams. Results showed that the presented ANN model could predict mid-span deflection of beam for different spans. Chaudhary et al. [12] developed neural networks to predict inelastic bending moments for composite beams. Results showed that the presented ANN model could predict bending moment at the span support

In the context of fault detection using AI techniques, most of the studies mention the use of ANN. The use of the SVR algorithm for damage detection has not been focused in the previous studies. In this thesis, the study is focused on SVRs algorithms and ANN algorithms for the damage detection and severity prediction of structure, and their performance is compared.

Chapter 3

Vibration-based monitoring of concrete steel composite girder bridge

3.1 Introduction

Structures are subjected to deterioration during their operational lifespan, affecting the safety and functionality of structures. Thus, structural health monitoring is essential to see whether damage occurs, where it occurs, and how severe it is. Damage is defined as a degradation in the structure's stiffness that negatively impacts the structure's performance, which may cause unwanted vibrations to the structure. As a result, damage identification is a significant requirement in evaluating structural systems and maintaining their safe operation throughout their service lifespan.

In the case of local damage, NDT techniques are used to monitor structure performance. Acoustic emission-based monitoring, electro-magnetic-based approaches, radiography-based, ultrasonic-based, and eddy current-based monitoring are well-known NDT techniques for damage detection[1]. For all these approaches, prior localization of the damaged zones is required. Vibration-based methods, which provide a global damage analysis, can overcome the limitations of local methodologies. Vibration-based health monitoring relates two attributes, i.e., structural and modal parameters. Mass, damping, and stiffness are the structural parameters, and mode shape and natural frequencies are the modal parameters.

Natural frequencies and mode shapes are dynamic features of a structure that are functions of its mass stiffness. Changes in mode shape and natural frequencies can be a good predictor of structural degradation. Vibration-based damage detection methods assess the variations in physical parameters that indicate structural deterioration by measuring changes in dynamic characteristics. The fundamental concept is that modal characteristics such as mode shape and natural frequencies are functions of the structure's stiffness. As a result, modal properties will be affected by changes in physical properties. Any reduction in structural stiffness may indicate structural damage. Modal analysis is a useful method for identifying the modal parameters. Any damage to structural elements causes stiffness reduction, resulting in a reduction of natural frequency. This chapter uses natural frequencies as a damage indicator in bridge structure.

3.2 Finite element model of composite girder bridge

The primary goal of this work was to identify damage in a concrete-steel composite girder bridge. The finite element model for the concrete-steel composite girder bridge is developed to perform numerical modal analysis to evaluate the modal parameters of the bridge.

Table 3.1: Dimension of concrete-steel composite girder bridge [13].

Slab	**Beam**
Length=3200mm	Length=3200mm
Width=1200mm	Flange Width=75mm
Thickness=100mm	Section Depth =150mm Thickness of Flange =7mm Thickness of Web =5mm

The length of a concrete slab is 3200 mm, the width is 1200 mm, and the thickness is 100 mm. The steel beams have a 75 mm flange width, a 150 mm section depth, 7 mm flange thickness, and 5 mm web thickness [13]. A schematic view of the dimension of the concrete-steel composite girder bridge is shown in Fig. 3.1. For the steel material, the Modulus of elasticity is $210*10^3$ MPa, the density is 7850 kg/m^3, and the Poisson's ratio is 0.3. For the concrete material, the Modulus of elasticity is 37.5

MPa, Poisson's ratio is 0.2, and the density is 2400 kg/m^3 was considered.

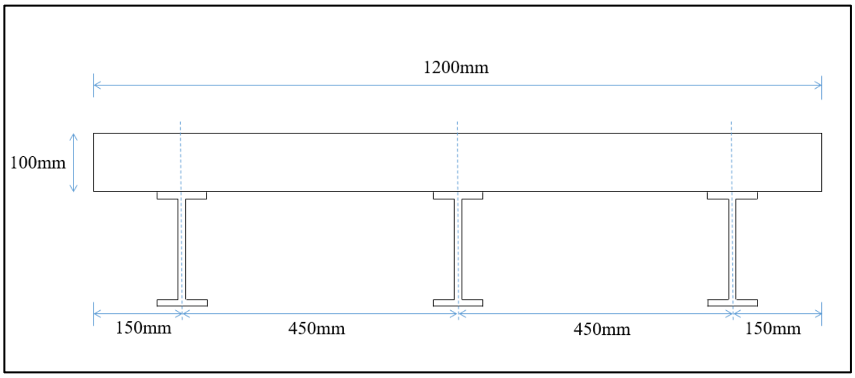

Fig. 3.1: Schematic view of the dimension of composite girder bridge

The FE model of the concrete-steel composite girder bridge is created using ANSYS Workbench 2021 R1 [14]. Fig. 3.2 shows the concrete-steel composite girder bridge geometry. The concrete material is assigned to the slab part, and the steel material is assigned to the beam part.

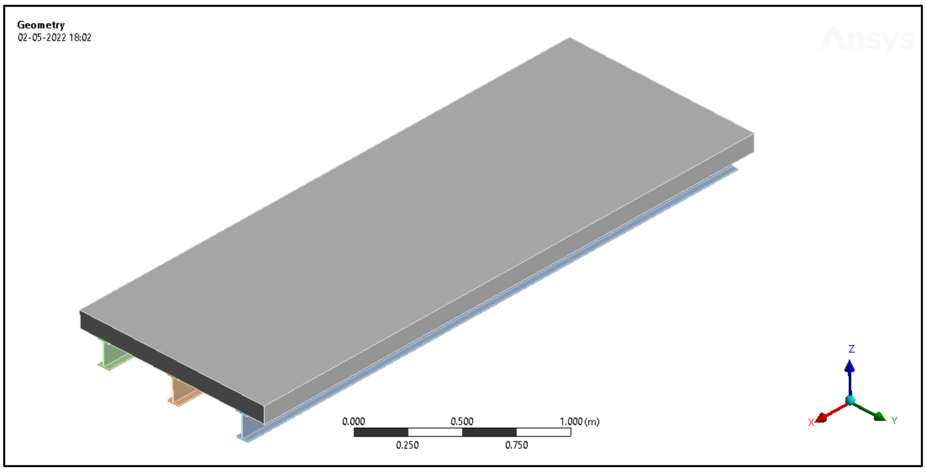

Fig. 3.2: The composite girder bridge geometry

The mesh configuration of the concrete-steel composite girder bridge is shown in Fig. 3.3. The FE model consists of 224041 nodes and 109613 elements. Bonded contact is provided between the slab and the beam surfaces.

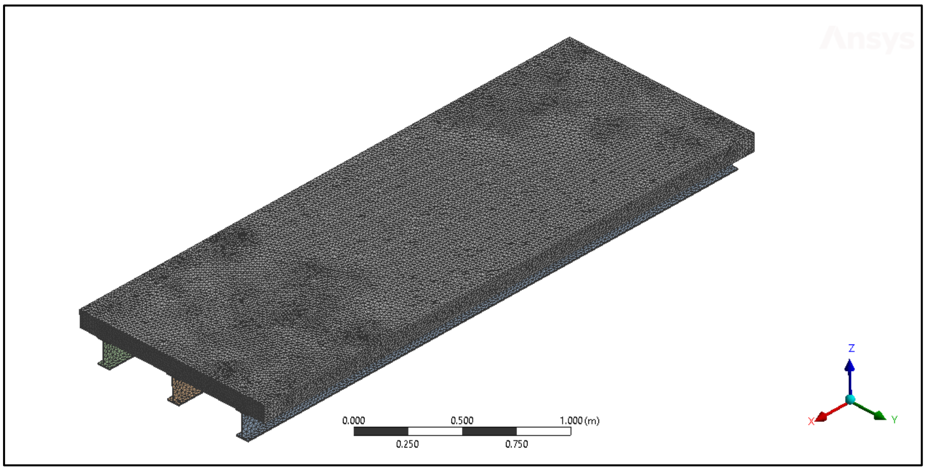

Fig. 3.3: Meshed model of the composite girder bridge

3.2.1 Numerical modal analysis of the composite girder bridge model

Modal analysis determines the natural frequencies at which a structure will resonate. It's one of the most useful techniques for determining modal parameters. Natural frequencies are extremely important in a variety of structural engineering. Modal analysis is a useful method for identifying the modal parameters. Any damage to structural elements causes stiffness reduction, resulting in a reduction of natural frequency. As a consequence, damage detection may be done using natural frequency measurements.

For numerical modal analysis, the support conditions on both sides are considered fixed for the z direction, while x directions and y directions are free. The boundary conditions provided to the FE model to evaluate the natural frequencies of a model are shown in Fig. 3.4. Then the model is post-processed, and the first four natural frequencies of flexural modes are extracted using ANSYS Workbench 2021R1.

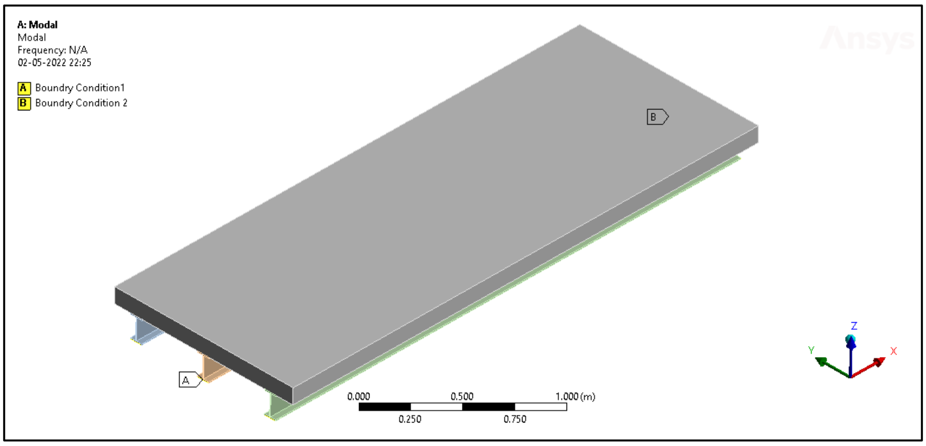

Fig. 3.4: Boundary conditions for the model

Table 3.2 shows the natural frequencies first four bridge model, and their respective mode shapes are illustrated in Fig. 3.5. A deflected shape associated with a specific natural frequency is called a mode shape that depicts the structure displacement for the particular modes. The natural frequencies obtained by numerical modal analysis are compared with the experimentally obtained natural frequencies by [13] to validate the numerical model.

Table 3.2: Numerically obtained the first four natural frequencies of the concrete-steel composite girder bridge

Mode	**Natural Frequency (Hz)**
1	37.793
2	265.34
3	400.27
4	533.76

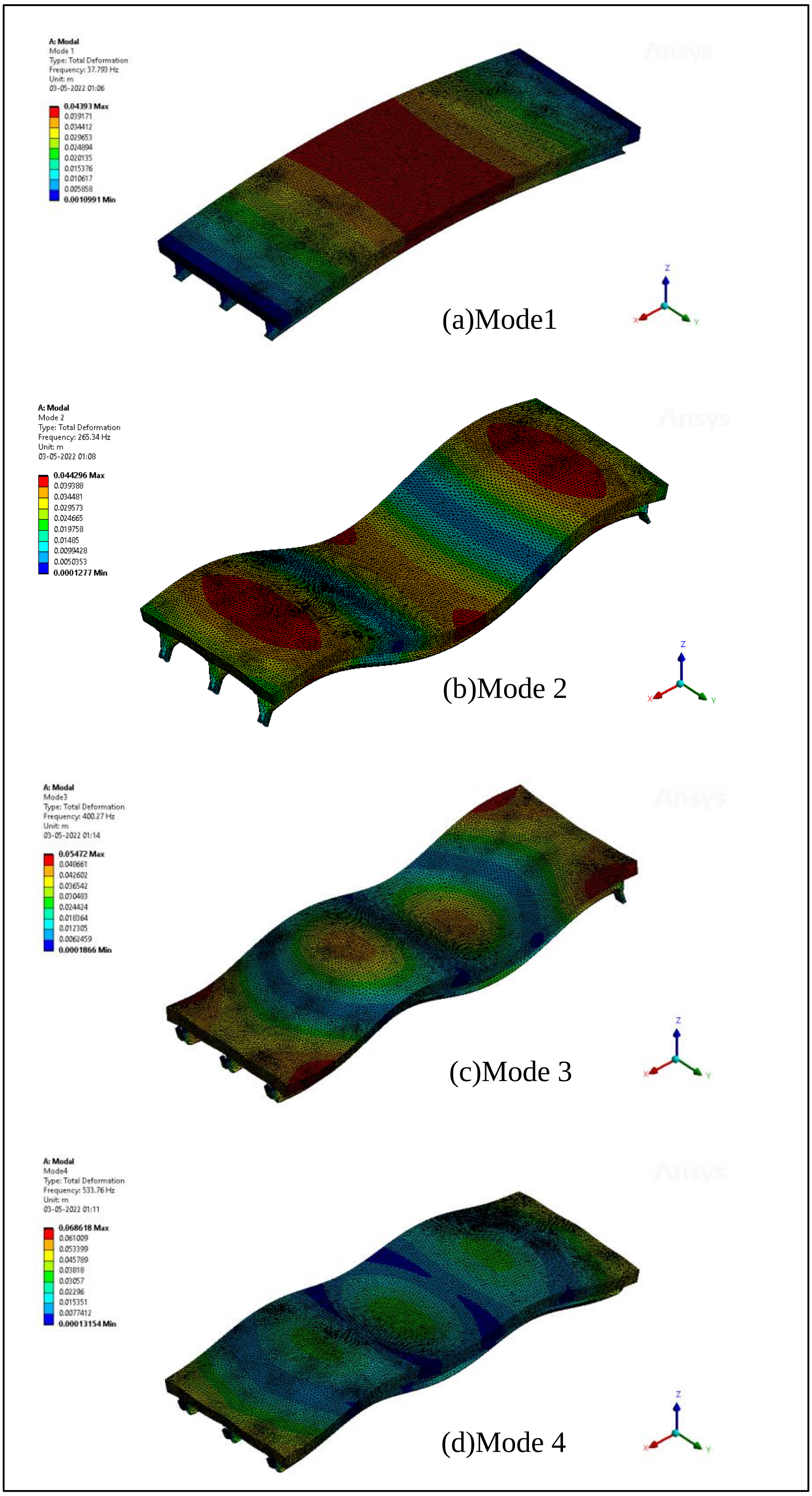

Fig. 3.5: Mode shapes frequencies of the composite girder bridge obtained using FEM

Table 3.3 compares the numerically obtained natural frequencies with the experimentally obtained natural frequencies. The results showed a good agreement between numerically obtained natural frequencies and the experimentally obtained natural frequencies. The proposed damage detection approach was demonstrated using this validated FE model.

Table 3.3: Numerically obtained the first four natural frequencies of the composite girder bridge

Mode	Numerical Natural Frequency (Hz)	Experimental Natural Frequency (Hz)
1	37.793	33.01
2	265.34	256.32
3	400.27	391.29
4	533.76	554.69

3.2.2 Numerical modal analysis of the damaged bridge structure

Numerical modal analysis of damaged bride structure is performed to detect the damage in the structure. Four damage scenarios were given to the beam of structure, and the severity of damage was defined. Fig.3.6 shows the locations of four damage scenarios with a damage depth of 75mm. Fig. 3.6 illustrates the damage scenarios D1, D2, D3, and D4, where the damage is located at L/2, 3L/4, and L/4 of the length of the beam. For damage D1, a 5 mm wide cut slot and 3 mm depth increments up to 75 mm (Fig. 3.7), i.e., 25 levels of cut slots located at L/2 and L/4 of beam, were considered in the beam to investigate the damage severity.

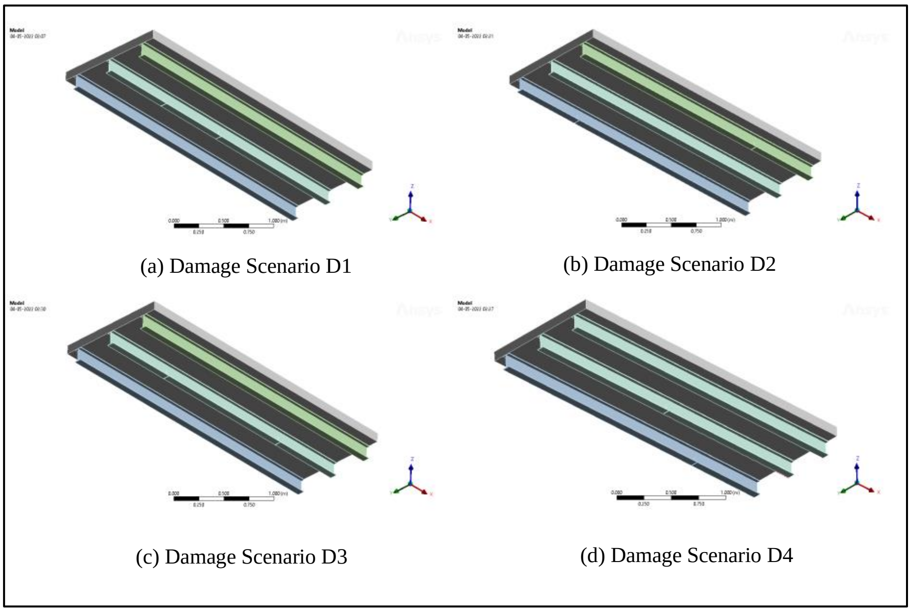

Fig. 3.6: Different damage scenarios applied to the structural model

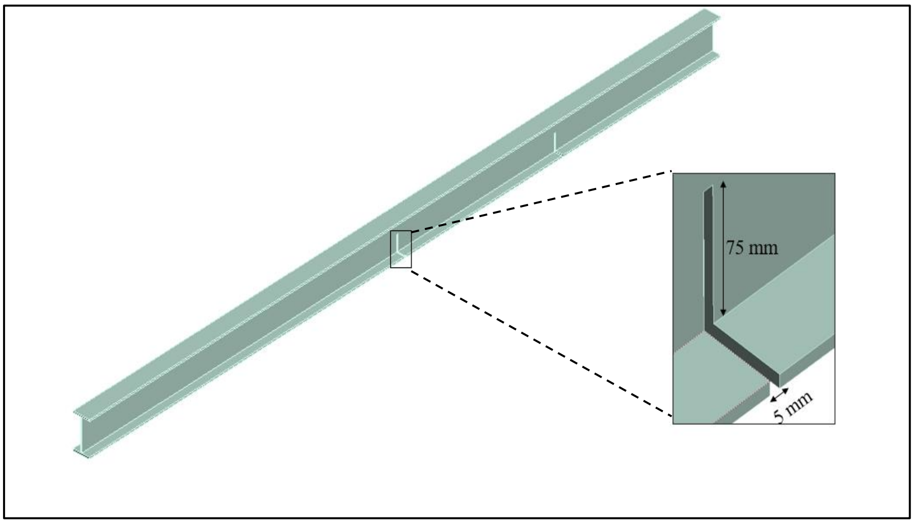

Fig. 3.7: Damage scenario with 5 mm width with 75 mm depth

The numerical modal analysis was performed on 100 damage scenarios with different damage severity. The damaged models are given the same boundary conditions as the undamaged model, and the first four natural frequencies of flexural modes are extracted using ANSYS Workbench 2021R1. The damage depth and the beam height ratio is defined as the damage severity index (d/h). Fig. 3.8 depicts the variation in natural frequencies with respect to different damage severities for different damage scenarios for different modes.

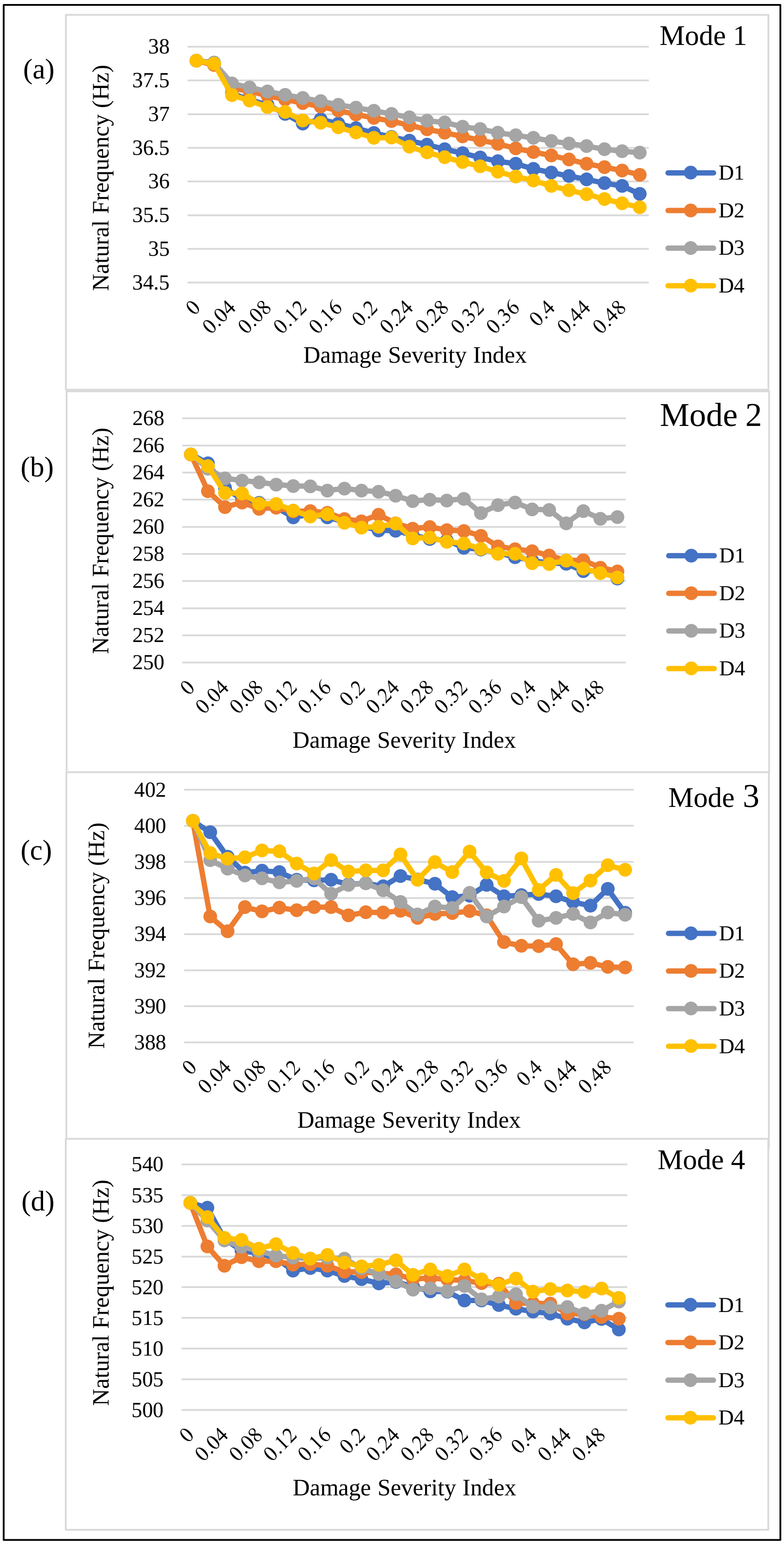

Fig. 3.8: Variation of natural frequencies w.r.t damage severity index for D1, D2, D3 and D4 in (a) Mode 1, (b) Mode 2, (c) Mode 3, and (d) Mode 4

From Fig. 3.8, it is observed that with an increase in the damage severity index, natural frequencies of structure decrease. In all damage scenarios, the existence of damage in beams causes a reduction in natural frequencies, which shows that the reduction in natural frequencies is a good indicator of damage and strongly influences the damage.

3.3 Damage severity prediction of structure using machine learning algorithms

Machine learning algorithms begin with preparing suitable and accurate data sets that can be used to train a network to recognize patterns in the data set. Data obtained from the numerical modal analysis is used to train and test the machine learning algorithm. 101 different data sets from the healthy and damaged bridge model were collected for damage severity prediction from the numerical modal analysis. The first four natural frequencies and the damage severity index were collected for the structure's damage severity prediction. Two different machine learning techniques, i.e., ANN and SVR, had been employed for damage severity prediction in structure.

3.3.1 Artificial neural network (ANN)

An ANN is a computing method based on the biological neural network structure. It has been used in a variety of modeling, pattern recognition, and system control [15]. Artificial neural networks could learn and generalize from examples and expertise to provide meaningful solutions for problems even when the input data has errors. As a result, ANNs can be used to solve some complex engineering challenges. Herein ANN is employed to predict damage severity in structure.

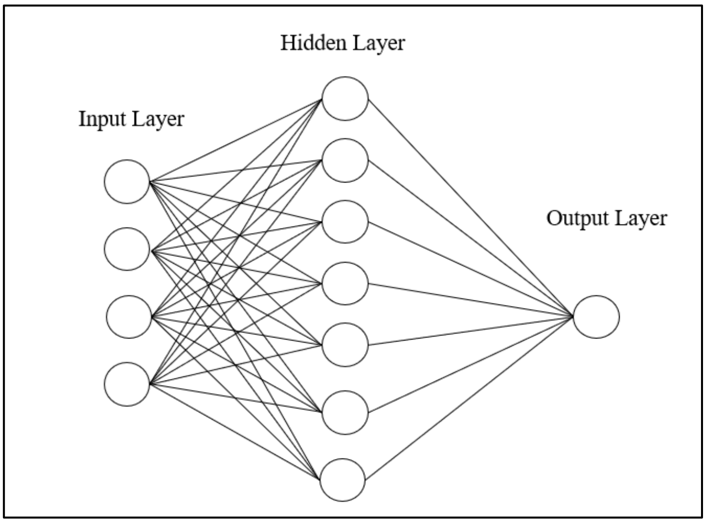

Fig. 3.9: Artificial neural network

There are three layers in an ANN input, hidden, and output layer (Fig. 3.9). The input layer neurons represent the independent variable values. The hidden layer neurons are used for computational purposes, and the one dependent variable is computed by each of the output neurons. Signals are passed from the input layer, then transit through the hidden layer, and arrive in the output layer. All the neurons are connected to the neurons in the subsequent layer through the weights and bias.

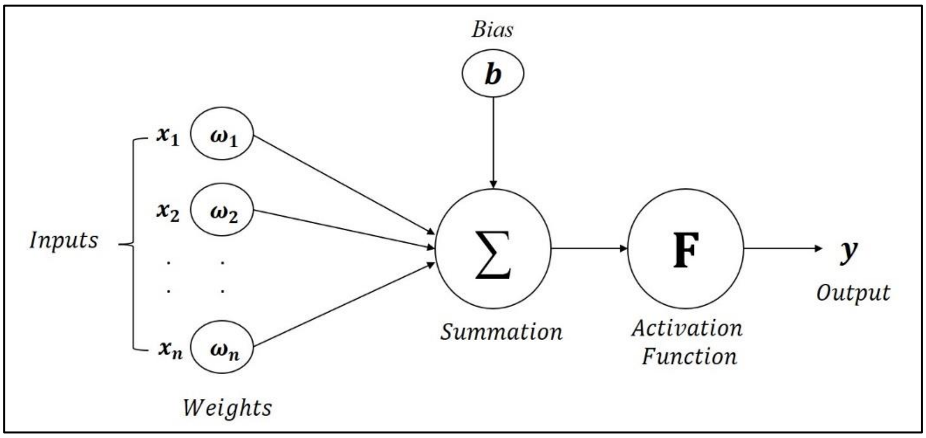

Fig. 3.10: Schematic of neural network architecture

Every input node has a weight attached that may have either a positive or a negative value. Fig. 3.10 shows a network structure with input $(x_1, x_2, \dots x_n)$ being connected to neurons with weights $(\omega_1, \omega_2, \dots \omega_n)$ on each connection [16]. The neuron adds up all of the signals it receives, multiplying each signal by the connection's associated weights to produce an activation signal z (eq. 3.1). With the addition of a bias, b is then transit to an activation function to give the final output y (eq. 3.2). The most commonly used function is the sigmoid activation, which is convenient when the backpropagation algorithm is applied.

$$z = \sum_{i=1}^{n} w_i x_i \tag{3.1}$$

$$y = f(b + z) \tag{3.2}$$

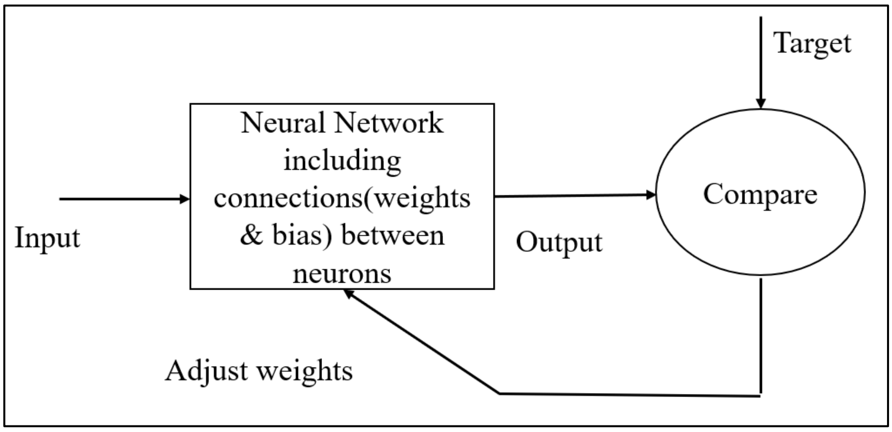

Fig. 3.11: Process of back-propagation

The backpropagation algorithm can learn the complex nonlinear interactions. Therefore, the backpropagation algorithm in multilayer feedforward networks is the most appropriate approach. Backpropagation is a procedure in which the weights are modified until good predictions are obtained (Fig. 3.11). The fundamental premise of the backpropagation algorithm is errors are sent backward, and the data is transferred forward [17]. The backpropagation algorithm's performance measure is the mean square error (MSE). The difference between the target and predicted output determines the MSE. This approach minimizes MSE by employing a gradient descent method that decreases the gradient error curve throughout all input patterns. The equation of MSE is mentioned in eq. 3.3.

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (t - o) \tag{3.3}$$

Where n is the number of the training samples, t is the target output, and o is the predicted output. The ability of an ANN to correctly predict the value is a significant advantage. Even when the network is trained with incorrect data, it can continue to learn and enhance its performance when additional training features are provided.

A multilayered feedforward neural network was employed, with all layers interconnected in a feedforward way. Several other algorithms and activation functions can be used to train the network, but the sigmoid activation function is utilized, and the backpropagation algorithm is considered to develop the network. The backpropagation tool of Levenberg-Marquardt is used to learn the connections between the input and output variables.

3.3.2 Performance of an ANN model

An ANN model consists of four input parameters, i.e., four natural frequencies, and one output parameter, the damage severity index. The neural network toolbox in the MATLAB R2021b is used to train and validate the network. Numerous trials are performed with various numbers of hidden layer neurons to train and test the network. The number of datasets considered is 101. Out of this, 70% of the data is utilized to train the model, 15% for validation, and 15% to test the model. The architecture of the ANN is shown in Fig. 3.12. The input layer consists of 4 neurons, i.e., 4 input features, the hidden layer comprises 10 neurons, and the output layer consists of 1 neuron, i.e., 1 output feature.

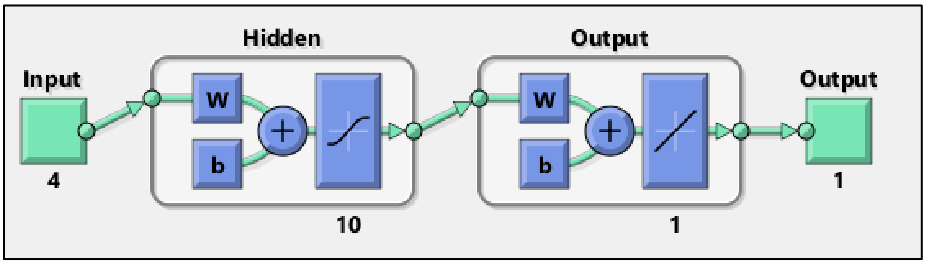

Fig. 3.12: Architecture of an ANN model

The performance plot of the trained ANN model is shown in Fig. 3.13. The performance plot of a trained model shows how the mean squared error (MSE) changes for different iterations. After 16 iterations, the model was trained, and after that, it stopped because validation errors started increasing from that point. The best Validation Performance is 0.000199 at epoch 16.

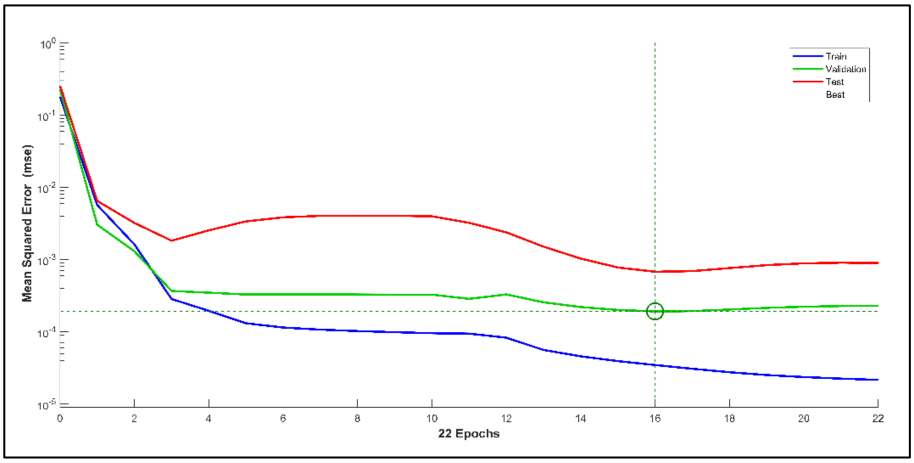

Fig. 3.13: Performance plot of an ANN model

The regression plot, the mean squared error, and R^2 value (Coefficient of determination) are used to assess an ANN model's performance. In Fig. 3.14, performance is shown for each training, validation, and test data set. A regression plot is a visual representation of how well a neural network fits the data. MATLAB R2021b is used to plot the regression across all data. The network outputs are shown against the associated target values in the regression plot. A good model has small errors, which means the predictions are scattered near the regression line. In Fig. 3.14, all the points lie on a regression line, which means the model has trained accurately.

R^2 value (Coefficient of determination) is another measure of how well the neural network fits the data. The R^2 value indicates how closely regression predictions match real data points. The regression predictions perfectly fit the data when the R^2 value is 1. When R^2 values are outside the range of 0 to 1, it means the model does not fit the data and the worst possible least-squares predictor. Table 3.4 shows the training results of an ANN model. It is noted that the R^2 value for the training dataset is 0.9983 and for validation and testing is 0.9935 and 0.9706, respectively, which states the model has trained accurately and will successfully predict the deflection of the beam when new samples are taken as an input with higher accuracy.

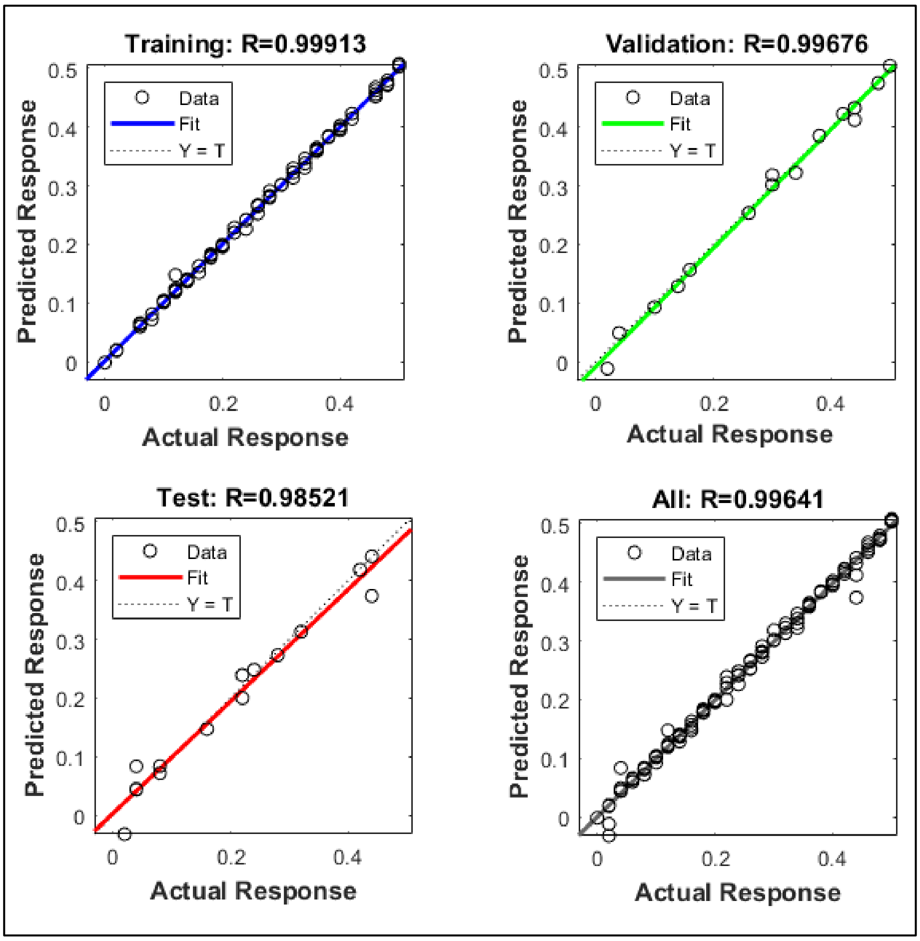

Fig. 3.14: Regression plots of an ANN model

Table 3.4: Training results of an ANN model

	Observations	MSE	R^2 Value
Training	71	1.6436e-4	0.9983
Validation	30	7.1168e-4	0.9935
Testing	30	4.0342e-4	0.9706

The trained and tested ANN model gives a close to one R^2 value, and a very low mean square error. The close to one R^2 value and low MSE value showed that a predicted output is near to the actual output, indicating that the neural network model is accurately trained and will successfully predict the output when a new sample is taken as an input.

3.3.3 Support vector regression (SVR)

A support vector machine (SVM) is a ML technique utilized to recognize patterns in large data sets. SVM is one of the supervised ML processes used efficiently for classification as well as regression problems [18]. SVM is classified into support vector classification (SVC) and support vector regression (SVR). In the supervised machine learning process, the data are always labeled, i.e., the training data are categorized in advance. SVM uses the high complexity data transformation to create the best hyperplane between the different categories of outputs with the help of various kernels. The marginal distance between two different categories is maximized, resulting in the error being least [19].

3.3.3.1 Hyperparameters of the Support Vector Machine Algorithm:

Hyperplane: In SVM, a hyperplane is essentially a dividing line between two data classes. This is the line that will be used to predict the continuous output in Support Vector Regression.

Support Vectors: The data points closest to the hyperplane are called support vectors. They influence the hyperplane's position and orientation. We must choose a hyperplane with the most significant margin.

Marginal Planes: Marginal planes or decision boundary is the parallel plane that is created through support vectors on both sides

Kernel: To perform regression at a higher level, SVM uses the functions that map data points from lower dimensions to higher dimensions. These functions are termed a kernel. Various types of kernel functions are used in SVM. Polynomial, linear, and radial basis functions or Gaussian kernel are among the examples. Table 3.5 shows the kernel type and its equation.

Table 3.5: Kernel type and its equation

Kernel Type	Equation
Linear kernel	$K(x, y) = x \,.\, y$
Polynomial kernel	$K(x, y) = (x \,.\, y + 1)^d$
Radial basis function (Gaussian) kernel	$K(x, y) = e^{\frac{-\lvert x-y\rvert^2}{2\sigma^2}}$

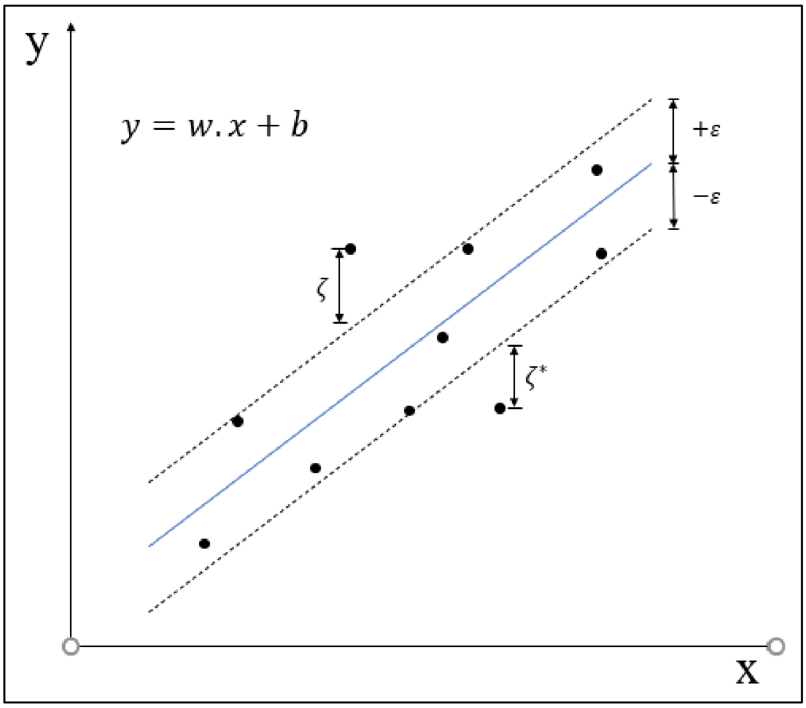

Fig. 3.15: Support vector machine representation

However, the major goal of SVR is to reduce error by customizing the hyperplane to optimize the margin while keeping in view that some error is tolerable[20]. To fit the model, the SVR method approximates the best values with a given margin called ε. SVR determines how much error is tolerable in the model and uses a hyperplane to fit the data [21]. The equation of hyperplane is mentioned in eq. 3.4.

$$y = w.x + b \tag{3.4}$$

The hyperplane is defined using mentioned constraints in eq. 3.5 and eq. 3.6

$$\text{Minimize: } \frac{1}{2}\left|\left|w\right|\right|^2 + C\sum_{i=1}^{N}(\zeta + \zeta^*) \tag{3.5}$$

$$\text{Constraints: } \left.\begin{aligned} & y_i - wx_i - b \leq \varepsilon + \zeta \\ & wx_i + b - y_i \leq \varepsilon + \zeta^* \\ & \zeta, \zeta^* \geq 0 \end{aligned}\right\} \tag{3.6}$$

3.3.4 Performance of the SVR model

The regression learner app in the MATLAB R2021b is used to train and test the model. Holdout validation is chosen to train the model 30% of the data to use as a validation set. The number of datasets considered is 101. Out of this, 70% of the data is utilized to train the model and 30% to test the model. The model is trained with different kernel functions, and the quadratic function gives the best performance.

The regression plot, the mean squared error, and R^2 value (Coefficient of determination) are used to assess the SVR model's performance. Fig. 3.16 and Fig. 3.17 show each training and testing data set performance. A regression plot is a visual representation of how well a model fits the data. MATLAB R2021b is used to plot the regression across all data. A good model has small errors, which means the predictions are scattered near the regression line. From Fig. 3.16 and Fig. 3.17, it is shown that all the points lie on a regression line which means the model has trained accurately.

R^2 value (Coefficient of determination) is another measure of how well the regression model fits the data. Table 3.6 shows the training results of an SVR model, which shows that the R^2 value for the training and testing dataset is 0.98 each. This means the model has trained accurately and will successfully predict the damage severity when new samples are taken as an input with higher accuracy.

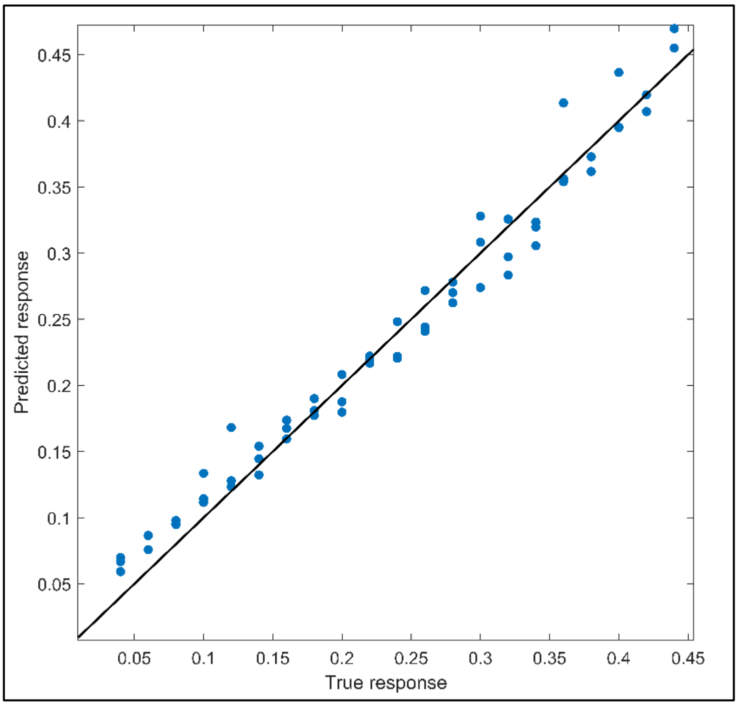

Fig. 3.16: Regression plot of the SVR model (Training dataset)

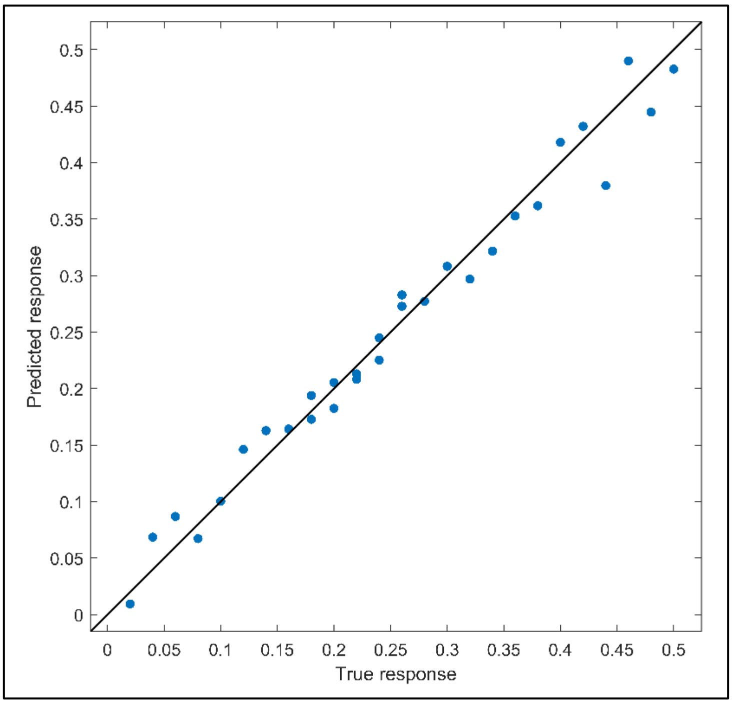

Fig. 3.17: Regression plot of the SVR model (Testing dataset)

Table 3.6: Training results of the SVR model

	Observations	MSE	R^2 Value
Training	71	3.357e-4	0.98
Testing	30	7.5752e-4	0.98

The trained and tested SVR model gives a high R^2 value and very low mean square error. The close to one R^2 value and low MSE value showed that the predicted value is near to the actual value, indicating that the SVR model is accurately trained and will successfully predict the output when a new sample is taken as an input.

3.4 Results and discussion

This work describes a study on damage severity prediction in the concrete-steel composite girder bridge model using ANN and SVR algorithms. A FE model of the concrete-steel composite girder bridge was created and validated by using the comparison of the experimental results. The numerical modal analysis is performed on the healthy and damaged structure showed that increasing damage depth in structure leads to a decrease in natural frequencies. It shows that a decrease in natural frequencies is the best indicator of damage.

ANN and SVR models were applied successfully using the numerically obtained natural frequencies of the healthy and damaged bridge models. The feasibility of ANN and SVR as powerful tools for damage severity prediction in a structure is evaluated. According to the results, ANN has a prediction accuracy of 99.83%, 99.35, and 97.06% for training, testing, and validation, respectively, for damage severity. SVR has a prediction accuracy of 98% for both training and testing for damage severity. Also, the results show a highly acceptable coefficient of determination between the predicted and actual data and imply that the presented ANN and SVR model can be applied as a perfect approach for identifying damage severity in the bridge structure.

Therefore, it is concluded that the severity of damage to the bridge structure could be assessed using an ANN and SVR model trained with natural frequencies extracted from numerical modal analysis as inputs.

Chapter 4

Deflection prediction in beam using machine learning techniques

4.1 Introduction

Bridges are frequently built using composite steel-concrete structures. The concrete-steel composite beam shown in Fig. 4.1 is a vital part of a bridge structure. Shear connections connect the steel beam and concrete slab. Because shear connectors are flexible, a slip between the steel beam and concrete slab could occur, causing a deflection structure. The deflection governs the design of conventional bridges made of high strength materials. The maximum deflection of a beam is a design criterion that occurs at or close to the middle of the span [22]. The cracking in concrete causes the elastic deflection change in the beam.

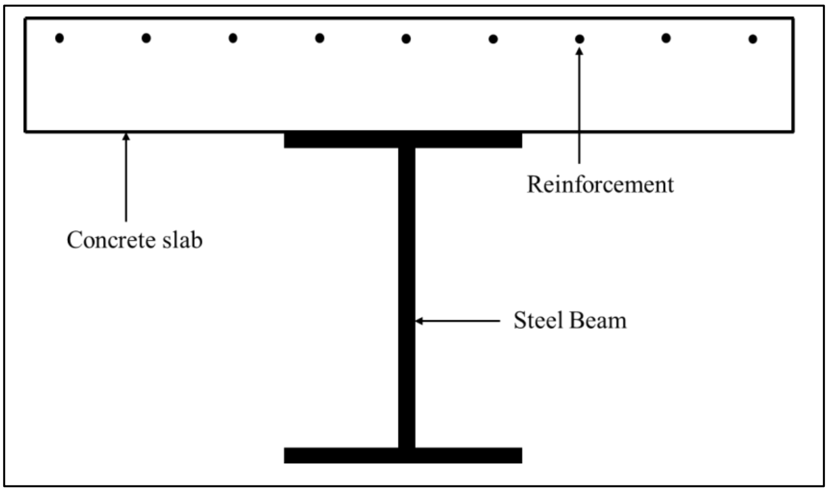

Fig. 4.1: Concrete-steel composite beam cross-section

Machine learning techniques have been widely used to predict the parameter without any computational efforts and experimental analysis. In this chapter, two different machine learning techniques, i.e., ANN and SVR, have been employed for deflection prediction in the beam.

4.2 Structural parameters

The elastic mid-span deflection, D^e changes due to cracking at the instantaneous stage and changes again due to creeping effect and shrinkage, resulting in inelastic mid-span deflection D^i. The change in mid-span deflection, i.e., elastic midspan deflection to inelastic midspan deflection of a span j of a beam, is stated in terms of an inelastic deflection ratio, which is defined as, $\delta_j = \{(D_j^i - D_j^e)/D_j^{eq}\}$, where $D_j^{eq} = (M^{cr} l_j^2/32EI)$ is the deflection at the middle of span j of a beam having both ends assumed fixed and a uniformly cracking load, w^{cr} is subjected, where w^{cr} is the minimum load at which the beam cracks and M^{cr} is the cracking moment at the fixed [23]. An inelastic deflection ratio is used as an output feature for ANN and SVR models.

Input features to train ANN and SVR for span with end joints j and $j+1$, are taken as[23]:

1. $R_{j-1}^r(M_{j-1}^{e,r}/M^{cr})$ is the cracking moment on the right side of joint $j-1$,
2. $R_j^l(M_j^{e,l}/M^{cr})$ is the ratio of cracking moment on the left side of joint j ,
3. $R_j^r(M_j^{e,r}/ M^{cr})$ is the ratio of cracking moment on the right side of joint j ,
4. $R_{j+1}^l(M_{j+1}^{e,l}/M^{cr})$ is the ratio of cracking moment on the left side of joint $j+1$,
5. $R_{j+1}^r(M_{j+1}^{e,r}/M^{cr})$ is the ratio of cracking moment on the right side of joint $j+1$,
6. $R_{j+2}^l(M_{j+2}^{e,l}/M^{cr})$ is the ratio of cracking moment on the left side of joint $j+2$,
7. S_{j-1}/S_j is the adjacent spans stiffness ratio at joint j , where, $S_j = EI^{un}/l_j$,
8. S_j/S_{j+1} is the adjacent spans stiffness ratio at joint $j+1$,
9. w_{j-1}/w_j is the adjacent spans load ratio of at joint j,

10. w_j/w_{j+1}, is the adjacent spans load ratio of at joint $j+1$,

11. The composite inertia ratio is I^{cr}/I^{un} ,

12. t_0 is loading age,

13. Gr is concrete grade,

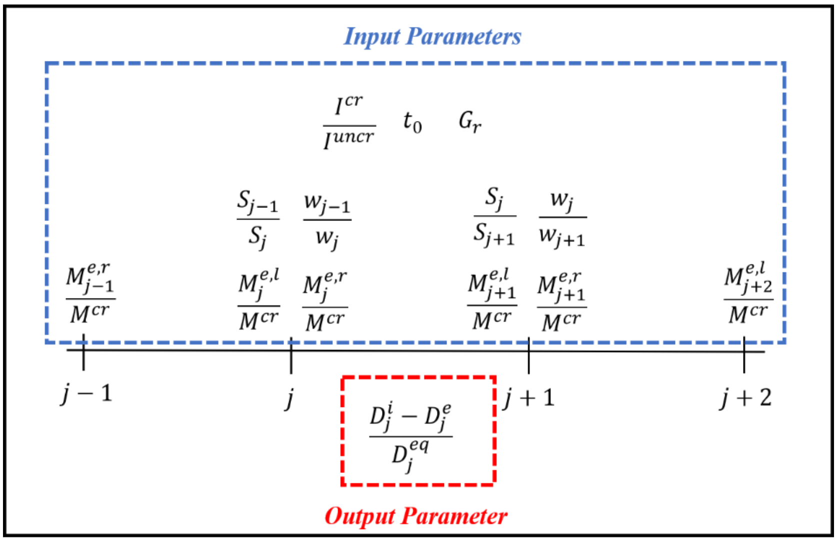

Fig. 4.2: Input and output parameters representation

4.3 Machine learning approach for deflection prediction

4.3.1 Artificial neural network (ANN)

The details of an ANN are described in chapter 3(3.3.1).

A multilayered feedforward neural network was employed, with all layers interconnected in a feedforward way. Several other algorithms and activation functions can be used to train the network, but the sigmoid activation function is utilized, and the backpropagation algorithm is considered to develop the network. The backpropagation tool of Levenberg-Marquardt is used to learn the connections between the input and output variables. The fundamental premise of the backpropagation algorithm is that error is sent back, and data is transferred forward. The neural network toolbox in MATLAB R2021b has been used to train, validate, and test the ANN model. The number of hidden neurons is selected by trial and error. Three ANN models, one for an interior span of the beam, one for a left exterior span of the beam, and one for a right exterior span of the beam, were trained and tested. A hybrid analytical-numerical analysis procedure was used to create datasets required to develop ANN and SVR models [23].

4.3.1.1 ANN model for an interior span of the beam

The deflections change in the adjacent spans is affected by cracking at a joint. As a result, the structural parameters that impact the deflection change of a span j are those parameters that affect the cracking at the joints j and $j + 1$. The cracking at joint j is influenced by several parameters. Those parameters are: $R^r_{j-1}, R^l_j, R^r_j, R^l_{j+1}, S_{j-1}/S_j, w_{j-1}/w_j$, I^{cr}/I^{un}, t_0 and Gr, and parameters that affect cracking at joint $j + 1$ are: R^r_j, R^l_{j+1}, R^r_{j+1}, R^l_{j+2}, S_j/S_{j+1}, w_j/w_{j+1}, I^{cr}/I^{un}, t_0 and Gr. Five parameters are common in these parameters, and those parameters are, R^r_j, R^l_{j+1}, I^{cr}/I^{un}, t_0 and Gr. Therefore, an ANN model for an interior span j, consists of thirteen input parameters, R^r_{j-1}, R^l_j, R^r_j, R^l_{j+1}, R^r_{j+1}, R^l_{j+2}, S_{j-1}/S_j, S_j/S_{j+1}, w_{j-1}/w_j, w_j/w_{j+1}, I^{cr}/I^{un}, t_0 and Gr and one output parameter, δ_j [23]

The neural network toolbox in the MATLAB R2021b is used to train and validate the network. Numerous trials are performed with various numbers of hidden layer neurons to train the network. The number of datasets considered for the interior span is 14104. Out of this, 70% of the data is utilized to train the model, 15% for validation, and 15% to test the model. The architecture of an ANN model for an interior span is shown in Fig. 4.3, which consists of 13 neurons in the input layer, i.e., 13 input features. In the hidden layer, there are 17 neurons, and in the output layer, there is 1 neuron, i.e., 1 output feature.

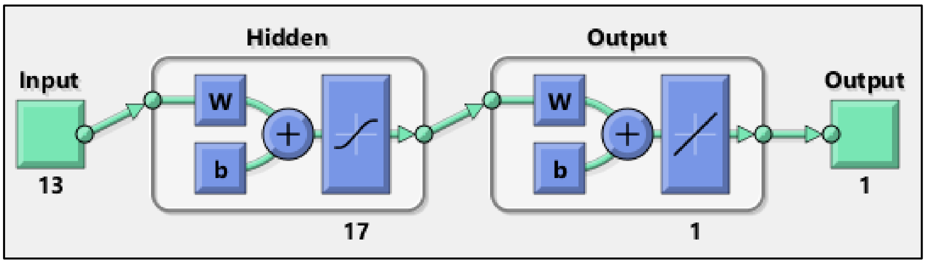

Fig. 4.3: Architecture of an ANN (Interior span)

The performance plot of a trained model is shown in Fig. 4.4, which shows how the mean squared error (MSE) changes for different iterations. After 116 iterations model was trained, and after that, it stopped because validation error started increasing from that point. The best Validation Performance is 0.00028513 at epoch 116.

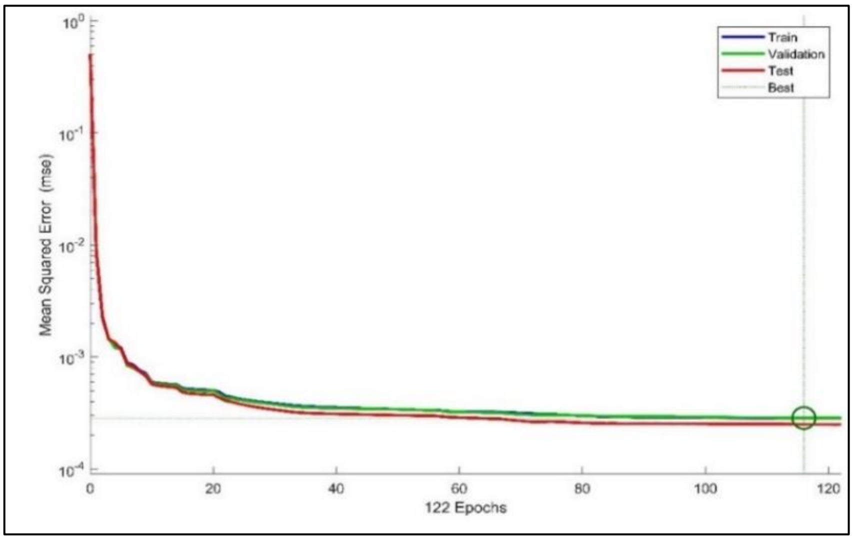

Fig. 4.4: Performance plot of an ANN model (Interior span)

4.3.1.2 Performance of an ANN model for an interior span of a beam

The regression plot, the mean squared error, and R^2 value (Coefficient of determination) are used to assess an ANN model's performance. In Fig. 4.5, performance is shown for each training, validation, and test data set. A regression plot is a visual representation of how well a neural network fits the data. MATLAB R2021b is used to plot the regression across all data. The network outputs are shown against the associated target values in the regression plot. A good model has small errors, which means the predictions are scattered near the regression line. In Fig. 4.5, all the points lie on a regression line, which means the model has trained accurately.

R^2 value (Coefficient of determination) is another measure of how well the neural network fits the data. The R^2 value indicates how closely regression predictions match real data points. The regression predictions perfectly fit the data when the R^2 value is 1. When R^2 values are outside the range of 0 to 1, it means the model does not fit the data and the worst possible least-squares predictor. Table 4.1 shows the training results of a neural network model, which shows that the R^2 value for the training, validation and testing is 0.9619, 0.9627, and 0.9664, respectively. It implies that the model has trained accurately and will successfully predict the deflection of the beam when new samples are taken as an input with higher accuracy.

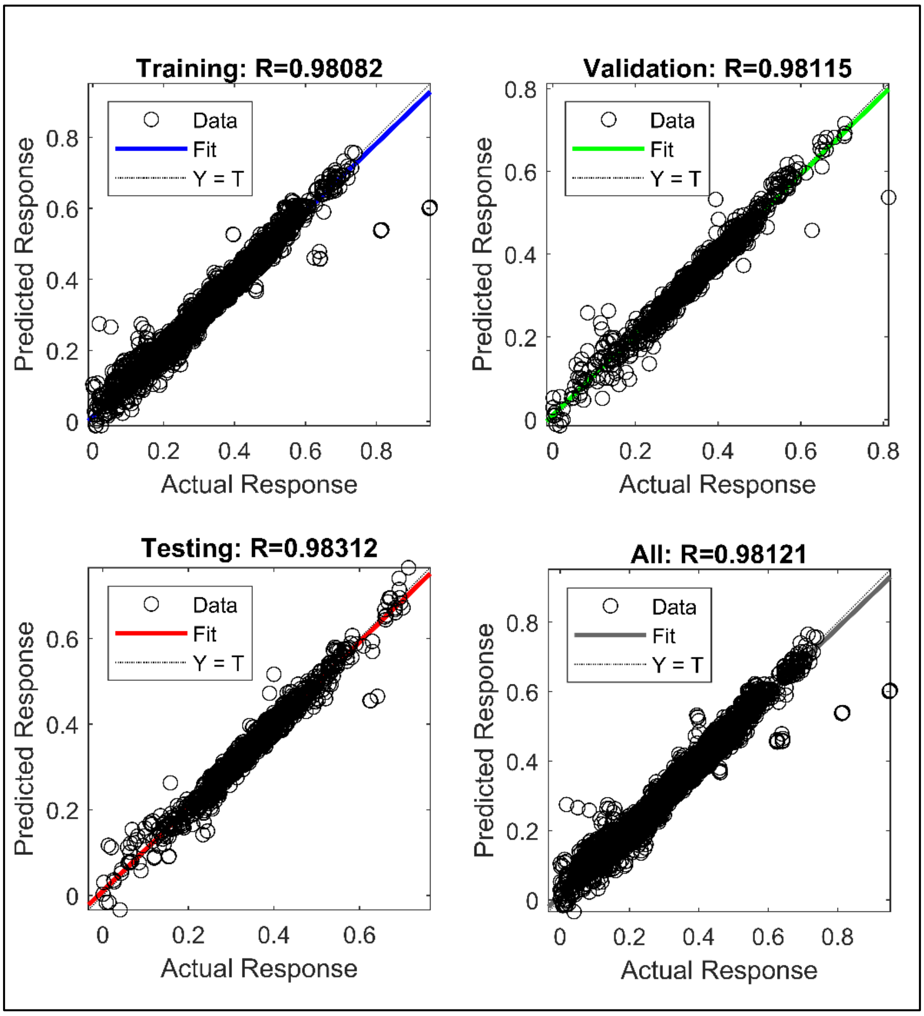

Fig. 4.5: Regression plots of an ANN model (Interior span)

Table 4.1: Training results of an ANN model (Interior span)

	Observations	MSE	R^2 Value
Training	9872	2.8530e-4	0.9619
Validation	2116	2.8513e-4	0.9627
Testing	2116	2.5029e-4	0.9664

The trained and tested ANN model for an interior span of the beam gives a close to one R^2 value, and a very low mean square error. The close to one R^2 value and low MSE value showed that a predicted output is near to the actual output, indicating that the neural network model is accurately trained and will successfully predict the output when a new sample is taken as an input

4.3.1.3 ANN model for a left exterior span of the beam

In the case of the left exterior span of the beam, the input parameters, $R_{j-1}^r, R_j^l,\ S_{j-1}/S_j, w_{j-1}\ /w_j$ are nonexistent. Therefore input parameters for an ANN model for a left exterior span consist of nine parameters, R_j^r , $R_{j+1}^l, R_{j+1}^r, R_{j+2}^l,\ S_j/S_{j+1}, w_j/w_{j+1}, I^{cr}/I^{un}, t_0$ and Gr and one output parameter, δ_j[23]. The neural network toolbox in the MATLAB R2021b is used to train and validate the network. Numerous trials are performed with various numbers of hidden layer neurons to train and test the network. The number of datasets considered for the left exterior span is 4197. Out of this, 70% of data is utilized to train the model, 15% for validation, and 15% to test the model. The architecture of an ANN model is shown in Fig. 4.6, which has 9 neurons in the input layer, i.e., 9 input features. In the hidden layer, there are 10 neurons, and in the output layer, there is 1 neuron, i.e., 1 output feature.

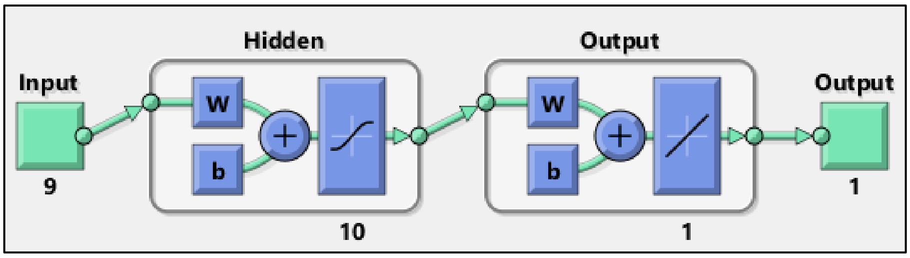

Fig. 4.6: Architecture of an ANN model (Left exterior span)

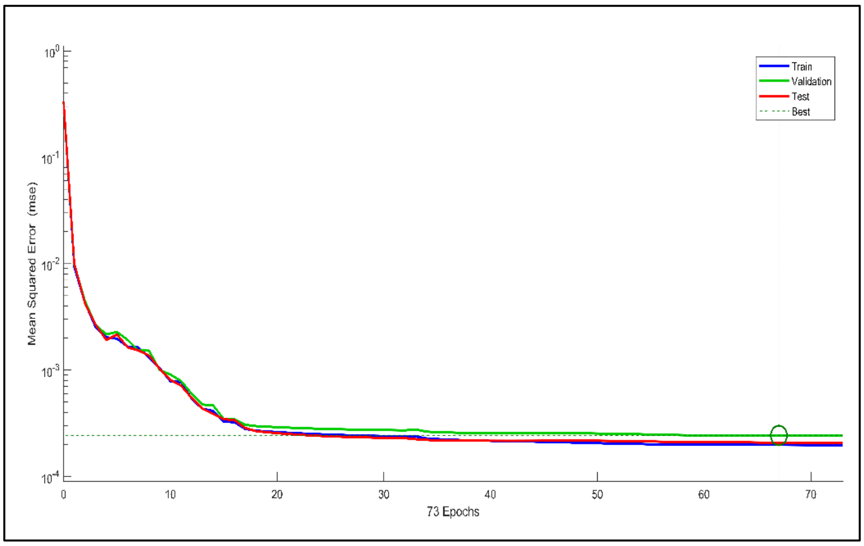

Fig. 4.7: Performance plot of an ANN model (Left exterior span)

The performance plot of a trained ANN model is shown in Fig. 4.7, which shows how the mean squared error (MSE) changes for different iterations. After 67 iterations model was trained, and after that, it stopped because validation error started increasing from that point. The best Validation Performance is 0.00024277 at epoch 67.

4.3.1.4 Performance of an ANN model for a left exterior of a beam

The network's performance is assessed using the mean squared error, regression plot, and R^2 value (Coefficient of determination). In Fig. 4.8, performance is shown for each training, validation, and test data set. A regression plot is a visual representation of how well a neural network fits the data. MATLAB R2021b is used to plot the regression across all data. The network outputs are shown against the associated target values in the regression plot. A good model has small errors, which means the predictions are scattered near the regression line. In Fig. 4.8, all the points lie on a regression line, which means the model has trained accurately.

Table 4.2 shows the training results of a neural network model, which shows that the R^2 value for the training, validation, and the testing dataset is 0.9837, 0.9793, and 0.9842, respectively. It implies that the model has trained accurately and will successfully predict the deflection of the beam when new samples are taken as an input with higher accuracy.

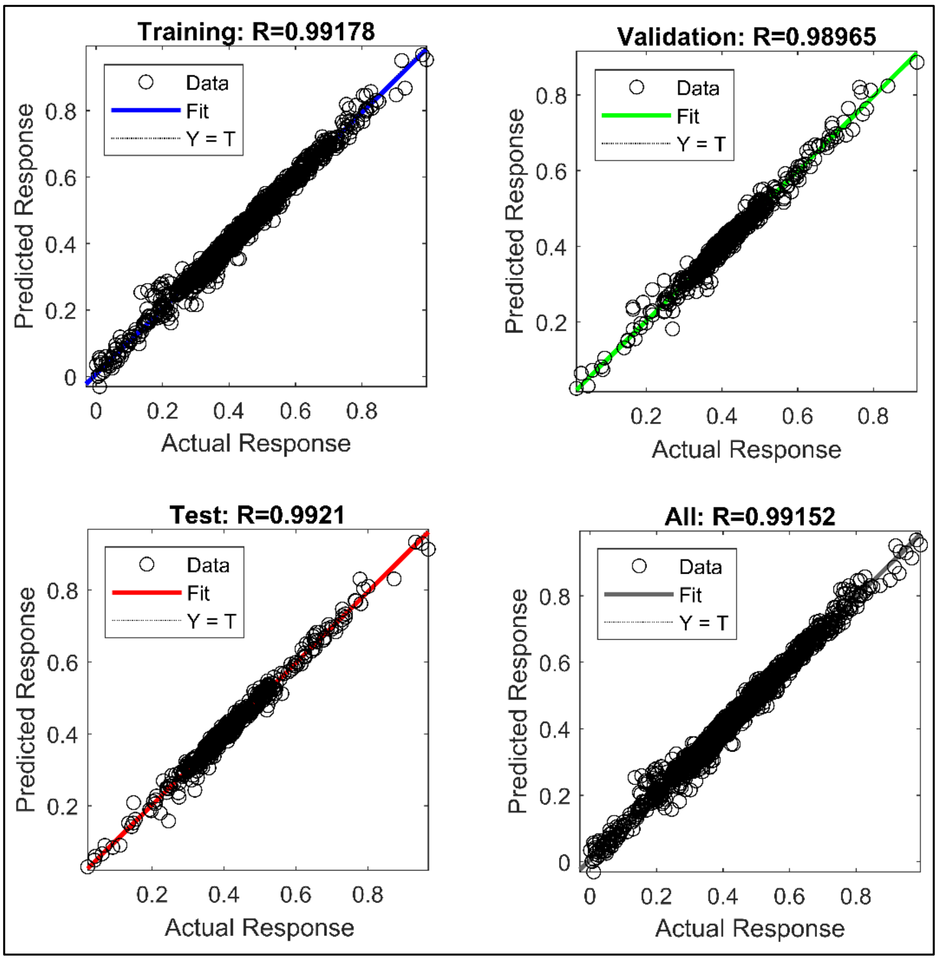

Fig. 4.8: Regression plots of ANN (Left exterior span)

Table 4.2: Training results of an ANN model (Left exterior span)

	Observations	MSE	R^2 Value
Training	2937	2.8530e-4	0.9837
Validation	630	2.8513e-4	0.9793
Testing	630	2.5029e-4	0.9842

The trained and tested ANN model for a left exterior span of the beam gives a close to one R^2 value, and a very low mean square error. The close to one R^2 value and low MSE value showed that a predicted output is near to the actual output, indicating that the neural network model is accurately trained and will successfully predict the output when a new sample is taken as an input

4.3.1.5 ANN model for a right exterior span of the beam

In the case of the right exterior span of the beam, the input parameters, R_{j+1}^{r}, R_{j+2}^{l}, S_j/S_{j+1}, w_j/w_{j+1} are nonexistent. R_{j-1}^{r}, R_j^{l} , R_j^{r} , R_{j+1}^{l} , S_{j-1}/S_j , w_{j-1}/w_j, I^{cr}/I^{un}, t_0 and Gr and one output parameter, δ_j [23]. The neural network toolbox in the MATLAB R2021b is used to train and validate the network. Numerous trials are performed with various numbers of hidden layer neurons to train and test the network. The number of datasets considered for a right span is 4201. Out of this, 70% of data is utilized to train the model, 15% for validation, and 15% to test the model. The architecture of an ANN model is shown in Fig. 4.9, which has 9 neurons in the input layer, i.e., 9 input features. In the hidden layer, there are 15 neurons, and in the output layer, there is 1 neuron, i.e., 1 output feature.

The performance plot of a trained model is shown in Fig. 4.10. The performance plot of a trained model which shows how the mean squared error (MSE) changes for different iterations. After the 304 iterations model was trained, it stopped because validation errors started increasing from that point. The best Validation Performance is 0.0001074 at epoch 304.

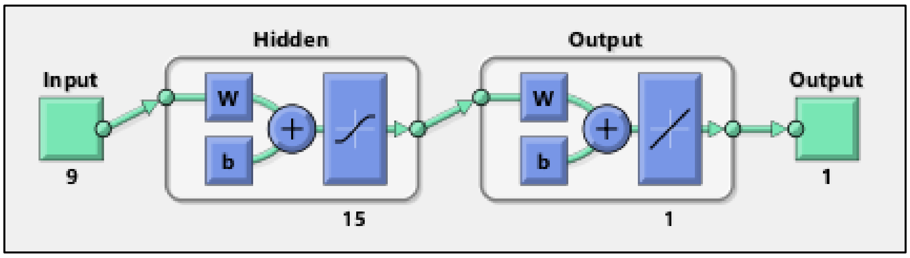

Fig. 4.9: Architecture of an ANN model (Right exterior span)

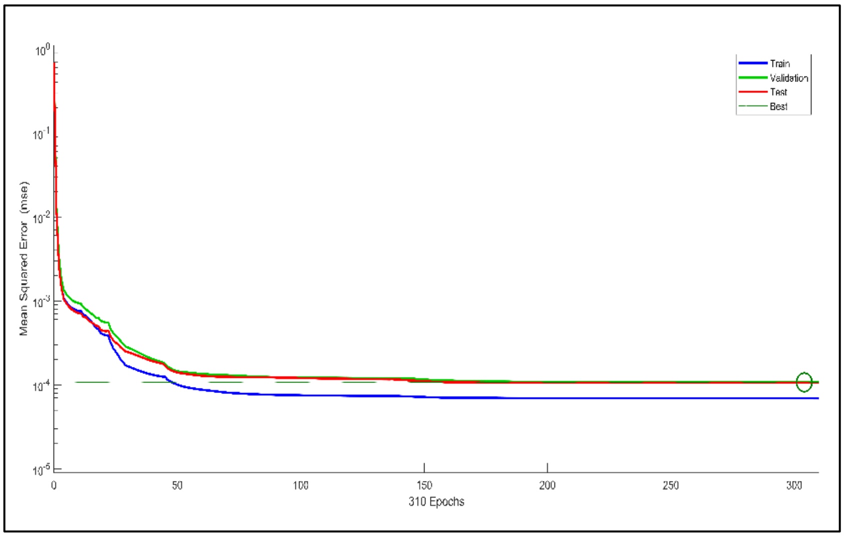

Fig. 4.10: Performance plot of an ANN model (Right exterior span)

4.3.1.6 Performance of an ANN model for a right exterior of a beam

The regression plot, the mean squared error, and R^2 value (Coefficient of determination) are used to assess an ANN model's performance. In Fig. 4.10, performance is shown for each training, validation, and test data set. A regression plot is a visual representation of how well a neural network fits the data. MATLAB R2021b is used to plot the regression across all data. The network outputs are shown against the associated target values in the regression plot. In Fig. 4.11, all the points lie on a regression line, which means the model has trained accurately. Table 4.3 shows the training results of a neural network model. It is observed that the R^2 value for the training, validation, and the testing dataset is 0.9942, 0.9962, and 0.9912, respectively. It implies that the model has trained accurately and will successfully predict the deflection of the beam when new samples are taken as an input with higher accuracy.

Table 4.3: Training results of an ANN model (Right exterior span)

	Observations	MSE	R^2 Value
Training	2941	6.9181e-5	0.9942
Validation	630	1.0746e-4	0.9926
Testing	630	1.0621e-4	0.9912

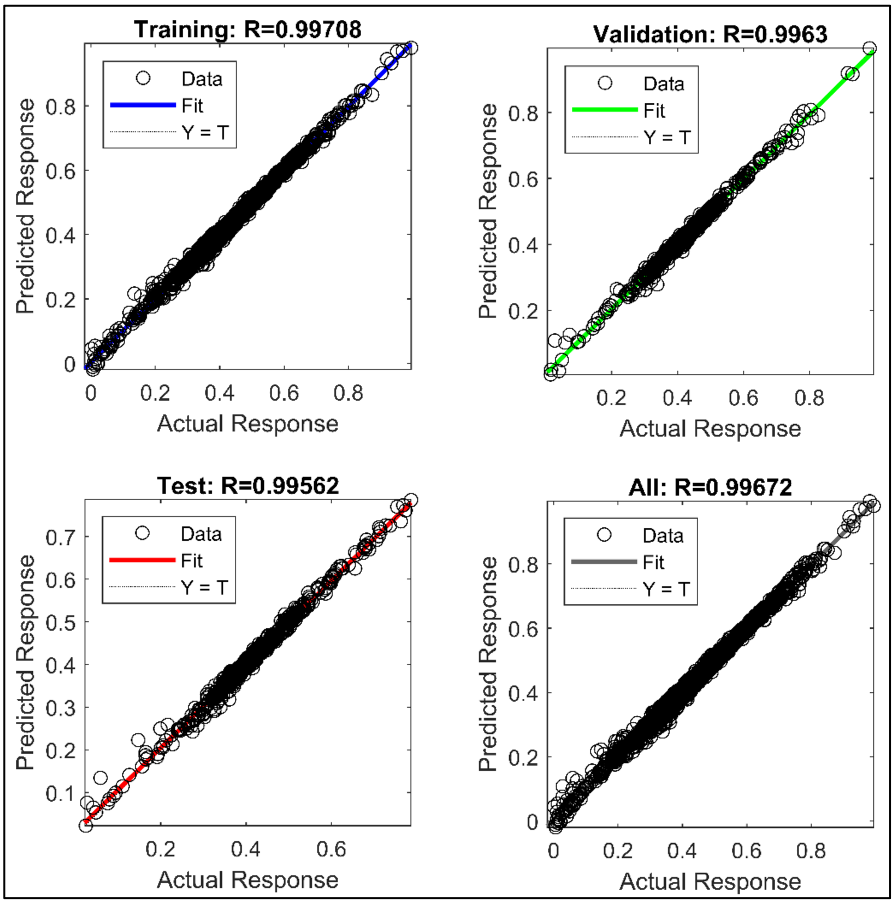

Fig. 4.11: Regression plots of an ANN model (Right exterior span)

The trained and tested ANN model for a right exterior span of the beam gives a close to one R^2 value and a very low mean square error. The close to one R^2 value and low MSE value showed that a predicted output is near to the actual output, indicating that the neural network model is accurately trained and will successfully predict the output when a new sample is taken as an input

4.3.2 Support vector regression

The details of the SVR are described in chapter 3(3.3.3). Three support vector regression models, one for an interior span of beam, one for a left exterior span of the beam, and one for a right exterior span of the beam, are trained and tested, and performance is measured.

4.3.2.1 The SVR model for an interior span of the beam

The SVR model for an interior span j, of a beam consists of thirteen input parameters, R_{j-1}^{r}, R_{j}^{l}, R_{j}^{r} , R_{j+1}^{l}, R_{j+1}^{r}, R_{j+2}^{l}, S_{j-1}/S_{j}, S_{j}/S_{j+1}, w_{j-1}/w_{j}, w_{j}/w_{j+1}, I^{cr}/I^{un}, t_0 and Gr and one output parameter, δ_j[23]. The training of the model is carried out using the regression learner app in the MATLAB R2021b. Holdout validation is chosen to train the model 30% of the data to use as a validation set. The number of datasets for the interior span is 14104. Out of 14104 datasets, 9900 datasets are utilized for training, and 4204 datasets are utilized to test the model. The model is trained with different kernel functions and the Gaussian radial basis function gives the best performance.

4.3.2.2 Performance of the SVR model for an interior span of the beam

The regression plot, the mean squared error, and R^2 value (Coefficient of determination) is used to assess the SVR model's performance. Fig. 4.12 and Fig. 4.13 show performance for each training and testing data set. A regression plot is a visual representation of how well a model fits the data. MATLAB R2021b is used to plot the regression across all data. A good model has small errors, which means the predictions are scattered near the regression line. Fig. 4.12 and Fig. 4.13 show that all the points lie on a regression line, which means the model has trained accurately.

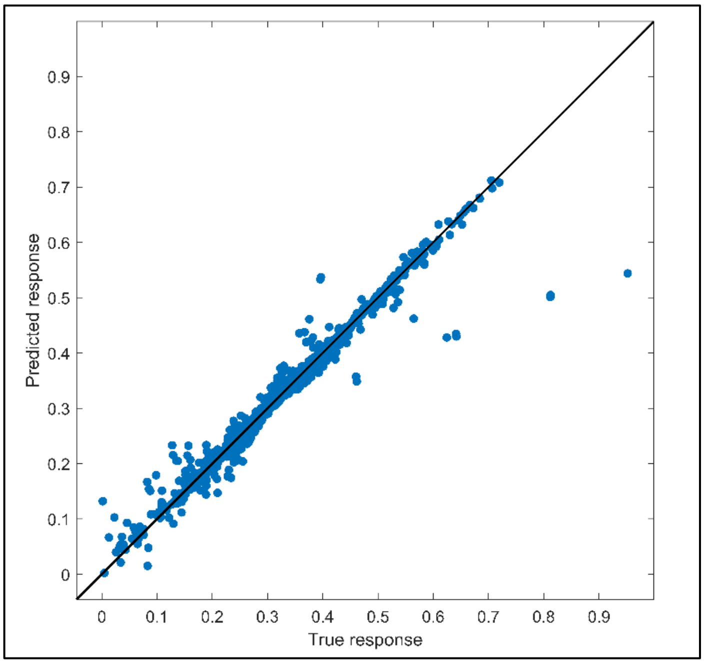

Fig. 4.12: Regression plot of the SVR model for the training dataset (Interior span)

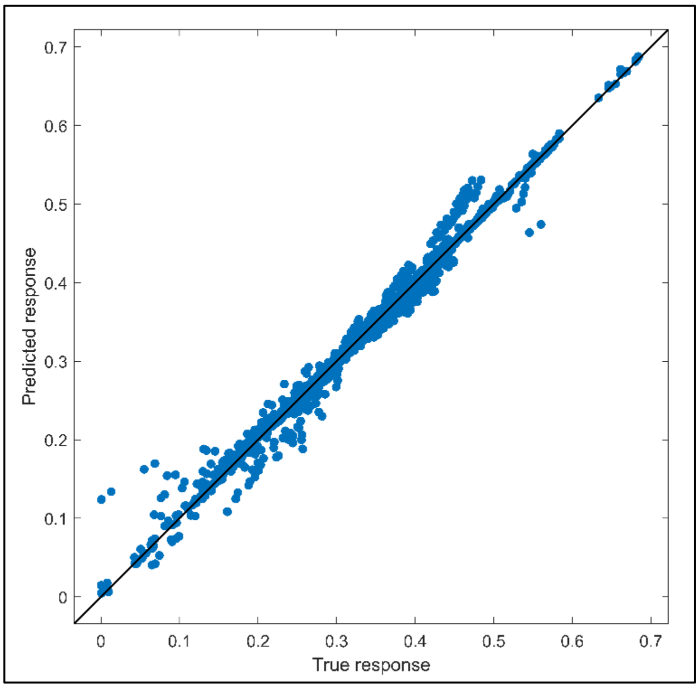

Fig. 4.13: Regression plot of the SVR model for the testing dataset (Interior span)

R^2 value (Coefficient of determination) is another measure of how well the neural network fits the data. Table 4.4 shows the training results of an SVR model, which shows that the R^2 value for the training and testing dataset is 0.96 and 0.99, respectively. This means the model has trained accurately and will successfully predict the deflection of the beam when new samples are taken as an input with higher accuracy.

Table 4.4: Training results of a SVR model (Interior span)

	Observations	MSE	R^2 Value
Training	9900	3.357e-4	0.96
Testing	4204	7.5752e-4	0.99

The trained and tested SVR model for an interior span of the beam gives a close to one R^2 value, and a very low mean square error. The close to one R^2 value and low MSE value showed that a predicted output is near to the actual output, indicating that the SVR model is accurately trained

4.3.2.3 The SVR model for a left exterior span of the beam

In the case of the left exterior span, the input parameters, R_{j-1}^{r}, R_{j}^{l}, S_{j-1}/S_{j}, w_{j-1}/w_{j} are nonexistent. Therefore, input parameters for the SVR model for a left exterior span of beam consist of nine parameters, R_{j}^{r} , R_{j+1}^{l}, R_{j+1}^{r}, R_{j+2}^{l}, S_{j}/S_{j+1}, w_{j}/w_{j+1}, I^{cr}/I^{un}, t_{0} and Gr and one output parameter, δ_{j}[23]. The training of the model is carried out using the regression learner app in the MATLAB R2021b. Holdout validation is chosen to train the model 30% of the data to use as a validation set. The number of datasets for the left exterior span is 4197. Out of 4197 datasets, 2838 datasets are utilized for training the model, and 1359 datasets are utilized to test the model. The model is trained with different kernel functions and the cubic kernel function gives the best performance.

4.3.2.4 Performance of the SVR model for a left exterior span of the beam

The regression plot, the mean squared error, and R^2 value (Coefficient of determination) is used to assess the SVR model's performance. Fig. 4.14 and Fig. 4.15 show performance for each training and testing data set. A regression plot is a visual representation of how well a model fits the data. MATLAB R2021b is used to plot the regression across all data. A good model has small errors, which means the predictions are scattered near the regression line. From Fig. 4.14 and Fig. 4.15, it is shown that all the points lie on a regression line which means the model has trained accurately.

Table 4.5 shows the training results of an SVR model for a left exterior span of the beam, which shows that the R^2 value for the training and testing dataset is 0.96 and 0.97, respectively. This means the model has trained accurately and will successfully predict the deflection of the beam when new samples are taken as an input with higher accuracy.

Table 4.5: Training results of a SVR model (Left exterior span)

	Observations	MSE	R^2 Value
Training	2838	5.0745e-4	0.96
Testing	1359	2.9356e-4	0.97

The trained and tested SVR model for a left exterior span of the beam gives a close to one R^2 value and a very low mean square error. The close to one R^2 value and low MSE value showed that a predicted output is near to the actual output, indicating that the SVR model is accurately trained

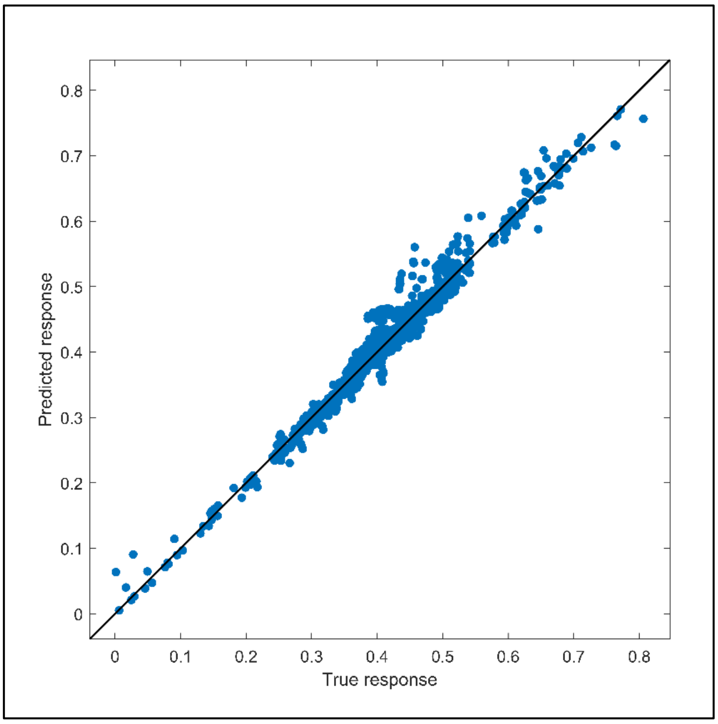

Fig. 4.14: Regression plot of the SVR model for the training dataset (Left exterior span)

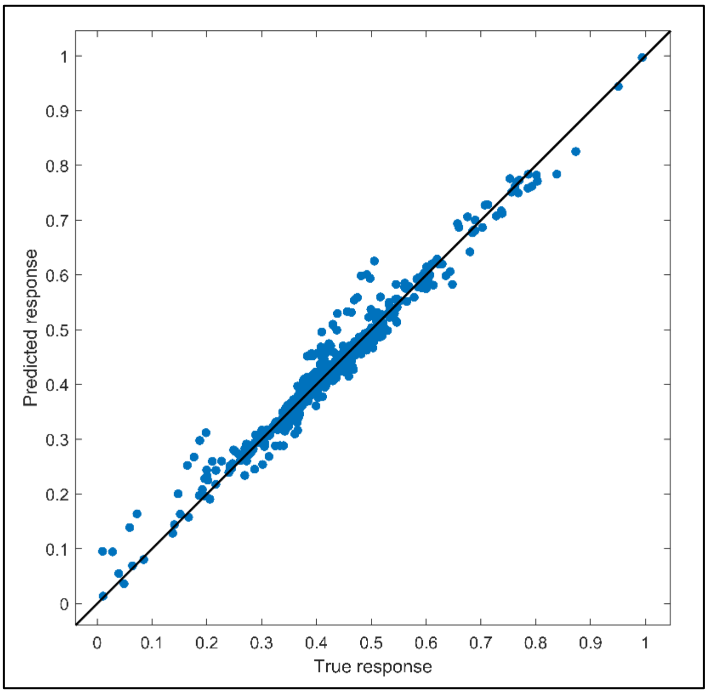

Fig. 4.15: Regression plot of the SVR model for the testing dataset (Left exterior span)

4.3.2.5 The SVR model for a right exterior span of the beam

In the case of the right exterior span, the input parameters, R_{j+1}^{r}, R_{j+2}^{l}, S_j/S_{j+1}, w_j/w_{j+1} are nonexistent. R_{j-1}^{r}, R_j^l , R_j^r , R_{j+1}^{l} , S_{j-1}/S_j , w_{j-1}/w_j, I^{cr}/I^{un}, t_0 and Gr and one output parameter, δ_j[23].The training is carried out using the regression learner app in the MATLAB R2021b. Holdout validation is chosen to train the model 30% of the data to use as a validation set. The number of datasets considered for the right exterior span is 4201. Out of 4201 datasets, 2969 datasets are utilized for training, and 1262 datasets are utilized to test the model. The model is trained with different kernel functions and the cubic kernel function gives the best performance.

4.3.2.6 Performance of the SVR model for a right exterior span of the beam

The regression plot, the mean squared error, and R^2 value (Coefficient of determination) is used to assess the SVR model's performance. Fig. 4.16 and Fig. 4.17 show each training and testing data set performance. A regression plot is a visual representation of how well a model fits the data. MATLAB R2021b is used to plot the regression across all data. A good model has small errors, which means the predictions are scattered near the regression line. From Fig. 4.16 and Fig. 4.17, it is shown that all the points lie on a regression line which means the model has trained accurately.

Table 4.6 shows the training results of an SVR model, which shows that the R^2 value for the training and testing dataset is 0.98 each. This means the model has trained accurately and will successfully predict the deflection of the beam when new samples are taken as an input with higher accuracy.

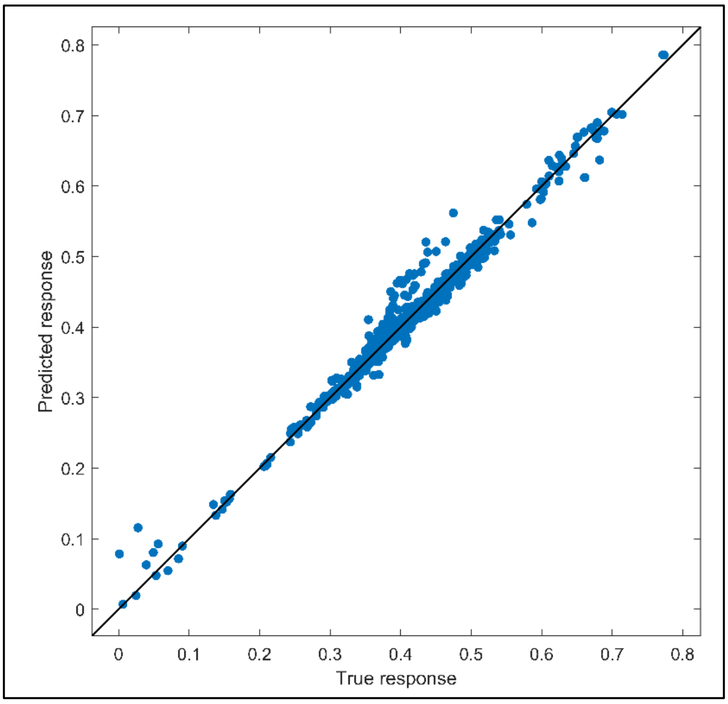

Fig. 4.16: Regression plot of the SVR model for the training dataset (Right exterior span)

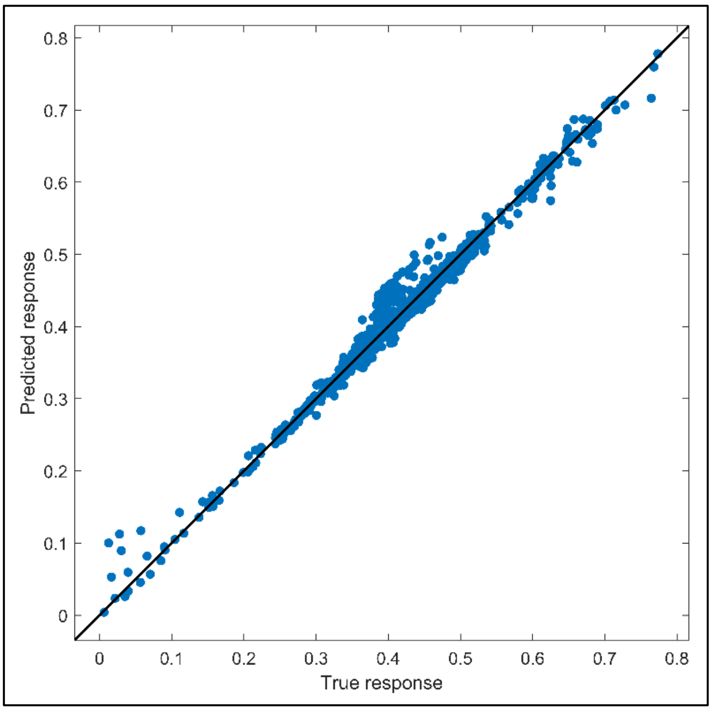

Fig. 4.17: Regression plot of the SVR model for the testing dataset (Right exterior span)

Table 4.6: Training results of a SVR model (Right exterior span)

	Observations	MSE	R^2 Value
Training	2939	2.1681e-4	0.98
Testing	1262	1.6628e-4	0.98

The trained and tested SVR model for a right exterior span of the beam gives a close to one R^2 value, and a very low mean square error. The close to one R^2 value and low MSE value showed that a predicted output is near to the actual output, indicating that the SVR model is accurately trained

4.4 Results and discussion

This work describes the deflection prediction of the beam using an ANN and the SVM algorithms. It compares the performance of an ANN and the SVR for deflection prediction. Three ANN and three SVR models have been developed to predict inelastic midspan deflection of an interior span, a left exterior span, and a right exterior span.

The feasibility of ANN and SVR as powerful tools for predicting beam deflection is investigated. According to the results, ANN could predict the deflection for an interior span, a left exterior span, and a right exterior span with 96.36 %, 98.24 %, and 99.26% accuracy, respectively. While SVR could predict the deflection for an interior span, a left exterior span, and a right exterior span with 97.50 %, 96.50 %, and 98.00 % accuracy, respectively. Also, the results show a highly acceptable coefficient of determination between the predicted and actual data and imply that the developed ANN and SVR model can be applied as a perfect tool for identifying deflection in the beam

Chapter 5

Conclusion and future scope

5.1 Conclusion

This work aims to extract natural frequencies from a numerical modal analysis of a girder bridge based on finite element simulation for damage detection. The work also highlighted ML-based techniques like ANN and SVM for damage severity prediction and deflection prediction. The conclusions drawn from this study are listed below:

- A reduction in natural frequencies is a reliable sign of damage to the structure.
- ANN had a 98.75 % accuracy rate in predicting the severity of the damage, while SVR had a 98 % accuracy rate in predicting the severity of the damage.
- ANN could predict the deflection for an interior span, a right exterior span, and a left exterior span with the accuracy of 96.36 %, 99.26%, and 98.24 %, respectively. In contrast, SVR could predict the deflection for an interior span, a right exterior span, and a left exterior span with the accuracy of 97.50 %, 98.00%, and 96.50 %, respectively.

5.2 Future scope

Although the suggested damage detection approach is effective, a few concerns need to be addressed. Future research efforts might be focused on the following areas:

- The work does not entirely address the prediction of damage location and the remaining service life of the structure. To provide relevant information for decision making, efforts might be directed in the fields of fracture mechanics and fatigue life analysis.

- The present work does not address fault detection at the local level. Efforts in the field of acoustic emission-based monitoring to identify local level damage might be directed.

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