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Computational and Experimental Modeling of Curved Crack Effects on the Dynamic Response of Plate Structures

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ABSTRACT: Cracks can severely degrade the integrity and service performance of plate structures. Although most existing studies focus on identifying straight crack patterns using dynamic response data, curved crack paths have received far less attention, despite being more realistic in practice and having a stronger influence on structural behaviour. This study presents a computational and experimental framework for analyzing and identifying curved crack paths in cantilever plate structures based on dynamic response characteristics. Curved crack paths are modelled using second-order polynomial equations. Finite Element Analysis (FEA) is employed to evaluate the effects of polynomial coefficients and crack end abscissa (x_{end}) on natural frequency and resonance amplitude, while experimental modal analysis (EMA) on damping ratio. Forward and inverse identification models are then developed using linear regression (LR) and artificial neural networks (ANN) to predict dynamic response characteristics and estimate crack path. Results show that the quadratic coefficient (a) and linear coefficient (b) of the crack path have the most decisive influence on the plate's vibration characteristics, whereas the constant term (c) has a negligible effect. Also, the crack paths with greater curvature and inclination, represented by higher a and b coefficients, especially at smaller end abscissae (x_{end}), tend to reduce natural frequencies and increase vibration amplitudes and damping ratios. In contrast, smoother, less curved cracks exhibit the opposite behaviour. These curved crack geometries cause greater stiffness degradation by altering both axial and shear stiffness. Consequently, local flexibility and energy dissipation increase due to enhanced crack-surface interaction and localised deformation. The proposed computational models are experimentally validated using 15 fabricated plates with different curved crack profiles, demonstrating high prediction accuracy. Overall, the study enhances the computational identification and characterization of curved cracks in plate structures, contributing to improved damage assessment and structural health monitoring (SHM) based on dynamic response.

KEYWORDS: Curved crack paths; computational modeling; dynamic response analysis; finite element analysis (FEA); artificial neural networks

1 Introduction

In the field of structural health monitoring (SHM), dynamic response analysis is a fundamental, widely adopted approach for damage detection. By examining variations in vibration signals, this technique enables the identification of structural changes or defects [1–3]. Extensive academic research and review studies have highlighted the importance and effectiveness of the dynamic response in assessing damage [4–7].

Cracks in plate structures represent a significant concern in engineering, as they can compromise the integrity and performance of various mechanical components. The propagation of these cracks can take several forms, including straight, curved, and random paths, each influenced by the material properties, loading conditions, and environmental factors.

Early investigations into cracked thin plates were primarily based on Levy- or Navier-type solution forms, from which various integral formulations were derived. Such approaches are mainly suitable for simply supported rectangular plates. For instance, Lynn and Kumbasar [8] employed a Levy–Nadai approach to obtain a Fredholm integral formulation in its first-kind form and, via numerical integration, reduced the problem of a simply supported plate with a narrow crack to a set of algebraic equations, enabling evaluation of natural frequencies and mode shapes. Building on this work, NEZU [9] used a Levy approach solution to construct Green's functions for simply supported plates with straight through notches. At the same time, Solecki [10] examined vibration in a plate containing a crack placed symmetrically and running parallel to the long edge, utilising a solution expressed in Navier form. In a related investigation, Hirano and Okazaki [11] derived formulations that meet the simply supported plate on two opposite edges with a crack perpendicular to them using the weighted residual method and Levy–Nadia approach.

Moreover, numerous researchers have employed numerical techniques to analyse the vibration behaviour of cracked plates. Among these, finite element and advanced modelling techniques have been extensively utilised [12–15]. Vibration-based approaches have also been widely adopted for damage detection and localisation using modal and experimental methods [16–19]. Furthermore, model updating strategies have significantly improved the accuracy of structural damage identification [20–22]. More recently, intelligent and hybrid techniques have been introduced to enhance structural integrity prediction [23]. For example, Ranjbaran and Seifi [24] use the generalised differential quadrature method (GDQ) to predict the free vibration behaviour of thin, isotropic plates that contain central cracks either part-through on the surface or internal and run parallel to one edge and subject to different boundary conditions. The study focuses on determining the influence on the plate's natural frequencies. Lai and Zhang [25] use the discrete singular convolution method (DSC) to analyse how central surface crack and temperature together affect the vibration and stability of thin rectangular plates made from either isotropic or orthotropic materials. Lai and Zhang [25] use the quadrature element method (QEM) to compute crack-tip asymptotic field coefficients by dividing the domain into subdomains and embedding the crack-tip displacement expressions near the central crack. Zhong et al. [26] use the coordinate mapping method (CMM) to evaluate the free vibration behaviour of arbitrarily shaped plates that contain complex holes and curved cracks. Dai et al. [27] established a theoretical framework to describe plate bending vibrations that can handle any number, size, and layout of cutouts subject to arbitrary boundary conditions, achieved by partitioning the plate into double-cutout primitive cells and analysing each cell using the Chebyshev–Lagrangian technique. Ammendolea et al. [28] proposed an enhanced finite element model to simulate dynamic crack propagation and branching in brittle materials, addressing the high computational cost and remeshing limitations of conventional FEM. The method combines a moving mesh (MM) technique based on the Arbitrary Lagrangian–Eulerian (ALE) formulation with fracture-mechanics-based criteria for crack initiation and velocity-dependent propagation. Similarly, Ammendolea et al. [29] developed an MM finite element method to model dynamic crack propagation and branching in brittle materials. The approach combines ALE-based mesh motion with fracture-mechanics criteria using dynamic stress intensity factors. The study investigates crack paths and branching behavior under different dynamic loading conditions. Wang et al. [30] developed a phase-field finite element model (PF-FEM) to investigate dynamic crack propagation and branching in brittle materials. The study examines crack trajectories and branching behavior under dynamic loading conditions.

Several researchers have extended the analysis to nonlinear phenomena, such as quasiperiodic responses, chaotic motions, and bifurcations to evaluate the nonlinear dynamics of cracked plates [31–33]. For instance, Israr [34] analysed the nonlinear dynamic response of a plate containing a central part-through crack using the equilibrium principle, Galerkin's procedure, and Berger's formulation. Results showed that the plate's natural frequency decreased significantly as the crack extended, highlighting a nonlinear dependence on amplitude. Ismail and Cartmell [35] introduced an analytical formulation for plates containing a centrally located, obliquely oriented surface crack, analysed under three types of boundary support in forced vibration. Their results show that, for all three boundary conditions, the frequency showed an upward trend up to 60° and a downward trend beyond that. Yang et al. [36] examined a simply supported functionally graded (FG) rectangular plate with a through-width surface crack, modelling its nonlinear vibrational response based on Reddy's third-order shear deformation theory. The study showed how the crack flexibility modifies the plate's dynamic response under transverse excitation. Saito et al. [37] analyse the nonlinear dynamic response of a cantilevered plate containing a crack running parallel to the cantilevered edge. By including crack-closure nonlinearity and using a harmonic-balance-based hybrid method, it proposes an efficient way to estimate the nonlinear resonant frequencies near these veerings. AsadiGorgi et al. [38] examine nonlinear vibrations of rectangular panels of moderate thickness that contain an all-over part-through crack. Wu and Shih [39] theoretically studied the nonlinear response of rectangular plates containing an edge crack under periodic in-plane loading. Using Galerkin reduction to a Mathieu-type equation and solving it with the incremental harmonic balance method, this study shows how the crack ratio, plate aspect ratio, and vibration amplitude shift the parametric instability regions and modify the nonlinear vibration behaviour.

Many investigations have concentrated on the fundamental scenario of cracked thin rectangular plates, encompassing both isotropic materials [40–42] and advanced materials [43–45]. For instance, Bose and Mohanty [46] investigated the impact of part-through surface cracks of varying lengths and orientations on the vibrational behaviour of rectangular thin isotropic plates, using modified line spring models and Duffing equations [47,48]. Beigi et al. [47] examined how the presence of cracks influences the vibration response of plate structures through finite element modelling. The crack was prepared with different lengths and orientations. Natarajan et al. [48] use the 8-noded shear-flexible finite element to study the linear free flexural vibration of FGM plates containing a through-centre crack. Furthermore, many studies have employed domain decomposition techniques to formulate analytical or semi-analytical solutions for cracked plates, which are then applied to free vibration analysis. For instance, Song et al. [49,50] proposed a Ritz-based procedure for determining the free vibration characteristics of polygonal thin plates incorporating straight through-cracks and subjected to arbitrary boundary conditions, in which the cracked polygon is decomposed into polygonal subdomains tied by spring connections. In addition, Huang and Leissa conducted a series of studies on vibration and stability of cracked plates using Ritz-type formulations. In their work on rectangular plates with side cracks, they enriched the Ritz trial space with singular functions to capture crack-tip behaviour and displacement jumps [51]. They later extended the formulation to rectangular plates containing internal cracks or slits, treating the embedded discontinuity directly within the Ritz framework [52]. To improve flexibility for cracks at arbitrary positions and orientations, Huang and Chan combined the moving least-squares interpolation functions with the Ritz approach (MLS–Ritz) [53]. A closed-form-like treatment was also proposed through a modified Fourier series for rectangular plates with a straight through crack [54]. Furthermore, the MLS–Ritz strategy was applied to the combined vibration–buckling analysis of square plates containing internal cracks [55].

Recently, the use of artificial neural networks (ANNs) for damage detection analysis has attracted significant interest, owing to their capacity to learn from data, to represent strongly nonlinear behaviour, and to provide computationally effective approaches to challenging fracture mechanics problems. Montalvão [56], the adoption of the ANN for damage detection is particularly suitable given the complexity of structural systems and the possibility of damage occurring at multiple locations. In this context, Zang and Imregun [57] employed the frequency response functions (FRFs) acquired from experimental measurements as the ANN inputs to detect structural damage. While Szewczyk and Hajela [58] formulated damage identification as an inverse task and solved it with the ANN, successfully determining both the location and the severity of damage. Paulraj et al. [59] showed that vibration features extracted from intact and damaged steel plates can serve as training data for a feed-forward ANN to identify plate condition. The ANN, tuned via the Fahlman criterion, reliably distinguished healthy from damaged states, confirming the effectiveness of the ANN-based vibration diagnosis for damaged plates. Khatir et al. [60] employed the ANN, optimised by an arithmetic optimisation algorithm, to quantify defects in FG plates. The network was trained using damage-related indices extracted from vibration data, enabling it to map these inputs to corresponding damage levels. The ANN demonstrated high accuracy in estimating the severity of damage across different FGM configurations. Fu et al. [61] applied the ANN to damage detection in composite materials using laser ultrasonic testing data. Wavelet packet-decomposed energy ratios from the measured signals were used as the ANN inputs, allowing the network to distinguish damaged from undamaged regions. The trained three-layer ANN achieved about 99.6% accuracy for crack detection and was able to estimate damage location and size with high precision. Zara et al. [62] trained an ANN on experimental and ABAQUS-simulated natural frequencies of glass fibre reinforced polymer (GFRP) composite plate to predict crack length. By tuning the ANN with modern optimisation algorithms, most effectively the enhanced Jaya method, they achieved accurate crack-size identification, showing the ANN-based frequency data can be used for reliable damage assessment.

The reviewed studies indicate that most existing research has focused on plates containing straight cracks, whereas curved crack paths have received comparatively limited attention due to the difficulty of accurately parameterizing and modeling such geometries. To address this gap, this paper proposes a systematic scheme for representing curved cracks using second-order polynomial equations. The effects of the polynomial coefficients and the crack end abscissa (x_{end}) on the dynamic characteristics are then investigated primarily through finite element analysis (FEA), with experimental modal analysis (EMA) used for validation. Finally, forward and inverse models are developed and validated for predicting dynamic responses and identifying curved crack parameters.

2 Methodology

2.1 Specimen and Material Description

The specimens were designed with dimensions of 150 mm × 100 mm × 5 mm, as illustrated in Fig. 1. The plates were fabricated from aluminum (5083), with properties summarized in Table 1. Aluminum was selected for its broad utilization in engineering structures, superior strength-to-weight ratio, corrosion resistance, and reliable mechanical performance [63].

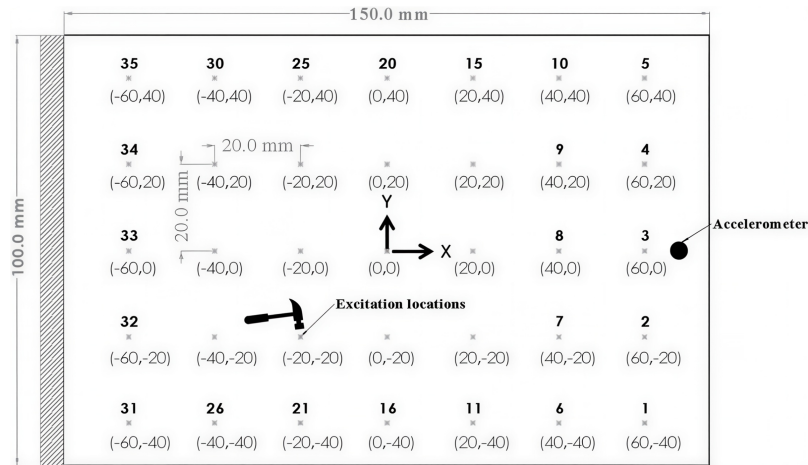


Figure 1: Schematic diagram of the experimental setup for impact hammer testing conducted on a 150 mm × 100 mm × 5 mm plate. The grid of excitation points, identified by their respective coordinates, represents the designated locations for hammer impact used for data acquisition. The accelerometer is fixed in position at (70, 0).

Table 1: Material properties.

Property	Value
Young's Modulus	70 GPa
Poisson's Ratio	0.33
Density	2660 Kg/m ³
Shear Modulus	26.3 GPa

2.2 Computational Representation of Curved Crack Paths

Several distinct curved crack paths were configured in the cantilever plate to enable comparison of their respective dynamic responses. All cracks were created on the surface of the plate with a width of 1 mm and a depth of 2.5 mm. Each crack originates from the point (0, 0), positioned 75 mm from the fixed end of the plate, and terminates at various end coordinates. All cracks are confined within a 50 mm × 50 mm area, as shown in Fig. 2. This specific region is chosen because, under cantilever boundary conditions, cracks are assumed to propagate from the center toward the free end. Additionally, placing the crack on one side takes advantage of the plate's symmetry, as the dynamic response is expected to be identical for symmetrical crack placements on opposite sides. The selected area is divided into a 6 × 6 grid, creating 36 points spaced 10 mm apart along both the x and y directions. The 10 mm spacing is based on the author's experience and a previous study [34], which indicates that smaller intervals result in minimal changes in dynamic response. This spacing also helps reduce the amount of data needed, making the approach more feasible for experimental studies.

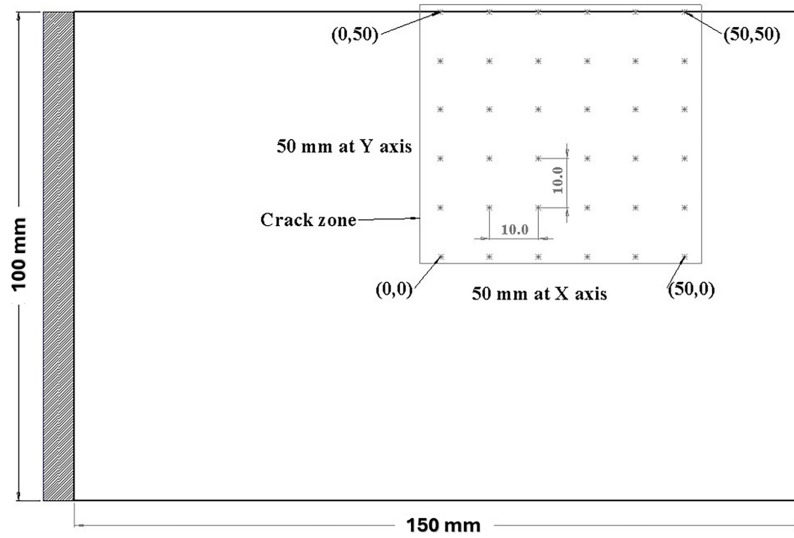


Figure 2: Plate geometry and crack zone.

To model such curved paths, three points are required: a starting point (origin), a second point, and a third point. These points define a curve that can be represented using a second-order polynomial, as shown in Eq. (1).

$$y = ax^2 + bx + c \quad (1)$$

Here, a , b , and c are constants, with $a \neq 0$. The ax^2 term imparts the characteristic curvature of the parabola. As x increases, x^2 grows faster than x , creating a nonlinear relationship. The sign of the coefficient determines the curve's direction: positive coefficients yield an upward-opening parabola, whereas negative coefficients produce a downward-opening one. The bx term introduces a linear component that affects the horizontal orientation, and c determines where the curve crosses the y -axis. To identify all possible curved crack paths within the chosen area, it is divided into 36 grid points as shown in Fig. 2. A combinatorial approach is applied using the formula in Eq. (2).

$$C_k^n = \frac{n!}{k!(n-k)!} \quad (2)$$

where (n) denotes the total number of items, (k) the number selected and $(!)$ the factorial (product of all positive integers up to that number). Applying this formula yields 7140 possible combinations. However, this number is not practical for experimental or computational analysis due to financial and time constraints. To address this, some assumptions and restrictions are introduced, as summarized in Table 2. Based on these constraints, 20 valid options remain for selecting the second point of the crack path. The number of valid third points corresponding to each second point varies depending on its x -coordinate, as detailed in Table 3. This results in 300 possible curved crack paths. However, some of these paths are straight, and some are curved paths, but outside the plate. After excluding these paths, the number of unique curved crack paths is reduced to 252, as shown in Fig. 3.

Table 2: Assumptions for curved crack path selection.

Point	Assumptions/Constraints
First Point	Always fixed at the origin (0, 0). Must not be (0, 0).
Second Point	Cannot lie on the y-axis (i.e., $x = 0$). Cannot lie on the boundary ($x = 50, y = 50$) or at the corner (50, 50). Must not be (0, 0).
Third Point	Must be different from the second point. Must have an x-coordinate greater than that of the second point (to ensure forward propagation).

Table 3: Valid combinations for curved crack paths.

X-Coordinate of the Second Point	Number of the Second Point Options	Valid Third Point Options Per Second Point	Total Combinations
10 mm	5	24	$5 \times 24 = 120$
20 mm	5	18	$5 \times 18 = 90$
30 mm	5	12	$5 \times 12 = 60$
40 mm	5	6	$5 \times 6 = 30$
Total (including straight paths)	—	—	300
Total (after removing straight paths)	—	—	288
Total (after removing out plate paths)	—	—	252

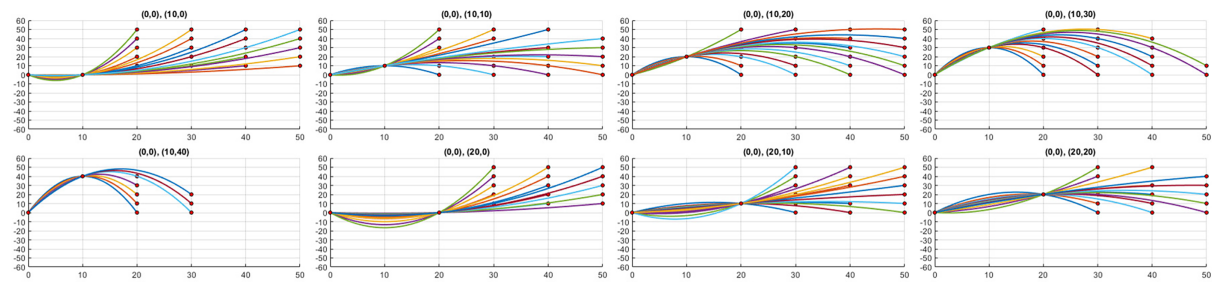


Figure 3: (Continued)

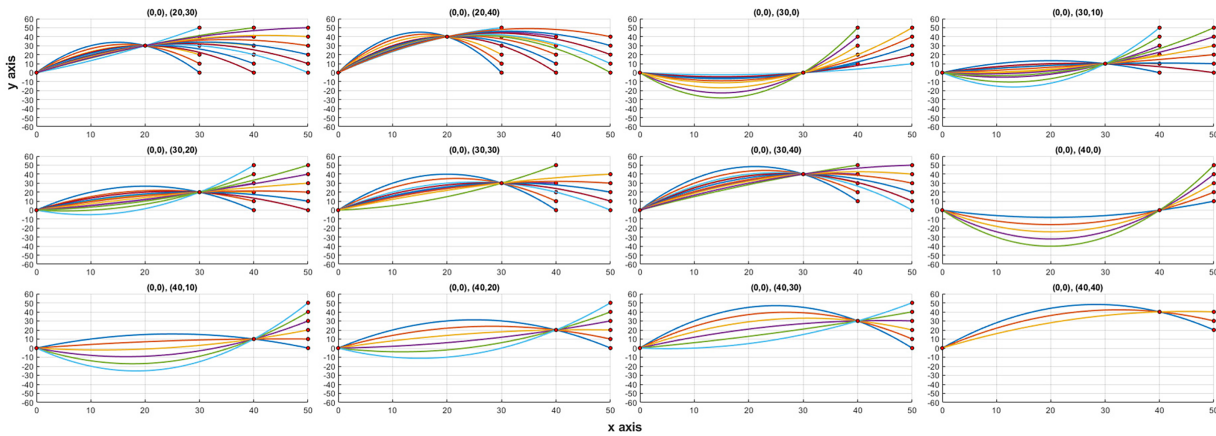


Figure 3: Visualisation of second-order polynomial curves passing through three points: the fixed origin $(0, 0)$, a selected second point, and a varying third point. Each subplot corresponds to a different second point configuration.

2.3 Finite Element Analysis (FEA) Procedures

ANSYS Modal and Harmonic Response were employed to determine the natural frequency and resonance amplitude of a 252 plate with different curved crack paths. After multiple mesh refinements with varying element sizes, a 5 mm element size was adopted to achieve converged solutions, as shown in Fig. 4a. Refined meshing or singular crack-tip elements were not employed because the present study does not aim to resolve crack-tip singular fields or compute fracture mechanics parameters (e.g., the stress intensity factor K or the J -integral). Instead, the objective is to evaluate the global dynamic response of the plate and to compare the relative changes in response across the predefined crack configurations. Then, a clamped boundary condition was imposed over the plate's fixed end ($100 \text{ mm} \times 76 \text{ mm}$) on both the top and bottom surfaces, as shown in Fig. 4b. Modal analysis was then conducted to extract the first three bending modes.

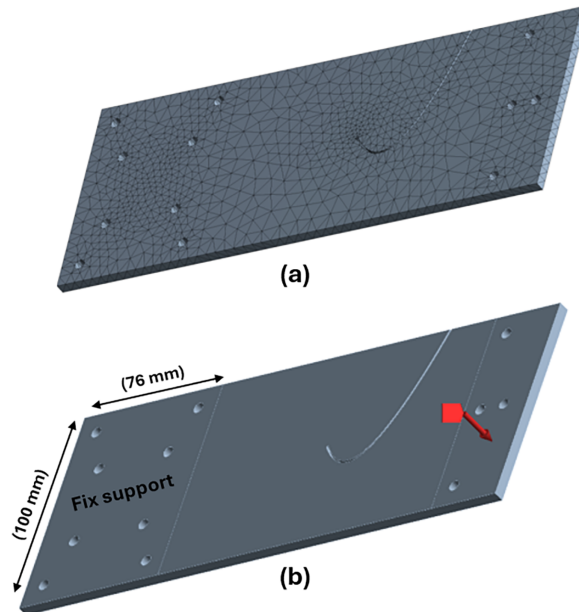


Figure 4: (a) Geometry and mesh generation; (b) the red marker and arrow indicate the response measurement point and the location of the applied force.

Subsequently, a harmonic response analysis was conducted to evaluate resonance amplitudes for the first mode. The damping ratio for each curved crack configuration was obtained from the corresponding experimental modal tests, as shown in Section 3.1.3. An excitation force of 1 N was applied at 150 mm from the fixed end of the plate, and the amplitude-based FRF was recorded at the same point, as shown in Fig. 4b.

2.4 Experimental Setup and Procedure

An experimental modal analysis was carried out to identify the dynamic characteristics of the aluminum plates [64]. As shown in Fig. 5, the specimens were tested under cantilever boundary conditions. A PCB 352A21 accelerometer (sensitivity: 10 mV/g) was placed on the plate's free end to record the acceleration response. Excitation was provided by a PCB 086C01 impact hammer with a sensitivity of 10.01 mV/N.

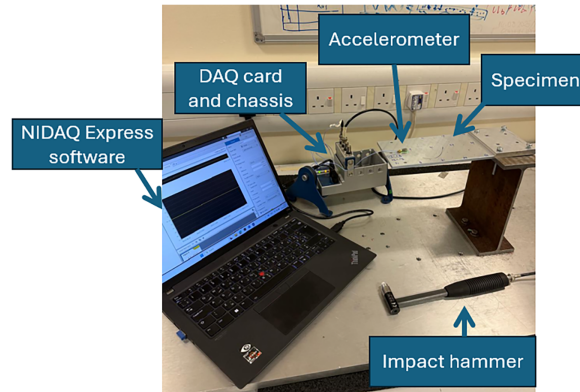


Figure 5: Experiment setup.

Each plate was excited at 35 discrete locations distributed over the plate surface, with an approximate spacing of 20 mm between successive impact points, as specified in Fig. 1. For every excitation point, three repeated impacts were applied to ensure measurement repeatability and improve data reliability.

The input force signals from the hammer and the corresponding acceleration responses from the accelerometer were acquired using a NI 9234 data acquisition (DAQ) module housed in an NI 9174 chassis (National Instruments, London, UK). Data acquisition was controlled via NI DAQExpress, and the recorded signals were then imported into MATLAB R2024a for post-processing. The FRFs were extracted in MATLAB and used to estimate the damping ratios.

Experimental Data Process

Frequency Response Function (FRF)

FRF is the primary dataset for experimental modal analysis. Time-domain measurements are transformed to the frequency domain commonly via the fast Fourier transform (FFT) to compute the FRF. In the frequency domain, the FRF is expressed as a quotient of the structure's output response and the applied input excitation. For clarity, a single-degree-of-freedom (SDOF) mass–spring–damper system is considered. The equation of motion for an SDOF system with viscous damping is given by Eq. (3).

$$m\ddot{x} + c\dot{x} + kx = F(t) \quad (3)$$

where m , c , k , and F are mass, damping coefficient, stiffness, and external force input. In the undamped SDOF case, the natural frequency (ω_r) and damping ratio (ζ_r) of the structure are shown in Eqs. (4) and (5).

$$\omega_r = \sqrt{\frac{k}{m}} \quad (4)$$

$$\zeta_r = \frac{c}{2\sqrt{km}} \quad (5)$$

For a harmonic external excitation $f(t) = Fe^{i\omega t}$, the associated steady-state displacement response can be expressed as $x(t) = Xe^{i\omega t}$. With this assumption, the receptance form of the FRF is derived in Eq. (6).

$$H(\omega) = \alpha(\omega) = \frac{X(\omega)}{F(\omega)} = \frac{1}{(K - \omega^2 m) + i(\omega c)} \quad (6)$$

In this expression, $X(\omega)$ and $F(\omega)$ denote the FFT of the output displacement and the applied excitation, respectively. For an N-degree-of-freedom system, a receptance matrix element can be expressed in modal form as shown in Eq. (7).

$$H_{ij}(\omega) = \frac{X_i(\omega)}{F_j(\omega)} = \sum_{r=1}^N \frac{\phi_i^r \phi_j^r / k_r}{\left(1 - \frac{\omega}{\omega_r}\right)^2 + 2i\zeta_r \left(\frac{\omega}{\omega_r}\right)} \quad (7)$$

where $H_{ij}(\omega)$ represents the receptance between coordinates i and j ; ϕ_i^r and ϕ_j^r are the r th modal displacement components at those two coordinates; ω is the forcing frequency; and k_r denotes the r th modal stiffness.

Half-Power Bandwidth Method

The half-power bandwidth method, also referred to as the peak-picking method, is a widely used procedure for estimating damping ratios in single-degree-of-freedom (SDOF) systems. The method begins by identifying the resonance frequency, $\omega_r = \omega_{peak}$, corresponding to the frequency at which the FRF attains its maximum amplitude for the mode under consideration. Two additional frequencies, ω_a and ω_b , are then determined on either side of this peak; these are the half-power points, defined as the frequencies at which the amplitude decreases to $1/\sqrt{2}$ of the peak value, as illustrated in Fig. 6. The damping loss factor (η_r) and the damping ratio (ζ_r) can subsequently be evaluated from these frequencies using Eqs. (8) and (9), respectively [64,65].

$$\eta_r = \frac{\omega_b^2 - \omega_a^2}{2\omega_r^2} \approx \frac{\omega_b - \omega_a}{\omega_r} \quad (8)$$

$$\zeta_r = \frac{\omega_b^2 - \omega_a^2}{4\omega_r^2} \approx \frac{\omega_b - \omega_a}{2\omega_r} \quad (9)$$

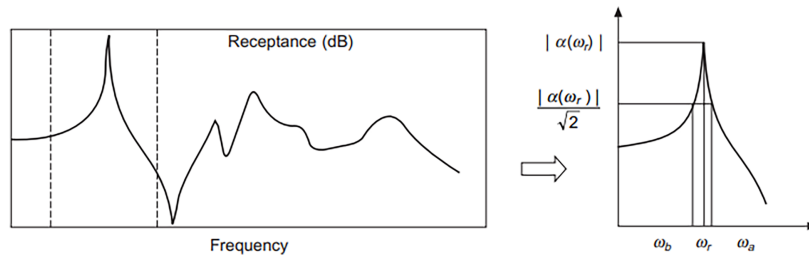


Figure 6: Half power bandwidth method [64].

2.5 Artificial Neural Network (ANN)

The ANN is a multilayer computational model inspired by the human brain's learning and decision-making mechanisms. They comprise interconnected artificial neurons that emulate the behavior of nerve cells, enabling data processing and representation learning across successive layers. The typical ANN includes an input layer, one or more hidden layers, and an output layer. Each layer applies an affine transformation to its inputs: multiplying by a weight matrix, adding a bias vector, and then applying a nonlinear activation function. For a hidden layer, the pre-activation (weighted sum) is shown in Eq. (10).

$$z^{(1)} = W^{(1)}x + b^{(1)} \quad (10)$$

where $W^{(1)}$ is the hidden-layer weight matrix, x is the input vector, and $b^{(1)}$ is the hidden-layer bias vector. The hidden-layer activation is obtained by applying a nonlinear function $f(\cdot)$ (e.g., sigmoid or ReLU) as shown in Eq. (11).

$$a^{(1)} = f(z^{(1)}) \quad (11)$$

The output layer performs an analogous operation as shown in Eq. (12), where $W^{(2)}$ and $b^{(2)}$ denote the output-layer weight matrix and bias vector, respectively. Followed by an output activation $f_{out}(\cdot)$ (see Eq. (13)) appropriate to the task (e.g., linear for regression, softmax for classification).

$$z^{(2)} = W^{(2)}a^{(1)} + b^{(2)} \quad (12)$$

$$y = f_{out}(z^{(2)}) \quad (13)$$

This research focused on developing a forward artificial neural network (FANN) model capable of predicting the plate's dynamic responses (natural frequencies, resonance amplitudes, and damping ratios) from input data describing curved crack paths. As a first stage, the available dataset from the experimental tests was pre-processed to represent each crack path by its geometric coordinates $(x_1, x_2, x_3, y_1, y_2, y_3)$, thereby providing a consistent input space for model training, as shown in Fig. 7. Also, it aims to develop an inverse artificial neural network (IANN) model to predict the crack's final coordinates (x_3, y_3) using second coordinates (x_2, y_2) , damping ratio, and resonance amplitude, as shown in Fig. 8. A feedforward ANN architecture was adopted, comprising six input and three output nodes for the FANN and four inputs and two output nodes for the IANN, a single hidden layer comprising 10 neurons for both models. The network was implemented in MATLAB using the Neural Network Toolbox's `fitnet` function. A logistic sigmoid (`logsig`) activation was employed in the hidden layer, while a linear (`purelin`) activation was used in the output layer to accommodate continuous target variables.

The dataset was split into training, testing, and validation subsets in the proportions 80%, 10%, and 10%, respectively. Network training was performed with the Levenberg–Marquardt (LM) backpropagation algorithm (`trainlm`), which is widely regarded as effective for problems of moderate size, providing fast convergence by blending gradient-descent updates with Gauss–Newton search directions. The training objective was to minimize the mean squared error (MSE) between the ANN predictions and the corresponding target values. To mitigate the influence of random weight initialization and to improve robustness, the training procedure was repeated 50 times; predictions from individual runs were accumulated and subsequently averaged to obtain stable estimates.

Finally, the trained ANN was evaluated using an independent validation set comprising fifteen additional crack-path configurations that were not considered in either the training or testing datasets, for which natural frequency, amplitude, and damping ratio were available from the experimental tests. This

evaluation confirmed the model's capability to generalize to new crack geometries beyond those used in model development.

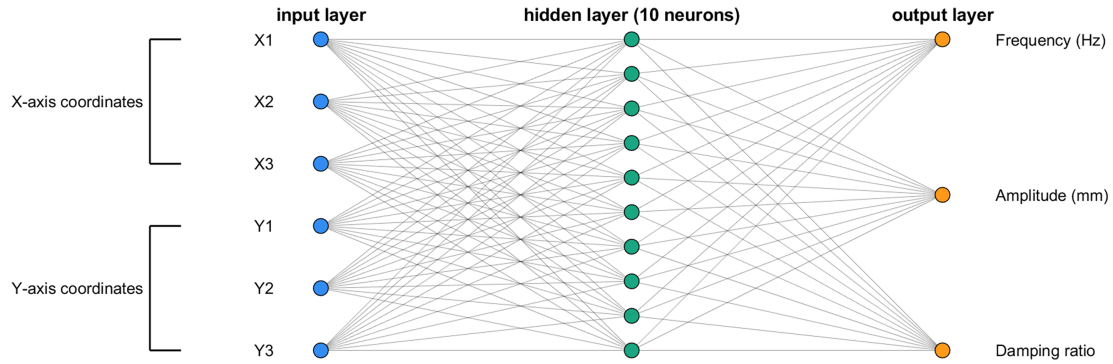


Figure 7: Schematic architecture of the forward ANN models used in this study.

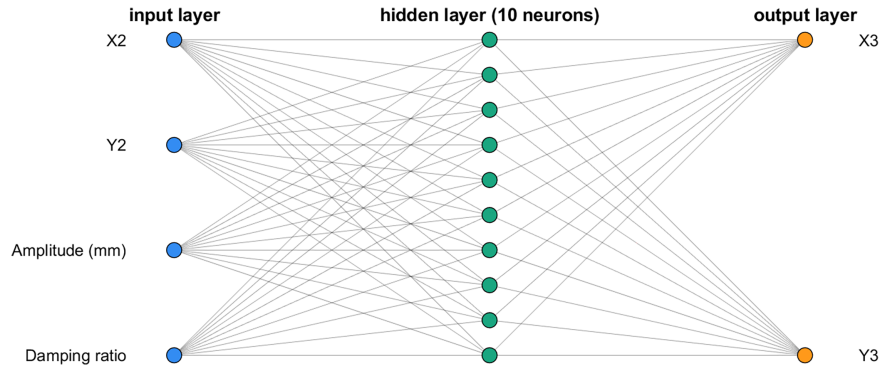


Figure 8: Schematic architecture of the inverse ANN models used in this study.

3 Result and Discussion

This section discusses the effect of the curved crack path on the plate's dynamic response and develops forward and inverse LR and ANN models. The forward models are formulated to estimate key dynamic parameters such as the natural frequency, amplitude, and damping ratio by relating them to the geometric characteristics of the crack path, and the inverse models are developed to predict the final crack coordinates. Finally, the accuracy and robustness of the proposed models are subsequently evaluated using 15 additional curved crack paths that were not included in the model development process.

3.1 Effect of Curved Crack Path on Dynamic Characteristics

The influence of polynomial coefficients on the dynamic characteristics of a cracked plate is analysed in terms of their effect on the natural frequency, amplitude, and damping ratio. Each coefficient represents a distinct characteristic of the curved crack path on the plate surface, with different end of the abscissa (x_{end}) values corresponding to varying crack lengths, while x_{start} remains fixed at zero. These coefficients are used to model the curvature, inclination, and vertical position of the crack path, allowing for a comprehensive assessment of how geometric variations influence the plate's dynamic behavior, which will be discussed in the following sections.

3.1.1 Effect of Polynomial Coefficient on Natural Frequency

The effect of the polynomial coefficients on the natural frequency for different values of x_{end} is presented in Fig. 9a–c. Fig. 9a presents the natural frequency vs. the quadratic coefficient a . The coefficient a controls the curvature of the crack path. The highest frequencies occur when a is close to zero. The maximum occurs at $a = 0$, corresponding to the healthy plate condition. As a becomes more positive or more negative, the frequency decreases. This trend is observed on both sides of zero. It indicates that the frequency is mainly governed by $|a|$ rather than the sign of a . The scatter also becomes more noticeable at larger $|a|$, especially for longer cracks (larger x_{end}). This occurs because increasing x_{end} increases the cracked region and reduces the remaining load-carrying area. It also increases the sensitivity of global stiffness to changes in crack geometry. As a result, small differences in curvature lead to larger differences in stiffness degradation and natural frequency.

Fig. 9b shows the natural frequency vs. the linear coefficient b . The coefficient b represents crack path inclination (asymmetry). The frequency again peaks near $b = 0$. It decreases as b becomes more positive or more negative. This confirms that a stronger inclination/asymmetry is associated with lower stiffness and lower natural frequency. The spread of the data also increases for larger $|b|$, particularly for longer cracks. Fig. 9c shows the effect of the constant term c . The points form an almost vertical band, and no clear trend is observed as c changes. This indicates that vertical translation of the crack path has a negligible effect on the natural frequency compared with changes in curvature or inclination. Overall, Fig. 9 confirms that the non-constant terms a and b strongly influence the natural frequency because they represent curvature and inclination effects. These geometric features degrade stiffness by altering both axial and shear stiffness, thereby reducing the natural frequency [66]. In contrast, c mainly shifts the crack path position and does not significantly alter the frequency.

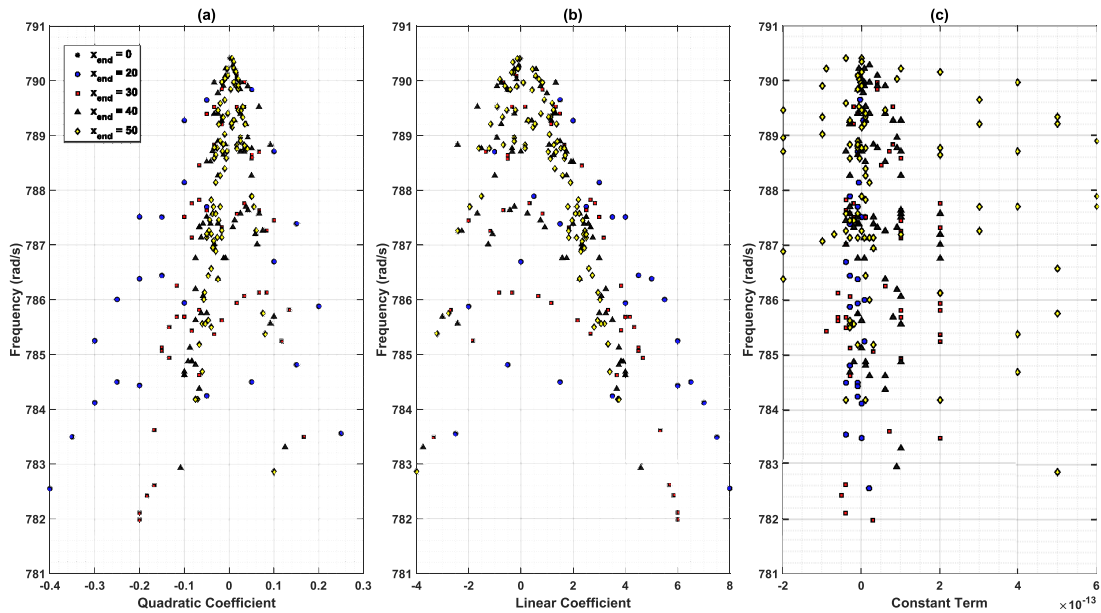


Figure 9: Relationship between the polynomial coefficients and the natural frequency for different values of x_{end} (numerical result): (a) quadratic coefficient a vs. natural frequency, (b) linear coefficient b vs. natural frequency, and (c) constant term c vs. natural frequency. The marker symbols (legend): $x_{\text{end}} = 0$ (black star), $x_{\text{end}} = 20$ (blue circle), $x_{\text{end}} = 30$ (red square), $x_{\text{end}} = 40$ (black triangle), $x_{\text{end}} = 50$ (yellow diamond).

3.1.2 Effect of Polynomial Coefficient on Resonance Amplitude

The effect of the polynomial coefficients on the resonance amplitude for different values of x_{end} is presented in Fig. 10a–c. Fig. 10a presents the resonance amplitude vs. a . The amplitude is lowest when a is close to zero. The minimum occurs at $a = 0$, which corresponds to the healthy plate condition. As a becomes more positive or more negative, the amplitude increases. This increase appears on both sides of zero. It shows that the amplitude is mainly governed by the magnitude $|a|$ rather than the sign of a . The scatter also becomes more noticeable at larger $|a|$, especially for longer cracks (larger x_{end}). This indicates that greater crack path curvature reduces the effective stiffness more significantly. As a result, the vibration amplitude increases. Fig. 10b shows the resonance amplitude vs. b . The amplitude remains relatively low when b is close to zero. This corresponds to a nearly symmetric crack path in the horizontal direction. As b becomes more positive or more negative, the amplitude increases. This trend is observed across all x_{end} groups, although the scatter increases with larger $|b|$. The increase in amplitude indicates that stronger crack path inclination/asymmetry results in a larger reduction in effective stiffness, leading to higher vibration amplitudes.

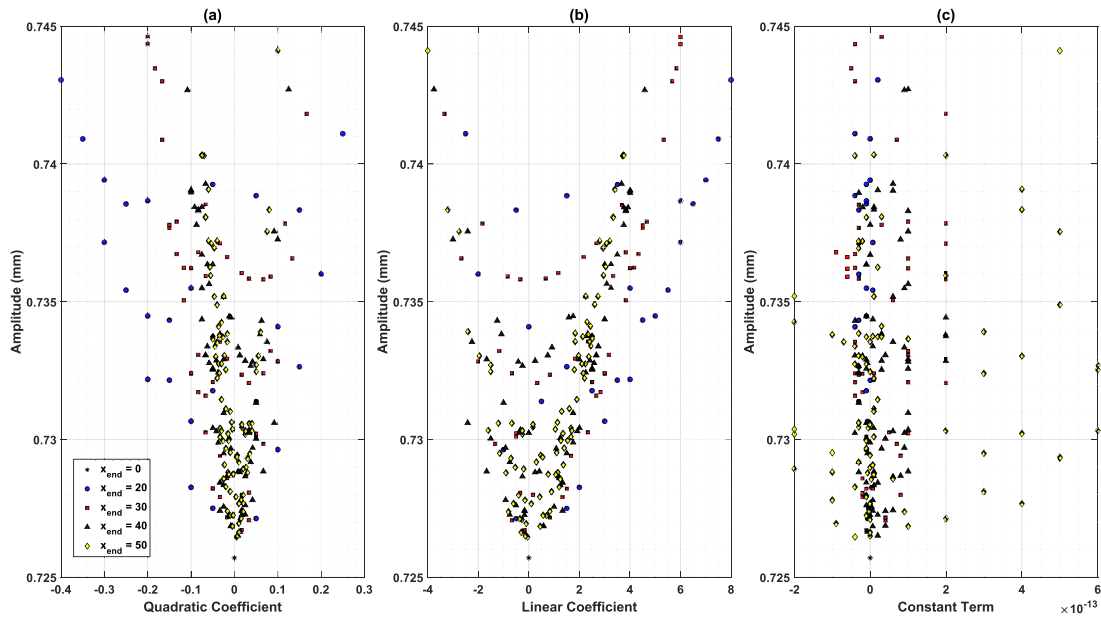


Figure 10: Relationship between the polynomial coefficients and the resonance amplitude for different values of x_{end} (numerical result): (a) quadratic coefficient a vs. resonance amplitude, (b) linear coefficient b resonance amplitude, and (c) constant term c vs. resonance amplitude. The marker symbols (legend): $x_{\text{end}} = 0$ (black star), $x_{\text{end}} = 20$ (blue circle), $x_{\text{end}} = 30$ (red square), $x_{\text{end}} = 40$ (black triangle), $x_{\text{end}} = 50$ (yellow diamond).

Fig. 10c presents the resonance amplitude vs. c . The data points form an almost vertical band, showing only small amplitude changes over the full range of c . No clear increasing or decreasing trend is observed as c varies. This indicates that shifting the crack path vertically within the plate domain has a limited influence on the global resonance amplitude compared with changing its curvature or inclination. A small scatter remains because different x_{end} groups and different combinations of a and b are included in the same plot. Overall, Fig. 10 confirms that the resonance amplitude is primarily governed by a and b , whereas c has a minor contribution. Larger curvature or inclination increases the compliance of the plate and reduces the effective axial and shear stiffness. This increases local flexibility and deformation, leading to higher resonance amplitudes [66].

3.1.3 Effect of Polynomial Coefficient on Damping Ratio

The effect of the polynomial coefficients on the damping ratio for different values of x_{end} is presented in Fig. 11a–c. Fig. 11a presents the damping ratio vs. a . The lowest damping ratios occur when a is close to zero. The minimum appears at $a = 0$, which corresponds to the healthy plate condition. As a becomes more positive or more negative, the damping ratio generally increases. This trend is observed on both sides of zero. It indicates that damping is mainly related to $|a|$ rather than the sign of a . The scatter also increases at larger $|a|$, especially for larger x_{end} . This is because longer cracks increase the crack-surface area and reduce the effective stiffness. As a result, small changes in curvature can produce larger differences in energy dissipation. Fig. 11b shows the damping ratio vs. b . The damping ratio remains relatively stable when b is close to zero. It increases when b becomes more positive or more negative. This indicates that a stronger inclination/asymmetry is associated with higher damping. The spread of data increases with $|b|$, particularly for longer cracks.

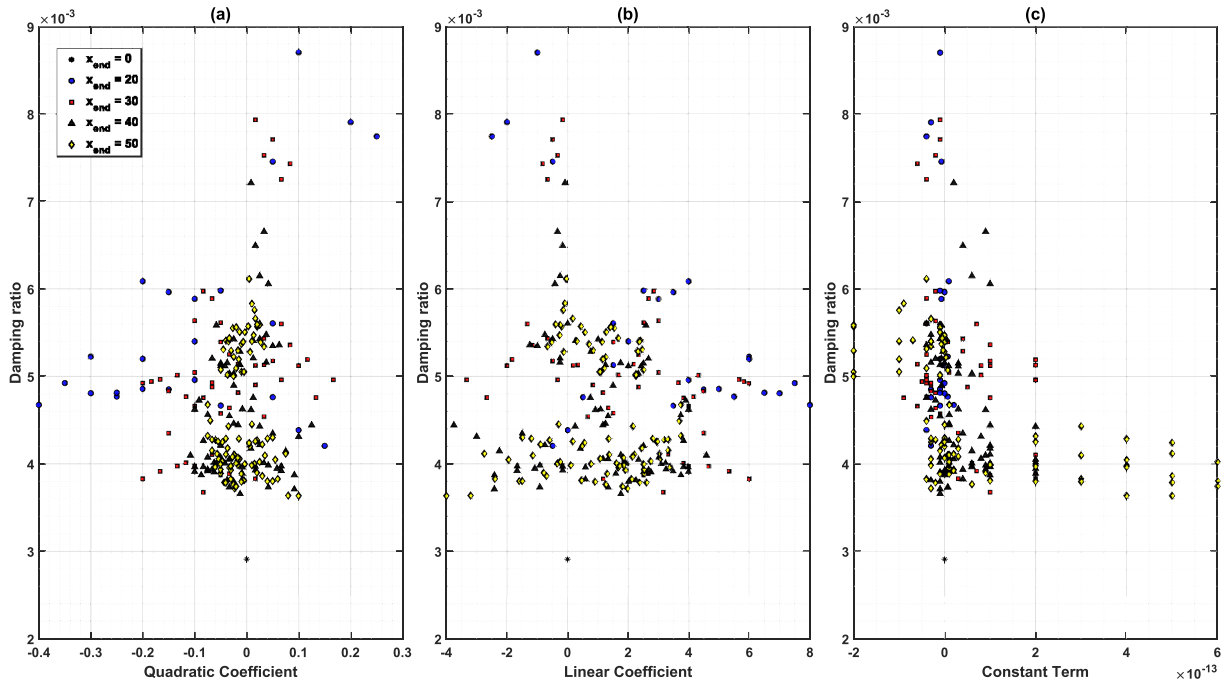


Figure 11: Relationship between the polynomial coefficients and the damping ratio for different values of x_{end} (Experiment result): (a) quadratic coefficient a vs. damping ratio, (b) linear coefficient b vs. damping ratio, and (c) constant term c vs. damping ratio. The marker symbols (legend): $x_{\text{end}} = 0$ (black star), $x_{\text{end}} = 20$ (blue circle), $x_{\text{end}} = 30$ (red square), $x_{\text{end}} = 40$ (black triangle), $x_{\text{end}} = 50$ (yellow diamond).

Fig. 11c shows the damping ratio vs. c . The points form a nearly vertical band with no clear trend. The damping ratio changes only slightly across the full range of c . This confirms that vertical translation of the crack path has a limited effect on damping compared with changes in curvature or inclination. Overall, Fig. 11 indicates that a and b have the strongest influence on damping, whereas c has a minor contribution. Higher curvature and inclination increase local deformation and crack-surface interaction [35]. This enhances frictional and local energy-loss mechanisms [67–70], which leads to higher damping ratios [71–74]. In contrast, c mainly shifts the crack path location and does not significantly change the damping characteristics.

3.1.4 Effect of the End of the Abscissa (x_{end}) on the Dynamic Response and Polynomial Coefficients

Figs. 9–11 show that, as the crack x_{end} increases, the plate's dynamic behavior undergoes noticeable changes in frequency, amplitude, and damping ratio, closely linked to the evolution of the polynomial coefficients representing the crack path. For larger x_{end} values, particularly at $x_{\text{end}} = 50$, both the a and b coefficients approach zero, indicating that the crack path becomes smoother and more linear. This geometric stabilization enhances structural stiffness, resulting in a higher, more stable natural frequency. Conversely, smaller x_{end} values (such as 20 and 30) are associated with larger deviations of these coefficients from zero, reflecting greater curvature and asymmetry in the crack path, which lead to nonlinear stiffness reduction and a corresponding decrease in natural frequency. The vibration amplitude follows an opposite trend, decreasing slightly as x_{end} increases due to the smoother crack geometry and more uniform stress distribution, which limit deformation. Similarly, the damping ratio tends to decrease with larger x_{end} because smoother crack surfaces reduce frictional energy losses and localized dissipation. In contrast, the c term exhibits an opposite trend, increasing with x_{end} as it represents a vertical shift of the crack path rather than a stiffness-related parameter.

3.2 Linear Regression (LR) Model Development

LR models were developed for curved cracked plates using 237 samples. These models were divided into forward and inverse models.

3.2.1 Forward Linear Regression (FLR) Models

The FLR models were built to predict the vibration characteristics, such as natural frequency (ω_r), amplitude (A), and damping ratio (ζ_r), based on second and third curved crack coordinates (x_2, y_2, x_3, y_3). The initial crack coordinates were not included because they were assumed to be at the center of the plate, where x_1 and y_1 are zero. The mathematical expressions are shown in Eqs. (14)–(16). The best fit was obtained for the damping ratio (RMSE $\approx 5.1 \times 10^{-4}$, $R^2 = 0.70$). A moderate fit was found for frequency (RMSE ≈ 0.5 , $R^2 = 0.30$). The weakest fit was observed for amplitude (RMSE ≈ 0.05 , $R^2 = 0.121$). Even with modest R^2 values, validation error remained below 5%, as shown in the validation section.

Fig. 12 presents six quadratic response surfaces from the FLR models. The surfaces relate the crack coordinates (x_2, y_2) and (x_3, y_3) to the vibration characteristics ω_r , A , and ζ_r . Each surface is plotted with respect to a single coordinate pair. However, the final FLR prediction is obtained by simultaneously accounting for both coordinate pairs in the full regression model.

For the natural frequency (top row), the (x_2, y_2) surface shows a broad maximum near mid-range coordinate values. The frequency decreases toward the edges of the (x_2, y_2) domain. A similar trend is observed for the (x_3, y_3) surface. The highest frequency occurs near the central region. It decreases as (x_3, y_3) moves toward the boundaries. This indicates that frequency is sensitive to the combination of crack location.

For the resonance amplitude (middle row), the (x_2, y_2) surface forms a shallow basin. The lowest amplitudes occur near the central region. The amplitude increases toward the domain boundaries. The (x_3, y_3) surface shows the same overall behavior. Amplitude is lower near the mid-range coordinates and higher near the edges. This indicates a stronger vibration response for coordinate combinations farther from the central region.

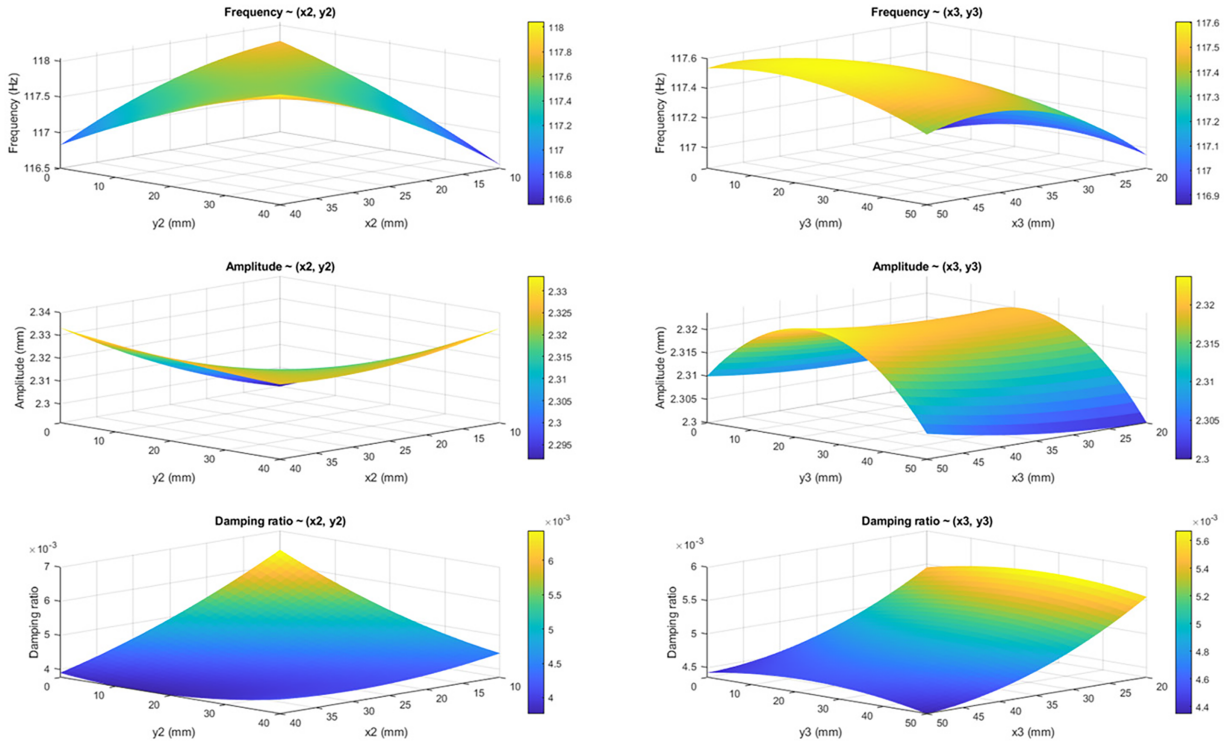


Figure 12: FLR quadratic response surfaces linking curved crack coordinates to vibration characteristics. Top row: natural frequency ω_r as a function of (x_2, y_2) (**left**) and (x_3, y_3) (**right**). Middle row: resonance amplitude A as a function of (x_2, y_2) (**left**) and (x_3, y_3) (**right**). Bottom row: damping ratio ζ_r as a function of (x_2, y_2) (**left**) and (x_3, y_3) (**right**). The colored surfaces represent the FLR model fits (Eqs. (14)–(16)) plotted with respect to one coordinate pair at a time.

For the damping ratio (bottom row), the (x_2, y_2) surface shows a clearer directional variation. The damping ratio increases toward larger coordinate values, and the highest values appear near one corner of the domain. The (x_3, y_3) surface shows a similar directional trend. The damping ratio increases along a sloped direction in the (x_3, y_3) plane. Overall, Fig. 12 highlights the regions where the predicted response is most sensitive to changes in crack coordinates.

$$\begin{aligned}
 \omega_r = & \left(1.1687 \times 10^2\right) - \left\{\left(2.5045 \times 10^{-2}\right)\left(x_2\right)\right\} - \left\{\left(3.9815 \times 10^{-2}\right)\left(y_2\right)\right\} + \left\{\left(7.1287 \times 10^{-2}\right)\left(x_3\right)\right\} \\
 & - \left\{\left(4.7998 \times 10^{-3}\right)\left(y_3\right)\right\} + \left\{\left(2.2678 \times 10^{-3}\right)\left(x_2\right)\left(y_2\right)\right\} + \left\{\left(6.0223 \times 10^{-4}\right)\left(x_2\right)\left(x_3\right)\right\} \\
 & - \left\{\left(1.5369 \times 10^{-4}\right)\left(x_2\right)\left(y_3\right)\right\} - \left\{\left(5.1716 \times 10^{-4}\right)\left(y_2\right)\left(x_3\right)\right\} + \left\{\left(4.8795 \times 10^{-4}\right)\left(y_2\right)\left(y_3\right)\right\} \\
 & - \left\{\left(4.1164 \times 10^{-6}\right)\left(x_3\right)\left(y_3\right)\right\} - \left\{\left(7.4233 \times 10^{-4}\right)\left(x_2^2\right)\right\} - \left\{\left(2.1011 \times 10^{-4}\right)\left(y_2^2\right)\right\} \\
 & - \left\{\left(8.6791 \times 10^{-4}\right)\left(x_3^2\right)\right\} - \left\{\left(1.0774 \times 10^{-4}\right)\left(y_3^2\right)\right\}
 \end{aligned} \tag{14}$$

$$\begin{aligned}
A = & (2.2967) - \{(2.6243 \times 10^{-3})(x_2)\} - \{(5.1377 \times 10^{-5})(y_2)\} + \{(1.6962 \times 10^{-3})(x_3)\} \\
& + \{(7.2582 \times 10^{-4})(y_3)\} - \{(6.7881 \times 10^{-5})(x_2)(y_2)\} + \{(1.2113 \times 10^{-4})(x_2)(x_3)\} \\
& - \{(1.7068 \times 10^{-5})(x_2)(y_3)\} + \{(3.3041 \times 10^{-5})(y_2)(x_3)\} + \{(1.9916 \times 10^{-5})(y_2)(y_3)\} \\
& + \{(9.2533 \times 10^{-6})(x_3)(y_3)\} - \{(1.5496 \times 10^{-5})(x_2^2)\} + \{(5.7924 \times 10^{-6})(y_2^2)\} \\
& - \{(5.8824 \times 10^{-5})(x_3^2)\} - \{(2.3627 \times 10^{-5})(y_3^2)\}
\end{aligned} \quad (15)$$

$$\begin{aligned}
\zeta_r = & (9.7873 \times 10^{-3}) - \{(1.4925 \times 10^{-4})(x_2)\} - \{(1.1127 \times 10^{-4})(y_2)\} - \{(8.6004 \times 10^{-5})(x_3)\} \\
& - \{(2.0509 \times 10^{-6})(y_3)\} + \{(1.7823 \times 10^{-6})(x_2)(y_2)\} + \{(1.5543 \times 10^{-6})(x_2)(x_3)\} \\
& + \{(1.0600 \times 10^{-7})(x_2)(y_3)\} + \{(5.3121 \times 10^{-7})(y_2)(x_3)\} - \{(1.8747 \times 10^{-8})(y_2)(y_3)\} \\
& + \{(1.0012 \times 10^{-7})(x_3)(y_3)\} - \{(8.8799 \times 10^{-8})(x_2^2)\} + \{(5.7497 \times 10^{-7})(y_2^2)\} \\
& + \{(5.1833 \times 10^{-7})(x_3^2)\} - \{(1.3336 \times 10^{-7})(y_3^2)\}
\end{aligned} \quad (16)$$

3.2.2 Inverse Linear Regression (ILR) Models

The ILR models were developed to predict the final curved crack path coordinates (x_3, y_3) . The models relate the final crack point to the damping ratio (ζ_r) , vibration amplitude (A) , and the intermediate crack coordinates (x_2, y_2) . The fitted equations are presented in Eqs. (17) and (18).

The model for x_3 showed a statistically highly significant overall fit ($p = 8.56 \times 10^{-72}$) with a coefficient of determination $R^2 = 0.40$, indicating that approximately 40% of the variability in the final crack X-coordinate is explained by the combined effects of x_2, y_2, ζ_r , and A . The corresponding model for y_3 was also statistically significant ($p = 2.38 \times 10^{-9}$), but with a lower coefficient of determination ($R^2 = 0.0963$), implying that the predictors account for about 9.6% of the variance in the final crack Y-coordinate.

Fig. 13 presents the ILR response surfaces used to estimate the final crack coordinates. The top row shows the predicted x_3 . The bottom row shows the predicted y_3 . The left column gives the predictions as functions of the intermediate coordinates (x_2, y_2) . The right column gives the predictions as functions of the measured response pair (ζ_r, A) . However, the final ILR prediction is obtained by simultaneously accounting for both the (x_2, y_2) and (ζ_r, A) in the full regression model.

In the left column, x_3 decreases as x_2 increases. The variation with y_2 is weaker, but it still changes the surface level. The y_3 surface also shows a clear gradient. It generally decreases as x_2 increases. It varies with y_2 as well. These trends confirm that the final crack location is strongly linked to the intermediate crack coordinates. In the right column, x_3 varies with both ζ_r and A . The surface shows an interaction between the two features. Higher x_3 values appear toward the region of lower ζ_r and A . Lower x_3 values appear at ζ_r and A . For y_3 , the surface shows stronger curvature. A ridge-like region is visible. This indicates a more nonlinear dependence on (ζ_r, A) compared with x_3 . Overall, the predicted surfaces provide a clear mapping from (x_2, y_2) and (ζ_r, A) to the final crack coordinates within the validated domain.

$$\begin{aligned}
x_3 = & - (1026.9) + \{(1.2516)(x_2)\} + \{(1.5717)(y_2)\} + \{(9.5263 \times 10^4)(D_R)\} + \{(7.0769 \times 10^2)(A)\} \\
& + \{(6.3252 \times 10^{-3})(x_2)(y_2)\} - \{(2.1973 \times 10^2)(x_2)(D_R)\} + \{(7.5941 \times 10^{-2})(x_2)(A)\} \\
& - \{(2.5144 \times 10^2)(y_2)(D_R)\} - \{(2.0833 \times 10^{-1})(y_2)(A)\} - \{(2.6076 \times 10^4)(D_R)(A)\} \\
& - \{(8.2047 \times 10^{-4})(x_2^2)\} - \{(4.8561 \times 10^{-3})(y_2^2)\} - \{(2.8574 \times 10^6)(D_R^2)\} - \{(1.2661 \times 10^2)(A^2)\}
\end{aligned} \quad (17)$$

$$\begin{aligned}
y_3 = & (5011.7) - \{(1.0592 \times 10^1)(x_2)\} - \{(1.2892 \times 10^1)(y_2)\} - \{(2.3605 \times 10^5)(D_R)\} \\
& - \{(3.5948 \times 10^3)(A)\} - \{(1.3486 \times 10^{-2})(x_2)(y_2)\} - \{(4.7400 \times 10^1)(x_2)(D_R)\} \\
& + \{(4.3671)(x_2)(A)\} + \{(3.1361 \times 10^1)(y_2)(D_R)\} + \{(5.2012)(y_2)(A)\} \\
& + \{(9.6805 \times 10^4)(D_R)(A)\} + \{(6.4872 \times 10^{-3})(x_2^2)\} + \{(4.5222 \times 10^{-3})(y_2^2)\} \\
& + \{(7.8599 \times 10^5)(D_R^2)\} + \{(6.3226 \times 10^2)(A^2)\}
\end{aligned} \tag{18}$$

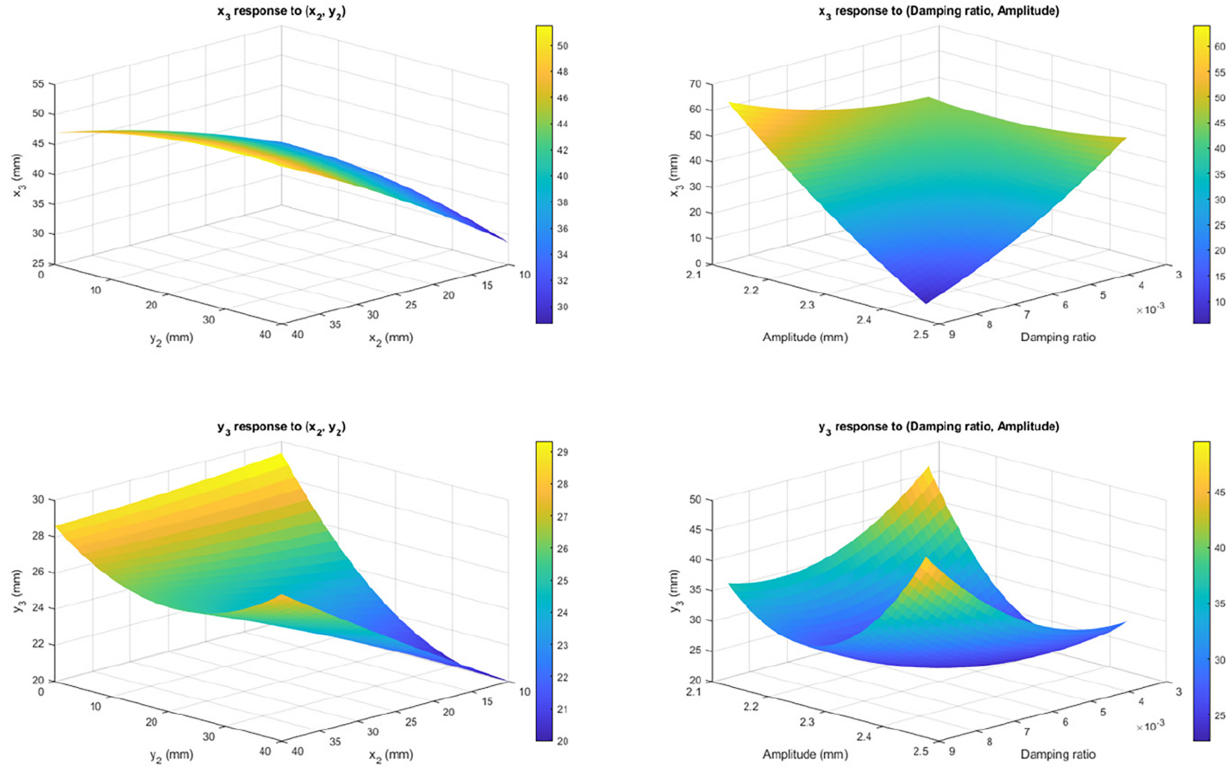


Figure 13: ILR response surfaces for estimating the final crack coordinates. Top row: predicted x_3 as a function of (x_2, y_2) (left) and (ζ_r, A) (right). Bottom row: predicted y_3 as a function of (x_2, y_2) (left) and (ζ_r, A) (right). The colored surfaces represent the fitted ILR model predictions plotted with respect to one input pair at a time.

3.3 Validation of the Forward and Inverse LR and ANN Models

To assess the predictive capability of the forward and inverse LR and ANN models, fifteen additional test cases were evaluated experimentally. These cases were not included in the dataset used to develop the LR models or to train the ANN models, and therefore provide an independent validation set.

For the forward models, the natural frequency, amplitude, and damping ratio predicted by the FLR and the FANN were compared with the corresponding experimental measurements. For the natural frequency (Table 4), the prediction errors remained very small, ranging from approximately 0%–0.6% for the FLR model and 0%–1.0% for the FANN model, with most cases below 0.5%. For the vibration amplitude (Table 5), the errors ranged from about 1.0%–6.2% for the FLR model and 0.3%–4.3% for the FANN model. For the damping ratio (Table 6), the FLR model errors ranged from 0.9% to 10.2%, while the FANN model errors ranged from 0.3% to 10.3%, with the majority of cases for both models remaining below 10%.

Table 4: Experimental validation of forward linear regression (FLR) and forward artificial neural network (FANN) prediction models for natural frequency.

Case	Inputs Parameters				Experimental Natural Frequency (Hz)	Predicted Natural Frequency (Hz)			
	Crack Path Second and Final Coordinates					FLR	Error [%]	FANN	Error [%]
	X2	Y2	X3	Y3					
1	10	0	40	30	117.982	117.957	0.0	117.79	0.2
2	10	20	30	20	117.857	117.369	0.4	117.412	0.4
3	10	30	30	20	116.691	117.035	0.3	116.741	0.0
4	20	0	40	30	117.769	117.679	0.1	117.514	0.2
5	20	0	50	40	117.295	117.573	0.2	117.459	0.1
6	20	0	50	50	117.301	117.396	0.1	117.339	0.0
7	20	10	40	30	117.969	117.653	0.3	117.357	0.5
8	20	20	40	20	117.926	117.621	0.3	117.275	0.6
9	30	0	40	30	117.963	117.252	0.6	117.508	0.4
10	30	10	40	30	116.723	117.453	0.6	117.403	0.6
11	30	20	50	30	117.272	117.619	0.3	117.424	0.1
12	40	0	50	20	116.305	117.013	0.6	117.426	1.0
13	40	20	50	30	118.134	117.557	0.5	117.511	0.5
14	40	30	50	20	117.912	117.868	0.0	117.865	0.0
15	40	40	50	30	117.647	118.099	0.4	117.591	0.0

Table 5: Experimental validation of forward linear regression (FLR) and forward artificial neural network (FANN) prediction models for resonance amplitude.

Case	Inputs Parameters				Experimental Resonance Amplitude (mm)	Predicted Resonance Amplitude (mm)			
	Crack Path Second and Final Coordinates					FLR	Error [%]	FANN	Error [%]
	X2	Y2	X3	Y3					
1	10	0	40	30	2.356	2.298	2.5	2.323	1.4
2	10	20	30	20	2.338	2.326	0.5	2.301	1.6
3	10	30	30	20	2.319	2.335	0.7	2.325	0.3
4	20	0	40	30	2.254	2.310	2.5	2.266	0.5
5	20	0	50	40	2.205	2.293	4.0	2.265	2.7
6	20	0	50	50	2.176	2.280	4.8	2.269	4.3
7	20	10	40	30	2.216	2.316	4.5	2.265	2.2
8	20	20	40	20	2.286	2.323	1.6	2.3	0.6
9	30	0	40	30	2.295	2.319	1.1	2.304	0.4
10	30	10	40	30	2.296	2.318	1.0	2.365	3.0
11	30	20	50	30	2.438	2.328	4.5	2.371	2.8
12	40	0	50	20	2.396	2.348	2.0	2.372	1.0
13	40	20	50	30	2.381	2.333	2.0	2.346	1.5
14	40	30	50	20	2.196	2.331	6.2	2.251	2.5
15	40	40	50	30	2.334	2.329	0.2	2.291	1.8

Table 6: Experimental validation of forward linear regression (FLR) and forward artificial neural network (FANN) prediction models for damping ratio.

Case	Inputs Parameters				Experimental Damping Ratio	Predicted Damping Ratio			
	Crack Path Second and Final Coordinates					FLR	Error [%]	FANN	Error [%]
	X2	Y2	X3	Y3					
1	10	0	40	30	0.00610	0.00627	2.8	0.00655	7.4
2	10	20	30	20	0.00590	0.00530	10.2	0.00529	10.3
3	10	30	30	20	0.00485	0.00481	0.9	0.00494	1.9
4	20	0	40	30	0.00553	0.00540	2.2	0.00526	4.8
5	20	0	50	40	0.00537	0.00531	1.3	0.00531	1.2
6	20	0	50	50	0.00538	0.00524	2.7	0.00526	2.3
7	20	10	40	30	0.00543	0.00491	9.6	0.00533	1.9
8	20	20	40	20	0.00482	0.00456	5.4	0.00504	4.6
9	30	0	40	30	0.00419	0.00452	7.9	0.0044	5.1
10	30	10	40	30	0.00399	0.00420	5.3	0.00395	1.0
11	30	20	50	30	0.00396	0.00421	6.5	0.00397	0.3
12	40	0	50	20	0.00381	0.00387	1.7	0.00382	0.4
13	40	20	50	30	0.00399	0.00383	4.0	0.00394	1.2
14	40	30	50	20	0.00439	0.00397	9.5	0.00424	3.4
15	40	40	50	30	0.00385	0.00424	9.9	0.00406	5.3

Overall, the average prediction error is 2.28%, indicating close agreement between predicted and measured responses and confirming that both FLR and FANN models are accurate and reliable in estimating the plate's dynamic behavior, with only slight differences in performance across response parameters.

For the inverse models, the target outputs x_3 and y_3 predicted by the ILR and the IANN models were compared with experimental values. For x_3 (Table 7), the ILR models prediction errors ranged from about 0.1% to 15.1%, whereas the IANN models errors ranged from 0% to 23.1%, with most cases for both models remaining below 10%. For y_3 (Table 8), the ILR model errors ranged from approximately 0.6% to 10.2%, while the IANN model errors ranged from approximately 1.3% to 29.7%. These observations indicate that, within the validated domain, both ILR and IANN models provide an overall average prediction error 8.26%, which is a practically acceptable accuracy for estimating x_3 and y_3 . While there is some variation in error levels between the two approaches in specific cases, their overall predictive capabilities are satisfactory for engineering applications.

Table 7: Validation of inverse linear regression (ILR) and inverse artificial neural network (IANN) models for predicting final crack X-axis coordinate (X3).

Case	Inputs Parameters				Predicted X3 (mm)				
	Experimental Second Crack Coordinates		Experimental Damping Ratio	Experimental Amplitude (mm)	Experimental X3 (mm)	ILR	Error [%]	IANN	Error [%]
	X2	Y2							
1	10	0	0.00610	2.356	40	38.5	3.8	42.3	5.8
2	10	20	0.00590	2.338	30	31.1	3.6	24.6	18.2
3	10	30	0.00485	2.319	30	32.0	6.8	30.4	1.3
4	20	0	0.00553	2.254	40	43.2	8.0	40.9	2.3
5	20	0	0.00537	2.205	50	42.8	14.3	39.3	21.4
6	20	0	0.00538	2.176	50	42.4	15.1	38.5	23.1
7	20	10	0.00543	2.216	40	41.3	3.2	41.7	4.2

(Continued)

Table 7 (continued)

Case	Inputs Parameters				Predicted X3 (mm)				
	Experimental Second Crack Coordinates		Experimental Damping Ratio	Experimental Amplitude (mm)	Experimental X3 (mm)	ILR	Error [%]	IANN	Error [%]
	X2	Y2							
8	20	20	0.00482	2.286	40	40.0	0.1	37.1	7.3
9	30	0	0.00419	2.295	40	43.0	7.6	45.3	13.2
10	30	10	0.00399	2.296	40	44.3	10.7	44.9	12.3
11	30	20	0.00396	2.438	50	46.1	7.9	45.5	9.0
12	40	0	0.00381	2.396	50	47.8	4.3	50.1	0.2
13	40	20	0.00399	2.381	50	52.7	5.4	50.0	0.0
14	40	30	0.00439	2.196	50	48.7	2.5	49.3	1.4
15	40	40	0.00385	2.334	50	54.2	8.5	50.2	0.4

Table 8: Validation of inverse linear regression (ILR) and inverse artificial neural network (IANN) models for predicting final crack Y -axis coordinate ($Y3$).

Case	Inputs Parameters				Predicted Y3 (mm)				
	Experimental Second Crack Coordinates		Experimental Damping Ratio	Experimental Amplitude (mm)	Experimental Y3 (mm)	ILR	Error [%]	IANN	Error [%]
	X2	Y2							
1	10	0	0.00610	2.356	30	27.2	9.5	33.2	10.6
2	10	20	0.00590	2.338	20	20.8	3.9	18.0	10.1
3	10	30	0.00485	2.319	20	19.4	3.0	19.7	1.3
4	20	0	0.00553	2.254	30	29.0	3.3	27.3	9.1
5	20	0	0.00537	2.205	40	38.9	2.9	35.3	11.8
6	20	0	0.00538	2.176	50	45.0	9.9	41.2	17.6
7	20	10	0.00543	2.216	30	27.1	9.7	24.4	18.6
8	20	20	0.00482	2.286	20	21.2	6.0	22.9	14.7
9	30	0	0.00419	2.295	30	30.2	0.6	31.0	3.2
10	30	10	0.00399	2.296	30	28.1	6.5	27.2	9.3
11	30	20	0.00396	2.438	30	27.8	7.2	26.0	13.3
12	40	0	0.00381	2.396	20	22.0	10.2	25.9	29.7
13	40	20	0.00399	2.381	30	27.2	9.4	23.7	20.9
14	40	30	0.00439	2.196	20	20.9	4.7	21.3	6.6
15	40	40	0.00385	2.334	30	29.1	3.1	28.0	6.7

4 Conclusion

This study presented a computational and experimental investigation into the effects of curved crack paths on the dynamic response of cantilever plate structures. Curved crack paths are modelled using second-order polynomial equations. Finite element analysis (FEA) with experimental modal analysis (EMA) was employed as the primary tool to evaluate the influence of these paths' parameters on natural frequencies, vibration amplitudes, and damping ratios. Using available datasets from the experimental tests, forward and inverse identification models are developed using linear regression (LR) and artificial neural networks (ANN) to predict dynamic response characteristics and estimate crack path, respectively. Finally, EMA was used to validate the developed models using 15 fabricated plates not used for training the developed models.

The results indicate that the quadratic and linear coefficients (a and b) of the crack path exert a dominant influence on the plate's stiffness and, consequently, its natural vibration characteristics. In contrast, the constant term (c) primarily translates the crack within the domain with negligible effect. Crack paths with

greater curvature and inclination are associated with higher (a and b) coefficients, particularly at the smaller end abscissae (x_{end}), lead to reduced natural frequencies and increased vibration amplitudes and damping ratios. In contrast, smoother, less curved cracks exhibit the opposite trend. These geometries cause significant stiffness degradation by altering axial and shear stiffness, increasing local flexibility, and enhancing energy dissipation through crack-surface interaction and localized deformation.

To support crack identification, forward and inverse prediction models based on linear regression (LR) and artificial neural networks (ANNs) were developed. The forward models accurately predicted key vibration characteristics, while the inverse models successfully estimated the final crack coordinates from dynamic response data. Experimental validation using fifteen independently fabricated plates confirmed the robustness and generalization capability of the proposed models, with low average prediction errors for both forward and inverse tasks.

Despite these promising results, several limitations should be acknowledged. The investigation was confined to thin, homogeneous, isotropic cantilever plates under controlled laboratory conditions; therefore, the findings may not be directly applicable to thick plates, composite materials, or structures with complex boundary conditions. Moreover, the second-order polynomial representation of curved cracks, although systematic and computationally efficient, may not fully capture highly irregular, tortuous, or branching crack paths encountered in practical structural components. In addition, environmental effects, particularly temperature variations, were not considered in the present study.

Overall, the proposed computational framework advances the modelling and identification of curved crack paths in plate structures. By explicitly accounting for crack path geometry and its influence on dynamic response, this work contributes to more accurate damage evaluation and enhances the effectiveness of vibration-based structural health monitoring. The methodology is general and can be extended to other plate configurations, materials, and damage scenarios, supporting future developments in computational damage detection and modelling.

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Abbreviations

FRF	Frequency response functions
LR	Linear regression
ANN	Artificial neural network
SHM	Structural health monitoring
FANN	Forward artificial neural network
IANN	Inverse artificial neural network
(x_{end})	End abscissae
FLR	Forward linear regression
ILR	Inverse linear regression

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Computational and experimental modeling of curved crack effects on the dynamic response of plate structures

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