

*Research Article*

Predicting the High Torsionality of Stepped Ultrasonic Horn Design in Longitudinal-Torsional Vibration-Assisted Micro Milling Using Finite Element Analysis and Surrogate Models

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Abstract: Longitudinal-torsional ultrasonic vibration-assisted milling has attracted considerable attention because of its ability to improve machining performance, particularly for materials that are difficult to machine. However, due to the complex nonlinear relationships between geometric parameters and dynamic characteristics, including torsionality, resonance frequency, and frequency separation. Conventional design approaches based on iterative finite element analysis (FEA) are computationally expensive and inefficient for extensive parametric studies. This study proposes an integrated FEA-surrogate modeling framework for designing and predicting high-torsionality stepped ultrasonic horns for micromilling applications. The horn geometry was parameterized using slit-related variables, including the number of slits, angle, length, width, and depth. Modal and harmonic response analyses were conducted in ANSYS to determine the resonance frequencies, vibration mode shapes, and torsional characteristics. The resulting dataset was used to develop and compare several predictive models, including multiple linear regression (MLR), Artificial Neural Networks (ANN), Response Surface Methodology (RSM), polynomial regression, kriging, random forest, and XGBoost. The results revealed that slit depth is the dominant parameter governing torsionality, whereas slit width and length have relatively minor effects. Among the evaluated models, Kriging achieved the highest prediction accuracy, whereas ANN demonstrated strong predictive capability ($R^2 = 0.9346$) and substantially outperformed conventional MLR. The proposed framework provides both predictive capability and engineering insight into the influence of slit geometry on the generation of longitudinal-torsional mode generation, enabling more efficient ultrasonic horn design while reducing the reliance on repeated FEA simulations.

Keywords: Frequency separation; Longitudinal-torsional vibration mode; Stepped horn; Torsionality; Ultrasonic horn

1. Introduction

In recent decades, ultrasonic devices have garnered considerable attention for their effectiveness in cutting, drilling, and welding (Yazdian & Karafi, 2022) of both metallic and non-metallic materials, including polymer composites (Han et al., 2025). The horn is the principal element of an ultrasonic device is the horn. It is commonly known as a sonotrode or tool holder and is distinguished by an input end with a greater cross-sectional area than the output end (Wang et al., 2021). The primary function is to enhance the vibration amplitude at the output end, where the cutting tool is affixed, while the input end acts as the interface for the transducer assembly (Lin et al., 2018).

Ultrasonic horns are typically categorized by their vibration mode and intended use as longitudinal, torsional, or flexural (Jalali Asbforoushani et al., 2020). Moreover, hybrid designs can be employed to generate intricate motion patterns, including longitudinal-torsional,

longitudinal–flexural, and torsional–flexural modes (Al-Budairi & Lucas, 2012; Al-Budairi et al., 2011; Tian et al., 2018). Among these configurations, the longitudinal–torsional mode is particularly attractive because it enables simultaneous axial and rotational motion (Tian et al., 2021).

Over the past decade, advancements in the design of longitudinal–torsional ultrasonic horn design have shown that horns functioning in longitudinal–torsional (LT) mode provide an efficient means of enhancing manufacturing performance, especially when machining hard-to-machine materials such as composites, ceramics, and titanium alloys. The LT mode has been shown to lower cutting forces (Ahmad et al., 2023; Ullah et al., 2025; Zhang et al., 2024), improve surface finish (Han et al., 2025; Li et al., 2023; Tong et al., 2026), and reduce tool wear (Li et al., 2023; Zhang et al., 2024).

An early investigation of longitudinal–torsional ultrasonic horns was reported by Li et al. (2022), who formulated the resonance frequency equation for an exponential horn and demonstrated that the longitudinal resonance can be adjusted to approach the torsional resonance. This finding enables the generation of large, efficient vibration amplitudes across a wide range of ultrasonic machining applications (Li et al., 2022).

A variety of design strategies have been proposed, including geometric alterations such as slits or grooves to transform longitudinal vibrations into longitudinal–torsional modes (Li et al., 2021; Wang et al., 2020), waveguide-based configurations to generate hybrid vibrations (Wang et al., 2020), equivalent circuit, and four-terminal network methods for predicting dynamic behavior (Zhao et al., 2022), and the widespread use of finite element analysis (FEA) for design optimization (Yang et al., 2019).

Nonetheless, despite these advancements, numerous fundamental restrictions remain. The majority of research continues to rely on FEA models to determine optimal design parameters, including helix angle, groove quantity, and overall horn size. For instance, Wang et al. (2019) reported that the LT ratio is highly sensitive to shape-related variables, such as helix angle and groove count (Wang et al., 2019). Nevertheless, an explicit mathematical relationship between design parameters and performance outputs has not yet been established, and the design process remains largely iterative.

Although longitudinal–torsional vibration-assisted machining has been extensively investigated in conventional milling, grinding, and ultrasonic machining processes, its application to micro-milling remains relatively unexplored. Most previous studies have focused on macro-scale machining, where coupled longitudinal–torsional vibrations reduce cutting forces, improve surface finish, enhance chip evacuation, and extend tool life. However, the implementation of longitudinal–torsional vibration assistance in micro-milling presents additional challenges due to the small tool dimensions, limited system stiffness, and stringent requirements for vibration stability and frequency control. Consequently, the development of a suitable ultrasonic horn capable of generating stable longitudinal–torsional vibrations is a critical prerequisite for future micromilling applications. Therefore, this study focuses on the design and optimization of a stepped ultrasonic horn intended for longitudinal–torsional vibration-assisted micro-milling (LTVAMM), providing a foundation for subsequent experimental investigations of machining performance.

Currently, no explicit predictive model directly correlates design parameters with the LT ratio, referred to as torsionality, defined as the ratio of torsional to longitudinal amplitudes at the horn tip. This limitation arises because systems such as Longitudinal-Torsional Vibration-Assisted Machining (LTVAM) involve complex multiphysics interactions and pronounced non-linear behavior, making it difficult to represent using purely analytical methods. Moreover, a comprehensive multiparameter model for predicting ultrasonic horn performance has yet to be established, primarily due to the large number of design variables and the shortcomings of conventional methods in handling high dimensionality.

Zhao et al. demonstrated that the incident wave angle significantly affects the LT ratio, with variations up to 4.9 times (Zhao et al., 2019). However, other important parameters—such

as slit depth, width, and the number of slits—have not yet been incorporated into a unified model, particularly given their interactions' intrinsic nonlinearity.

Another limitation concerns the resonance frequency and vibration modes. Zhang et al. (2023) reported that coupling a horn to a tool, such as a grinding wheel, can shift the resonance frequency and degrade the quality of vibration modes (Zhang et al., 2023). This finding suggests that many horn designs do not adequately account for interactions, particularly the effects of tool loading. In most studies, despite the inherently complex coupling among the horn, tool, and workpiece.

However, as modern manufacturing advances toward component miniaturization, higher precision, and the use of advanced materials, the application of LTVAM in micromilling (LTVAMM) remains relatively limited and underexplored. Micromilling has distinctive characteristics, including extremely small tool dimensions, pronounced size effects at the microscale, and high vibration sensitivity (Kiswanto et al., 2020). A poorly designed horn can result in inefficient energy transfer, unstable vibration behavior, and even failure of the machining process.

Moreover, the design of ultrasonic horns—particularly stepped configurations—entails complex, nonlinear correlations among geometric parameters (e.g., inclination angle, slit depth, length, and position) and dynamic responses (e.g., resonance frequency, frequency separation, and torsionality). Established approaches relying on trial-and-error or iterative finite element analysis (FEA) are computationally costly and inefficient for broad design exploration.

In this context, approaches based on artificial neural networks (ANNs) are highly relevant because they can detect complex nonlinear relationships and provide accurate predictions from both simulation and experimental data. Integrating FEA with ANN facilitates a faster, more efficient, and more flexible design process that can adapt to design parameter variations (Shahid et al., 2020; Umbrello et al., 2008).

From a practical standpoint, the findings of this study can have a significant impact in several areas, including the development of optimized ultrasonic horn designs for micro milling, the enhancement of energy efficiency and process stability, the reduction of cutting forces and tool wear, and the acceleration of the design process through an artificial intelligence-based predictive approach (Kumar Patel et al., 2021).

2. Methods

The object of this study is a stepped ultrasonic horn with slit modifications that is designed to generate combined longitudinal–torsional vibrations in a LTVAMM system. Figure 1 illustrates an integrated framework combining finite element analysis and artificial neural networks to predict torsionality in the stepped-horn design is illustrated in Figure 1.



Figure 1 Integrated FEA–ANN framework for ultrasonic horn design

The main hypothesis of this study is that the geometric parameters of the horn—specifically the slit characteristics, including number, angle, length, width, and depth—have a significant effect on torsionality, resonance frequency, and frequency separation, and that these relationships can be accurately predicted using an approach that integrates finite element analysis (FEA) with artificial neural networks (ANN).

Several assumptions were adopted in this study: the horn material is considered homogeneous, isotropic, and linearly elastic; material damping is neglected; interactions with the external environment are not considered; and the excitation is assumed to be harmonic and stable.

The following simplifications were also applied: the horn geometry is modeled without accounting for manufacturing tolerances; temperature effects and material nonlinearities are ignored; and the ANSYS-based FEA simulations do not include the direct interaction with the cutting process.

2.1 Ultrasonic Horn Design for the LTVAMM System

The design of an ultrasonic horn is a critical stage in the development of an LTVAMM system, as it serves both as an amplitude amplification component and as a converter of vibration modes from the transducer to the cutting tool. The horn length, geometric configuration, material properties, and dynamic characteristics, such as the resonant frequency and vibration mode distribution.

The length of an ultrasonic horn is governed at the operating (driving) frequency and the propagation velocity of waves within the horn material. To achieve optimal resonance, the horn is typically designed as a multiple of the ultrasonic wavelength (λ), creating a standing wave along its length. The wavelength can be expressed by Equation 1 (Satpute et al., 2023).

$$\lambda = c/f \quad (1)$$

where c represents the sound speeds (m/s) and f denotes the ultrasonic frequency (Hz). In practical design, the horn length is commonly set to $(\lambda/2)$, as a half-wavelength resonator to achieve maximum amplitude at the output end. However, other configurations, such as $(\lambda/4)$, or integer multiples of λ , may be employed depending on specific application requirements.

The propagation velocity of the wave within the horn material is governed by its mechanical properties—namely, the elastic modulus and density—and can be determined using Equation 2.

$$c = \sqrt{E/\rho} \quad (2)$$

where E denotes the elastic modulus (Pa), and ρ represents the material density (kg/m^3). In this study, SKD-11 tool steel was selected as the horn material, and its properties are presented in Table 1.

Table 1 Material properties of the SKD-11 tool steel.

Mechanical Properties	Value
Elastic modulus	210 GPa
Density	7700 $\frac{kg}{m^3}$
Poisson's ratio	0.3

For a stepped ultrasonic horn featuring different diameters on the input and output ends, Equation 1 is modified as follows:

$$\lambda = \frac{c}{2\pi f} \sqrt{(2\pi)^2 + (\ln n)^2} \quad (3)$$

where n represents the ratio between the output and input diameters (Hocheng & Kuo, 2002).

Beyond the length and material characteristics, the geometry of the horn significantly influences the amplitude distribution and overall vibration behavior. In this study, a stepped-type horn is employed, in which diameter variations along the horn length enhance amplitude amplification and enable adjustment of the vibration energy distribution.

2.2 Torsionality of the ultrasonic horn

In LTVAM systems, torsionality has a vital role in determining machining behavior and the quality of the machined outcome. Certain applications require high levels of torsionality to achieve maximum efficiency. Numerous studies have shown that increasing torsionality generally

improves machining efficiency and yields better results in vibration-assisted processes (Asami & Miura, 2022).

The displacement produced by the piezoelectric transducer layer, primarily in the longitudinal direction (Zhang et al., 2022). Diagonal slits are introduced along the horn body to generate coupled longitudinal-torsional motion, enabling mode conversion (Chen et al., 2022). The directions of the longitudinal and torsional amplitudes and their contour for a horn with diagonal slits are illustrated in Figure 2.

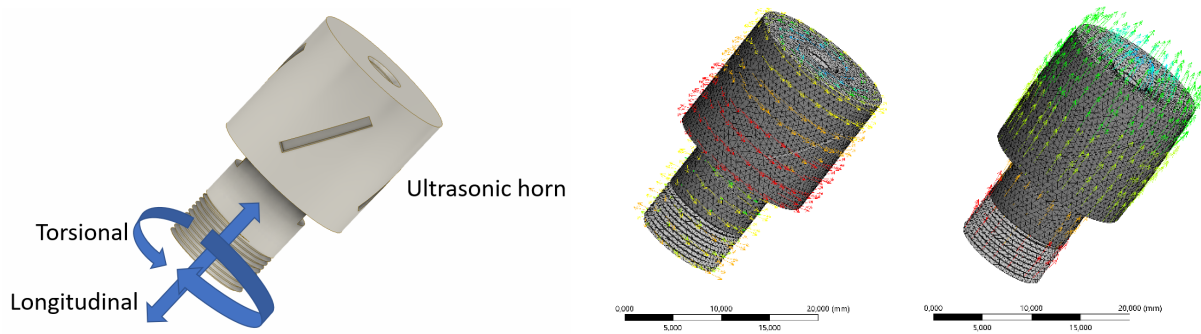


Figure 2 Directions of longitudinal and torsional amplitude directions and their contour on ultrasonic horns

The influence of slit parameters on the torsionality and resonance frequency of an ultrasonic horn. A stepped-type horn is employed, with slits introduced along the side of the horn body's larger-diameter section of the horn body. The parameters considered include the number of slits, inclination angle, length, width, and depth. Figure 3 illustrates the five slit parameters expected to affect the resulting torsionality.

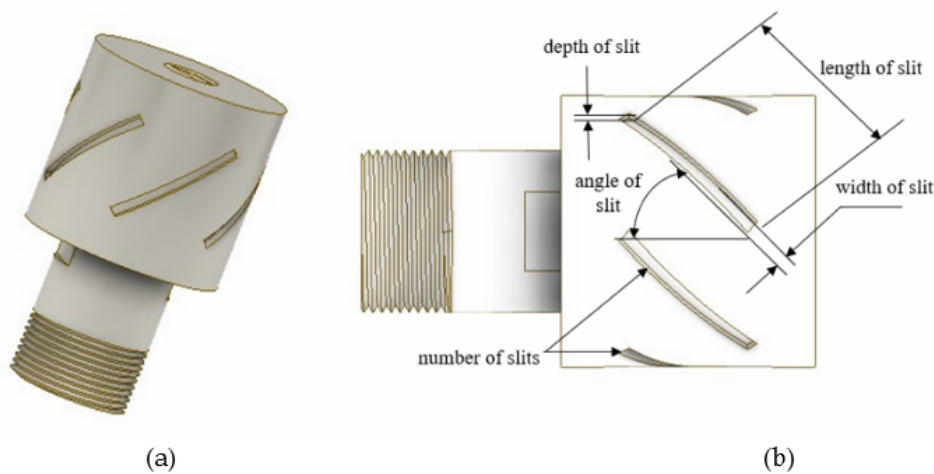


Figure 3 (a) 3D perspective view of the stepped ultrasonic horn (b) Enlarged schematic view of the slit geometry showing the five design parameters

Table 2 shows the five slit parameters of the ultrasonic horn and their influence on torsionality.

This modification permits a coupled vibration mode in which part of the longitudinal energy is transformed into a torsional component (Xie et al., 2022). The extent of this torsional motion is quantified by the torsionality parameter, which is defined as the ratio of torsional to longitudinal amplitudes at the horn tip, as given by Equation (4).

$$T = A_T/A_L \quad (4)$$

where; A_T denotes the torsional amplitude and A_L represents the longitudinal amplitude at the ultrasonic horn.

Table 2 Variables of slit parameters

Constant/Variable	Number of slits	Angle	Length	Width	Depth
Number of slits	Variable	45	9	0.5	0.5
Angle	6	Variable	9	0.5	0.5
Length	6	30	Variable	0.5	0.5
Width	6	30	13	Variable	0.5
Depth	6	30	13	1.00	Variable

However, the relationship between the horn's geometric parameters—such as the number of slits, inclination angle, length, width, and depth—and its torsional behavior is highly non-linear and difficult to describe analytically. In this study, horn models with varying parameter arrangements were developed in Autodesk Inventor for 3D modeling, and modal and harmonic response analyses were performed in ANSYS using modal and harmonic response analyses.

A fine mesh was applied around the slit regions to accurately capture the stress concentration and torsional deformation behavior. The mesh size ranged from approximately 0.2–0.5 mm in the slit area and 0.8–1.5 mm in the remaining horn body. Tetrahedral higher-order elements (SOLID186/SOLID187) were employed in ANSYS to improve the accuracy of the modal and harmonic response analyses. A mesh convergence study was conducted to ensure the independence of the solution from the mesh density.

Accordingly, a finite element analysis (FEA) approach implemented in ANSYS was used to assess the dynamic response of the horn, including the resonance frequency, mode shapes, and amplitude distribution.

2.3 Modal Analysis and Harmonic Response of a Stepped Ultrasonic Horn

The analysis was conducted using ANSYS software employing the finite element method (FEA).

2.3.1 Modal Analysis of the Stepped Ultrasonic Horn

The fundamental dynamic characteristics of a stepped ultrasonic horn, including its natural frequencies and corresponding mode shapes. This analysis ensures that the horn resonates with the operating frequency of the system while preventing interference from undesired vibration modes.

Fixed support was applied to the internal thread of the ultrasonic horn as a boundary condition in the simulations. The input end was constrained to the ultrasonic transducer system, while the output end remained free to vibrate and generate longitudinal–torsional motion. The outputs include the natural frequency spectrum and mode shapes for each mode. The primary modes of interest are longitudinal (axial), torsional (rotational), and bending (lateral) vibrations.

The primary goals of the modal analysis are to identify the principal resonance frequency near the operating frequency (e.g., 32 kHz), ensure that longitudinal–torsional modes dominate at the target frequency, and prevent the occurrence of bending modes that may compromise system steadiness.

The horn design performance is further assessed using the frequency separation parameter, defined as the difference between the target frequency and the nearest adjacent mode. This parameter is given in Equation 5 below.

$$\Delta f = |f_{\text{target}} - f_{\text{nearest}}| \quad (5)$$

A higher frequency separation value indicates that the longitudinal–torsional mode is sufficiently isolated from other modes, improving system stability and reducing the likelihood of undesired mode coupling (Ahmad et al., 2023; Al-Budairi & Lucas, 2012; Zhao et al., 2022).

2.3.2 Harmonic Response of the Stepped Ultrasonic Horn

Following the modal analysis, harmonic response analysis was conducted in ANSYS Mechanical by applying a longitudinal harmonic excitation at the horn input surface. To evaluate the dynamic response of the horn and identify the coupled longitudinal–torsional vibration mode, the excitation frequency was swept around the resonance frequencies identified from the modal analysis.

The vibration amplitudes were extracted at the horn's tool-side tip of the horn. The longitudinal amplitude (A_L) was obtained from the axial displacement component along the horn axis (Z-direction), whereas the torsional amplitude (A_T) was determined from the tangential displacement associated with rotational motion about the horn axis. These amplitudes were evaluated at the resonance frequency exhibiting simultaneous axial and rotational deformation, indicating coupled longitudinal–torsional vibrations. Subsequently, the torsionality parameter was subsequently calculated as the ratio of torsional to longitudinal amplitude (A_T/A_L).

A high torsionality ratio together with the coexistence of longitudinal and torsional motion at the horn tip, demonstrating effective longitudinal-to-torsional vibration conversion.

2.4 Dataset Preparation

The dataset used in this study was generated from finite element simulations of stepped ultrasonic horns with different slit geometries. Five geometric parameters, namely, slit number, slit angle, slit length, slit width, and slit depth, were selected as input variables, while the target output was the torsionality obtained from harmonic response analysis was used as the target output.

A total of 243 data samples were obtained from the FEA simulations. The input variables were normalized using the StandardScaler technique, which transforms each feature to zero mean and unit variance. The dataset was randomly partitioned into training and testing sets using an 80:20 split ratio. The surrogate models were developed using the training set (194 samples), whereas the testing set (49 samples) was reserved for independent performance evaluation. This procedure was applied consistently to all the predictive models considered in this study, including RSM, PR, kriging, ANN, random forest, and XGBoost.

2.5 Surrogate Modeling

Three commonly used approaches were investigated to evaluate the effectiveness of different surrogate modeling techniques for predicting horn torsionality, three commonly used approaches were investigated: Response Surface Methodology (RSM), Polynomial Regression (PR), and Kriging. These models were developed using the same FEA-generated dataset to establish predictive relationships between the geometric parameters of the slit-based ultrasonic horn and the resulting torsionality values.

2.5.1 Response Surface Methodology (RSM)

Response Surface Methodology (RSM) is a statistical and mathematical technique widely used to approximate nonlinear relationships between input variables and system responses (Pouget et al., 2025). In this study, a second-order polynomial response surface was employed to model the relationship between slit parameters and torsionality. The general form of the RSM model is expressed in Equation 6,

$$y = \beta_0 + \sum_{i=1}^n \beta_i x_i + \sum_{i=1}^n \beta_{ii} x_i^2 + \sum_{i < j}^n \beta_{ij} x_i x_j + \varepsilon \quad (6)$$

where (y) represents the predicted torsionality, (x_i) denotes the input variables, (β) are regression coefficients, and (ε) is the residual error term. The coefficients were estimated using the least-squares method.

The RSM was selected because of its simplicity, interpretability, and widespread use in engineering optimization studies involving multiple design variables.

2.5.2 Polynomial regression (PR)

Polynomial regression extends conventional linear regression by incorporating higher-order polynomial terms to capture nonlinear relationships between input and output variables. In this study, a second-order polynomial model was adopted to maintain consistency with the RSM formulation while providing an independent regression-based benchmark.

Polynomial features were generated from the original input variables, and the model parameters were estimated using ordinary least squares regression. Polynomial regression serves as a baseline nonlinear surrogate model against which the performance of more advanced techniques can be compared.

2.5.3 The Kriging Surrogate Model

Kriging, also known as Gaussian Process Regression, is a surrogate modeling technique that combines a global regression trend with a localized stochastic interpolation process. The predicted response can be expressed in Equation 7,

$$y(x) = f(x) + Z(x) \quad (7)$$

where $(f(x))$ is a deterministic regression function and $(Z(x))$ is a Gaussian stochastic process characterized by a covariance function.

A Gaussian correlation function was employed to describe the spatial correlation among design points. Kriging was selected because of its ability to represent highly nonlinear relationships and its widespread application in simulation-based engineering design optimization.

2.5.4 Model Evaluation

The predictive performance of all surrogate models was assessed using the same testing dataset. Model accuracy was evaluated using the coefficient of determination (R^2), Mean Absolute Error (MAE), root mean squared error (RMSE), and mean squared error (MSE).

The coefficient of determination (R^2) can be written in Equation 8 as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y}_i)^2} \quad (8)$$

where $(y_i - \hat{y}_i)^2$ represents the squared prediction error, and $(y_i - \bar{y}_i)^2$ represents the observed data's total variation. An R^2 value closer to 1 indicates better agreement between the predicted and actual values.

The mean absolute error (MAE) was used to quantify the average magnitude of prediction errors and is defined as Equation 9,

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (9)$$

where y_i and $\hat{y}_i$ denote the actual and predicted values, respectively. Lower MAE values indicate better predictive performance.

The Root Mean Squared Error (RMSE) was used to evaluate the prediction accuracy of the surrogate models and is defined as follows:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (10)$$

where (y_i) is the target value obtained from FEA simulations and $(\hat{y}_i)$ is the predicted value generated by the surrogate model.

The performance of RSM, Polynomial Regression, Kriging, Artificial Neural Network (ANN), Random Forest (RF), and Extreme Gradient Boosting (XGBoost) was subsequently compared to identify the most suitable predictive model for torsionality estimation and horn design optimization.

2.6 ANN Modeling

Various ANN architectures exist, including multilayer perceptrons (MLP), convolutional neural networks (CNN), and recurrent neural networks (RNN); however, the MLP is the most appropriate choice for predicting the torsionality of this ultrasonic horn (Shahid et al., 2020). Random forest algorithms have been widely applied for nonlinear prediction problems (Yang et al., 2025), while XGBoost algorithms have demonstrated strong capability in engineering prediction applications (Vu et al., 2021).

An artificial neural network (ANN) is composed of one or more layers, each containing multiple neurons. Neurons in one layer are interconnected with those in the subsequent layer, and these intermediate neurons are commonly referred to as hidden units. The first layer is the input layer, the intermediate layers are known as hidden layers, and the final layer is the output layer, which defines the type and magnitude of the predicted output (Hornik et al., 1989). The Artificial Neural Network (ANN) developed in this study adopts a feedforward Multilayer Perceptron (MLP) architecture for predicting the torsionality of the stepped ultrasonic horn based on slit geometric parameters. The ANN consists of an input layer, two hidden layers, and an output layer (Figure 4).

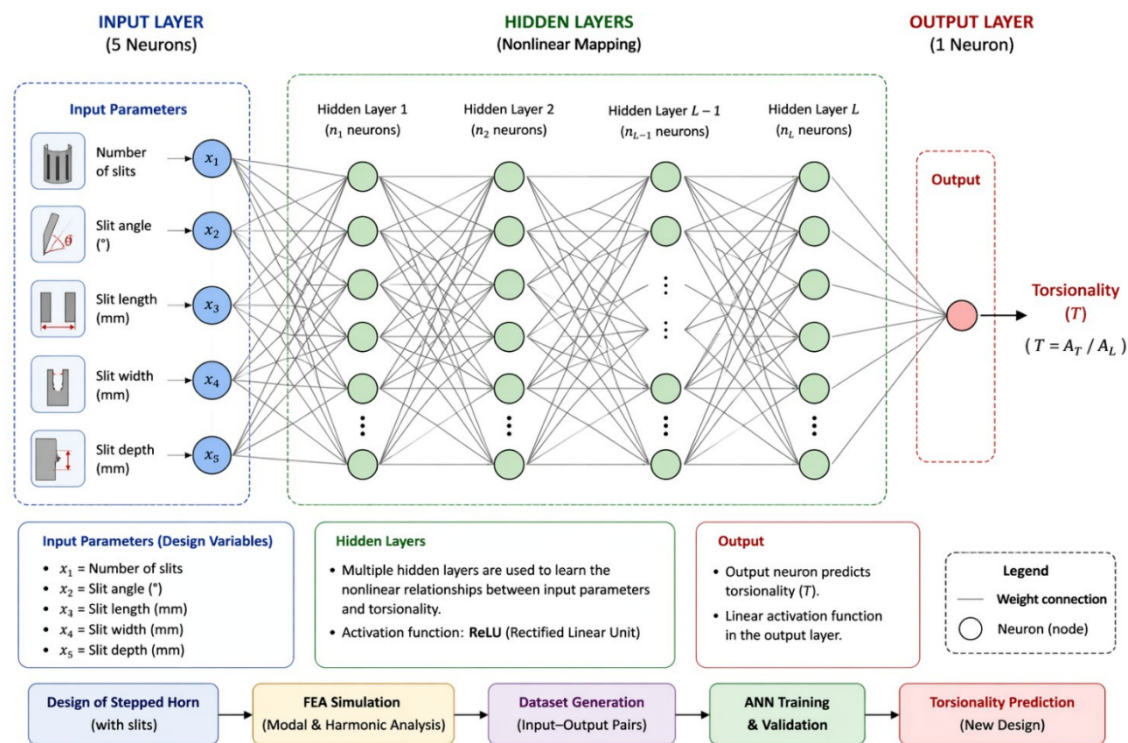


Figure 4 Detailed architecture of the multilayer perceptron (MLP)-based ANN model used for torsionality prediction

The input layer receives five geometric parameters of the slit configuration: the number of slits, slit angle, slit length, slit width, and slit depth. These parameters serve as the input features representing the horn geometry. The first hidden layer contains 8 neurons and uses the Rectified Linear Unit (ReLU) activation function. This layer captures the primary nonlinear

relationships between the geometric parameters and the torsional behavior of the horn. The second hidden layer consists of 4 neurons, also employing the ReLU activation function to refine the nonlinear feature extraction process and improve the prediction capability.

The output layer contains a single neuron with a linear activation function that generates continuous numerical predictions of torsionality. Since torsionality prediction is a regression problem, linear activation is selected to allow unrestricted output values.

Before training, all input data were normalized using the StandardScaler method to improve training stability and convergence. The dataset was divided into training and testing subsets with a ratio of 80 : 20. During training, the model employed the Adam optimizer with a learning rate of 0.001 and used Mean Squared Error (MSE) as the loss function, while Mean Absolute Error (MAE) was used as an additional evaluation metric.

The training process was run for up to 150 epochs with a batch size of 4. To prevent overfitting and improve model generalization, an early stopping strategy was implemented with a patience of 15 epochs based on validation loss. The final ANN model demonstrated a strong predictive performance, with an R^2 of 0.9346 for torsionality prediction.

3. Results and Discussion

The ultrasonic horn is manufactured from SKD-11 tool steel, with an elastic modulus of 210 GPa and a density of 7700 kg/m^3 , using Equation 2, the velocity of propagation of the longitudinal wave as follows:

$$c = \sqrt{\frac{E}{\rho}} = \sqrt{\frac{210 \times 10^9}{7700}} = 5222 \frac{m}{s} \quad (11)$$

Given the dimensional restrictions of the LTVAM system in micromilling for implementing the designed ultrasonic horn, the horn length in this study was set to 25 mm (Hasymi et al., 2024). With the horn designed as a quarter-wavelength ($\lambda/4$), resonator, the operating frequency can be determined using Equation 3, yielding the following result:

$$f = \frac{c}{\lambda} = \frac{5222 \frac{m}{s}}{4 \times 0.025 m} = 52.22 kHz \quad (12)$$

A detailed drawing of the stepped ultrasonic horn with added grooves/slits is shown in Figure 5.

The input-to-output diameter ratio directly influences the resulting amplitude gain. Applying Equation 3 to a stepped ultrasonic horn with differing diameters at the input and output ends, applying Equation 3 yields the following result:

$$\lambda = \frac{c}{2\pi f} \sqrt{(2\pi)^2 + (\ln n)^2} \quad (13)$$

Since n represents the ratio of the output diameter to the input diameter. For the stepped horn designed as shown in Fig. 5, we performed the following:

$$n = \frac{9 mm}{15 mm} = 0.6 \quad (14)$$

Thus, the natural frequency of the ultrasonic horn is obtained as follows:

$$f = \frac{c}{2\pi\lambda} \sqrt{(2\pi)^2 + (\ln n)^2} = \frac{5222 \frac{m}{s}}{2\pi \times 4 \times 0.025 m} \sqrt{(2\pi)^2 + (\ln 0.6)^2} = 52.40 kHz \quad (15)$$

The natural frequency of a uniform cross-sectional horn differs from that of a stepped horn because the diameter variation between the input and output sections directly alters the stiffness and wave transmission characteristics. The reduced output diameter in a stepped horn increases the structural stiffness-to-mass ratio, resulting in wave concentration along the horn body and typically producing a slightly higher natural frequency.

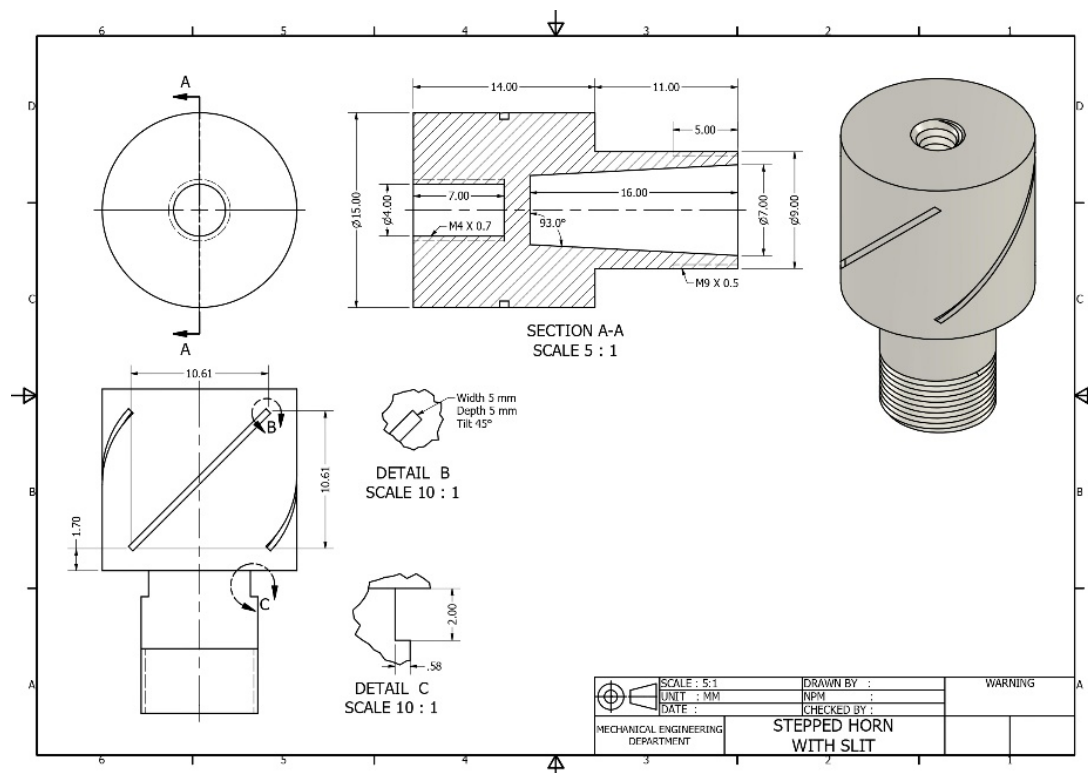


Figure 5 Detailed drawing of the stepped ultrasonic horn with slits

Horn models with varying parameter arrangements were developed for 3D modeling in Autodesk Inventor. A mesh convergence study was conducted to ensure accurate results from ANSYS simulations and analyses, a mesh convergence study was performed to assess the numerical accuracy of the FEA simulations. Several mesh densities were evaluated based on resonance frequency and torsionality response. The solution was considered to have converged when the frequency variation between successive mesh refinements was less than 1%. Finer meshes were applied in the slit regions to accurately capture the stress concentration and conversion of the longitudinal–torsional mode conversion. The final mesh employed higher-order tetrahedral elements with element sizes of approximately 0.2 – 0.5 mm near the slits and 0.8 – 1.5 mm in the remaining horn body.

The relationship between the geometric parameters of the horn and both torsionality and frequency is illustrated in Figure 6 (in the supplementary file).

The predictive model was developed using an Artificial Neural Network (ANN) based on a multilayer perceptron architecture. For the learning process, the dataset was partitioned into training, validation, and testing subsets for the learning process. The trained ANN model was then employed to estimate torsionality from the design parameters, eliminating the need for repeated FEA simulations. Table 3 presents representative examples of the FEA results. The Supplementary Material provides the complete dataset consisting of 243 simulation cases is provided in the Supplementary Material to facilitate reproducibility and further analysis.

In this study, the dataset consists of 243 samples, a portion of which is presented in Table 3. The data were split into a training set (80%) and a test set (20%) comprising 194 and 49 samples, respectively. The best performing model on the training set was retained and used to generate predictions on the test set. Figure 7 shows the training and validation loss curves for the ANN model.

Both curves decrease rapidly during the initial epochs, indicating that the nonlinear relationship between slit geometric parameters and torsionality was successfully learned. The loss values gradually stabilize after approximately 20 epochs, reflecting model convergence. The close agreement between training and validation losses implies strong generalization and minimal overfitting. The stable validation curve further demonstrates the effectiveness of both the

Adam optimizer and the ANN architecture for prediction of torsionality.

Table 3 A subdataset from the ultrasonic horn FEA results

No	Parameter of the slit					Torsionality
	Number (3, 4, 6)	Angle (15, 30, 45)	Length (mm) (9, 11, 13)	Width (mm) (0.5, 0.75, 1.00)	Depth (mm) (0.5, 1.0, and 1.5)	
1	3	15	9	0.5	0.5	2.43
2	3	15	9	0.5	1.0	4.33
3	3	15	9	0.5	1.5	7.02
4	3	15	9	0.75	0.5	2.39
5	3	15	9	0.75	1.0	4.29
6	3	15	9	0.75	1.5	7.15
7	3	15	9	1.00	0.5	2.55
...	...	...	...	...	...	...
241	6	45	13	1.00	0.5	5.41
242	6	45	13	1.00	1.0	15.83
243	6	45	13	1.00	1.5	39.86

The predicted torsionality values obtained from each surrogate model were compared with the corresponding target values from the test dataset, and Figure 8–9 (in the supplementary file) show two models, namely ANN and polynomial regression.

The torsionality predicted by the Multiple Linear Regression (MLR) is given by Equation 16 below.

$$\begin{aligned}
 \text{Torsionality} = & -30.55 + 2.26 \times (\text{number of slit}) + 0.20 \times (\text{angle of slit}) \\
 & + 0.69 \times (\text{length of slit}) + 2.49 \times (\text{width of slit}) = 16.03 \times (\text{depth of slit})
 \end{aligned}
 \tag{16}$$

The experimental results demonstrate that the proposed simple Artificial Neural Network (ANN) model achieved highly accurate torsionality prediction based on slit geometric parameters, obtaining an R^2 score of 0.9346 with relatively low prediction errors. Despite using a lightweight architecture with only two hidden layers, the ANN model substantially outperformed the conventional Multiple Linear Regression (MLR) approach, indicating nonlinear relationships between slit geometry and torsionality behavior. Although ensemble learning models such as Random Forest and XGBoost achieved slightly higher prediction accuracy, the simple ANN architecture offers computational simplicity, lightweight implementation, and practical applicability for intelligent engineering prediction tasks. These findings suggest that even a simple ANN model is highly effective for modeling nonlinear torsionality behavior in slit-based engineering structures.

The relationship between the geometric parameters of the horn and torsionality, as shown in Figure 6, can also be represented as a correlation heatmap (correlation matrix) illustrating the association between the geometric parameters of the horn and torsionality, as shown in Fig. 10 (in the supplementary file).

The results of this study provide important insights into the relationships between the geometric parameters of stepped ultrasonic horns and their dynamic characteristics, particularly torsionality. Based on the correlation matrix analysis (Figure 10), the depth of the slit has the greatest influence on torsionality, with a correlation coefficient of 0.74. This indicates that increasing the slit depth substantially improves the torsional vibration component.

The slit depth significantly increases torsionality because it modifies the local stiffness distribution and enhances the geometric asymmetry within the horn structure. The propagation path of the longitudinal elastic wave is increasingly distorted, promoting stronger conversion of longitudinal vibration energy into torsional motion. This phenomenon generates larger tangential displacement and local torsional moments, leading to higher torsional amplitudes. In

addition, deeper slits reduce torsional stiffness and facilitate torsional vibration mode. Consequently, the slit depth becomes the dominant geometric parameter influencing the torsionality of the stepped ultrasonic horn.

In contrast, the number of slits and slit angle exhibited moderate correlations with torsionality, with coefficients of 0.34 and 0.30, respectively. These parameters influence the wave movement's spatial pattern and direction of wave movement along the horn. Increasing the number of slits improves the cumulative effect of mode conversion, whereas the slit angle controls the directionality of energy transfer between the longitudinal and torsional components. However, their influence remains secondary to that of slit depth, indicating that these parameters primarily act as tuning variables rather than dominant drivers.

However, the length and width of slits show relatively weak correlations with torsionality (0.14 and 0.054, respectively). These parameters make a minimal contribution to the global dynamic traits. Physically, length and width primarily induce local distortions without substantially altering the overall energy distribution among vibrational modes. Therefore, these parameters are less critical for achieving high torsionality.

Increasing the slit depth significantly enhances torsionality by promoting stronger conversion of longitudinal-to-torsional energy conversion. However, deeper slits also introduce higher stress concentration around the slit edges because of local stiffness reduction and geometric discontinuity. The resulting increase in shear stress and localized deformation may reduce the structural rigidity of the horn and influence the resonance frequency. Consequently, although high torsionality improves vibration-assisted machining performance, excessive slit depth may lead to resonance frequency shifts, mode instability, and increased fatigue risk under ultrasonic cyclic loading conditions. Therefore, in stepped ultrasonic horn design, an optimal balance between torsionality enhancement and structural integrity is necessary in stepped ultrasonic horn design.

Unlike conventional longitudinal–torsional ultrasonic horn studies that rely on iterative FEA optimization, this study integrates FEA with ANNs to enable rapid prediction of torsionality and identify the most influential geometric parameters. The proposed approach decreases the computational effort during horn design and is particularly suitable for micromilling applications. However, its current limitations include a lack of experimental verification and the exclusion of tool–workpiece interaction effects.

4. Conclusions

In this study, we proposed an integrated FEA–surrogate modeling framework for the design and prediction of stepped longitudinal–torsional ultrasonic horns intended for future micromilling applications. To investigate the influence of slit geometry on horn dynamic performance, and the resulting dataset was used to develop and compare several predictive models, including MLR, RSM, polynomial regression, kriging, ANN, random forest, and XGBoost.

The results demonstrated that slit depth is the dominant geometric parameter governing torsionality, whereas slit width and length have comparatively minor effects. This observation indicates that torsional vibration generation is primarily controlled by geometric modifications that significantly alter local torsional stiffness and longitudinal–torsional mode coupling. Furthermore, the analysis revealed that increasing the slit depth enhances the conversion of longitudinal vibration into torsional motion, resulting in higher torsionality values.

Kriging achieved the highest prediction accuracy within the investigated design space. ANN also demonstrated strong predictive capability and substantially outperformed conventional MLR, confirming the suitability of machine-learning-based approaches for capturing the nonlinear relationship between slit geometry and torsionality. These findings provide both practical design guidance and a computationally efficient alternative to repeated FEA simulations during horn development.

4.1 Relationship Between Torsionality and Separation of Frequency

Although high torsionality is desirable for longitudinal–torsional vibration-assisted machining, it should not be considered independently from other dynamic performance indicators. The results indicate that geometric modifications that increase torsionality may simultaneously influence resonance frequency and frequency separation. In particular, increasing the slit depth not only enhances the longitudinal–torsional mode coupling but also reduces the horn’s effective structural stiffness of the horn, potentially altering the spacing between neighboring vibration modes.

Frequency separation is important in ensuring stable resonance behavior and minimizing the risk of unintended modal interactions. Horn designs with insufficient frequency separation may become more sensitive to manufacturing tolerances, assembly conditions, and operational loading, thereby inducing resonance frequency shifts and mode instability. Therefore, the optimal design is not necessarily the configuration with the highest torsionality but rather one that achieves a balanced combination of high torsionality, resonance stability, and adequate frequency separation. These findings highlight the importance of considering multiple performance criteria during ultrasonic horn design.

4.2 Limitations and Future Work

A limitation of this study is the absence of experimental validation of the proposed slit-based horn design. Although the developed surrogate models demonstrated excellent predictive performance using FEA-generated data, experimental verification of resonance frequency, vibration amplitude, mode shape, and torsionality is required to confirm the simulation-based predictions under actual operating conditions.

Future work will focus on fabricating an optimized horn prototype using high-precision machining techniques and characterizing its dynamic performance through impedance analysis and laser displacement measurements. Subsequently, the fabricated horn will subsequently be integrated into a micro-milling system to evaluate its influence on cutting forces, surface quality, tool wear, and dimensional accuracy.

Future studies will extend the proposed framework toward multi-objective optimization by simultaneously considering torsionality, resonance frequency stability, frequency separation, stress concentration, vibration amplitude, and structural integrity. The surrogate models developed in this study provide an efficient and computationally inexpensive objective function for optimization algorithms, enabling the identification of Pareto-optimal horn designs while substantially reducing the computational cost associated with repeated finite element analyses. The objective of this study is the development and validation of accurate surrogate models for torsionality prediction, which constitute a prerequisite for subsequent optimization rather than the optimization itself.

Author Contributions

Zulhendri Hasymi: Conceptualization, Methodology, Project administration, Software (FEA simulation using ANSYS; ANN model development in Python), Investigation, Writing – original draft; Gandjar Kiswanto: Conceptualization refinement, Supervision; Ario Sunar Baskoro: Methodology support, Validation; Jos Istiyanto: Writing – review & editing; Rendi Kurniawan: Visualization support, Technical review.

Conflict of Interest

The authors declare no conflict of Interest.

Declaration of AI

The authors confirm that artificial intelligence tools were utilized within acceptable ethical and scientific boundaries to support this research. All outputs generated by AI have been critically assessed and validated by the authors.

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