

Article

Deep Neural Network-Based Prediction of Flow-Induced Noise Around Cylindrical Bodies

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Abstract

Cylindrical bodies generate flow-induced noise when exposed to external flows, which can be predicted numerically using Computational Fluid Dynamics (CFD) combined with the Ffowcs Williams–Hawkings (FW–H) Equation. Accurate prediction, however, requires turbulence models such as Detached Eddy Simulation (DES) with fine spatial resolution and small time steps, in addition to time-dependent surface pressure data and receiver arrangements. These requirements greatly increase computational costs and limit the applicability of such methods during the design stage. To address this challenge, a Deep Neural Network (DNN) model was developed to predict flow-induced noise around a cylinder. Training data were generated from CFD cases using cylinder geometry and inflow velocity as design variables, with multiple receivers arranged in a polar coordinate system. Acoustic signals were computed using Farassat’s Formulation 1A, the time-domain surface solution of the FW–H Equation. The DNN was trained with design variables, receiver coordinates, and octave-band center frequencies as inputs, while the Sound Pressure Level (SPL) served as the output. Model performance was evaluated using the adjusted coefficient of determination (R^2_{adj}) and the root mean squared error (RMSE). In addition, interpolation capability was tested by varying receiver spacing to examine robustness under sparse data conditions. The results confirm that the proposed framework provides accurate and computationally efficient predictions suitable for early-stage design.



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1. Introduction

Two primary approaches are available for numerically predicting noise generated by external flows around marine structures: direct methods and hybrid methods. The hybrid method separates the flow field from the acoustic field and typically employs the Ffowcs Williams–Hawkings (FW–H) acoustic analogy for flow-induced noise prediction [1]. In contrast, the direct method evaluates pressure at receiver points within the flow domain, making it suitable for resolving nonlinear and spatially sensitive acoustic phenomena in the near field. Although this enables the capture of effects such as reflections and scattering caused by flow–structure interactions, the method requires an extremely fine mesh to resolve acoustic wavelengths, and the pressure data remain confined to the computational domain. These restrictions render the direct method impractical for large-scale hydroacoustic problems [2].

The hybrid method assumes linear propagation of acoustic waves in the far field, where acoustic energy decays inversely with distance. Because of its lower computational cost, FW–H-based prediction is widely applied in hydroacoustic research. For submarine applications, where the far-field acoustic dataset is of primary interest, the FW–H analogy provides a practical and reliable framework [3]. Furthermore, the method can be applied not only to fixed surfaces but also to rotating components such as marine propulsors [4,5]. Considering its widespread adoption and suitability for hydroacoustic analysis, the hybrid method was selected in this study to generate flow-induced noise data around cylinders.

Computational Fluid Dynamics (CFD) provides a rigorous methodology for predicting flow characteristics with high accuracy. Its application, however, is constrained by the substantial computational resources and time required. In the design stage, where development must be completed within strict time constraints, it is essential to identify critical design variables and evaluate their influence on performance in a rigorous manner. A conventional approach involves performing CFD simulations across a range of design variables and analyzing their effects on relevant performance indicators. More recently, numerous studies have focused on combining deep learning techniques with high-fidelity CFD data. This integration enables efficient exploration of the design space and facilitates rapid performance prediction without additional CFD simulations [6,7].

Recent advances in machine learning architectures have significantly expanded their applicability to CFD-related problems. Convolutional Neural Networks (CNNs) are effective for structured flow fields with spatially correlated grid data, whereas Graph Neural Networks (GNNs) are more suitable for unstructured meshes encountered in practical CFD simulations [8–10]. Physics-Informed Neural Networks (PINNs) incorporate governing equations such as the Navier–Stokes equations into the training process, thereby maintaining physical consistency even under sparse data conditions [11,12]. However, these models often require extensive preprocessing, problem-specific hyperparameter tuning, and long training times.

In contrast, the Deep Neural Network (DNN) adopted in this study offers a simpler and more computationally efficient framework for parametric acoustic prediction [13]. Because the input variables include flow velocity, cylinder aspect ratio, and receiver coordinates, which are scalar parameters rather than spatial grids, a fully connected DNN can effectively capture nonlinear relationships between flow conditions, cylinder geometry, and acoustic responses derived from the Ffowcs Williams–Hawkins (FW–H) formulation. Furthermore, the lightweight DNN architecture enables rapid prediction, making it suitable for submarine acoustic stealth optimization in the early design stage and real-time noise prediction under variable operating conditions.

Based on this motivation, a DNN model was developed in this study to predict the Sound Pressure Level (SPL) under varying input conditions. Training data were generated from CFD simulations with different inlet velocities and cylinder aspect ratios. The Detached Eddy Simulation (DES) turbulence model [14] was employed to efficiently capture the unsteady flow features responsible for broadband noise generation in water. In each simulation case, receivers were uniformly distributed in polar coordinates, and acoustic signals were computed using the FW–H analogy. Receiver coordinates and octave-band center frequencies were used as model inputs together with CFD design variables, while SPL served as the model output. Model performance was evaluated by comparing predictions with CFD-computed acoustic data.

Additionally, the interpolation performance of the model was examined by systematically filtering the training data according to receiver spacing and analyzing the resulting predictive accuracy. This assessment was conducted not only to evaluate the model's generalization capability but also to examine its ability to reproduce the physical characteristics

of flow-induced noise predicted by the FW-H formulation. In particular, variations in receiver spacing enabled investigation of how the DNN captured the geometrical spreading and dipole-like directivity inherent in the FW-H formulation. The observed interpolation trends demonstrate the model's physical interpretability and indicate that the trained DNN consistently captures the essential acoustic relationships between the flow field and the radiated sound.

2. Flow-Induced Noise Prediction for Cylinders

2.1. Computational Fluid Dynamics

Training data for the flow-induced noise prediction model were generated through a series of CFD simulations. A circular cylinder with a diameter of 0.02 m was selected as the baseline geometry, as it is widely recognized as a standard benchmark in CFD analysis. To approximate the geometry of a submarine sail, elliptical cylinders were constructed by varying the aspect ratio relative to the baseline diameter. For each geometric configuration, multiple inlet flow velocities were simulated to establish a dataset suitable for subsequent acoustic analysis.

The cylinder diameter was fixed at 0.02 m, and aspect ratios ranging from 1.0 to 3.0 were applied in increments of 0.5. Flow velocities of 3, 5, 7, and 9 m/s were simulated for each configuration, corresponding to Reynolds numbers (Re) from $6.7 \times 10^4 \sim 2.0 \times 10^5$, as summarized in Figure 1a and Table 1. For FW-H-based acoustic computations, receivers were placed in the far-field region. Radial positions ranged from 0.5 to 10.0 m in increments of 0.5 m, while angular positions extended from 0° to 359° with 10° spacing, as shown in Figure 1b. Pressure signals collected at the receivers were used for acoustic analysis, including application of the FW-H analogy and subsequent signal processing. Time-domain signals were transformed into frequency-domain spectra using the Fast Fourier Transform (FFT), yielding SPL distributions. Because acoustic analysis is conventionally conducted in logarithmic frequency bands, the raw spectra were converted into octave-band SPL values. This transformation reduced data dimensionality, improved stability during the learning process, and provided standardized acoustic features suitable for DNN-based prediction.

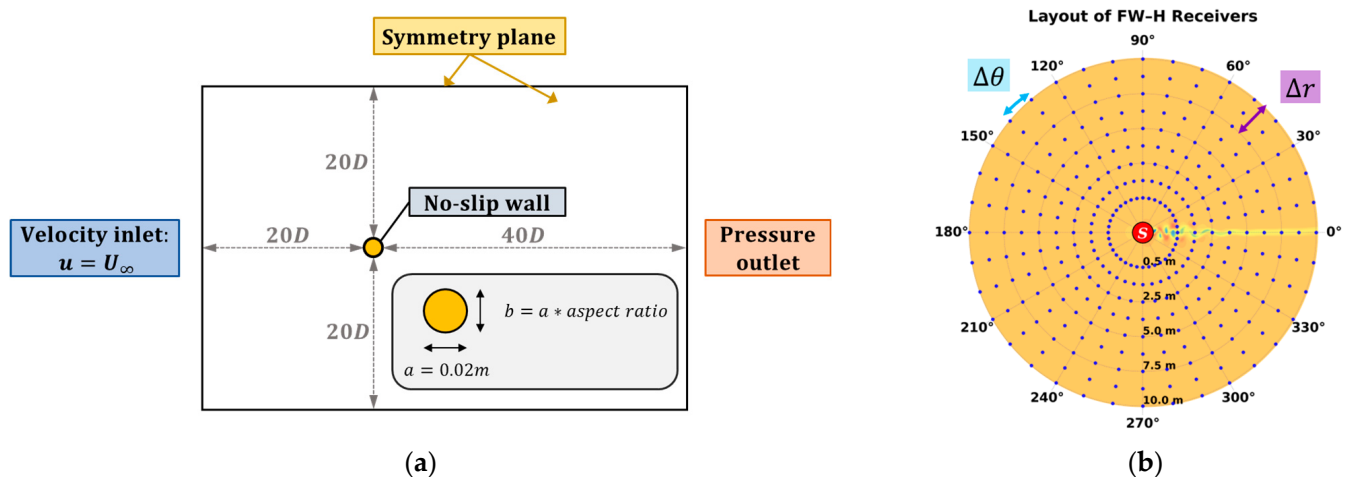


Figure 1. Computational setup and acoustic receiver layout: (a) CFD domain boundaries and cylinder geometry with applied boundary conditions; (b) Distribution of FW-H receivers for SPL measurements.

Table 1. Design variables used for CFD simulations and acoustic analysis.

Design Variables	Value
Inlet velocity (m/s)	3, 5, 7, 9
Cylinder diameter (m)	0.02 (fixed)
Cylinder aspect ratio	1.0, 1.5, 2.0, 2.5, 3.0
Radial receiver spacing (m)	0.5~10.0 (interval 0.5)
Angular receiver spacing (deg.)	0~359 (interval 10)

The accuracy of hydroacoustic prediction using the FW-H Equation depends fundamentally on the ability of CFD simulations to resolve unsteady pressure and velocity fluctuations within turbulent flow fields. Since Reynolds-Averaged Navier–Stokes (RANS) models cannot capture these fluctuations, high-fidelity turbulence modeling is required for broadband flow-noise prediction. Large Eddy Simulation (LES) is frequently employed for its ability to reproduce detailed turbulent structures, although its reliance on extremely fine near-wall meshes results in prohibitive computational cost. DES addresses this limitation by applying RANS modeling in the near-wall region and LES in the outer flow, thereby maintaining accuracy comparable to LES while improving computational efficiency. Accordingly, DES was adopted in this study to perform unsteady flow simulations of a submerged cylinder.

The simulations were conducted using Siemens STAR-CCM+. The computational domain employed inlet boundary conditions with varying flow velocities and no-slip walls applied to cylinders of different geometries, as illustrated in Figure 1a. To accurately capture the turbulent flow and near-wall behavior, mesh refinement and non-dimensional wall distance (Y^+) were carefully verified. The refinement region encompassed the turbulent wake, as shown in the pressure field distribution in Figure 2a. The near-wall mesh was configured to maintain $Y^+ \leq 1$, as indicated in Figure 2b. To satisfy the Courant–Friedrichs–Lewy (CFL) condition and ensure adequate frequency resolution under the Nyquist criterion, the simulation time step was set to 2.5×10^{-5} s. The flow domain was modeled as incompressible water, and the detailed grid and solver settings are summarized in Table 2.

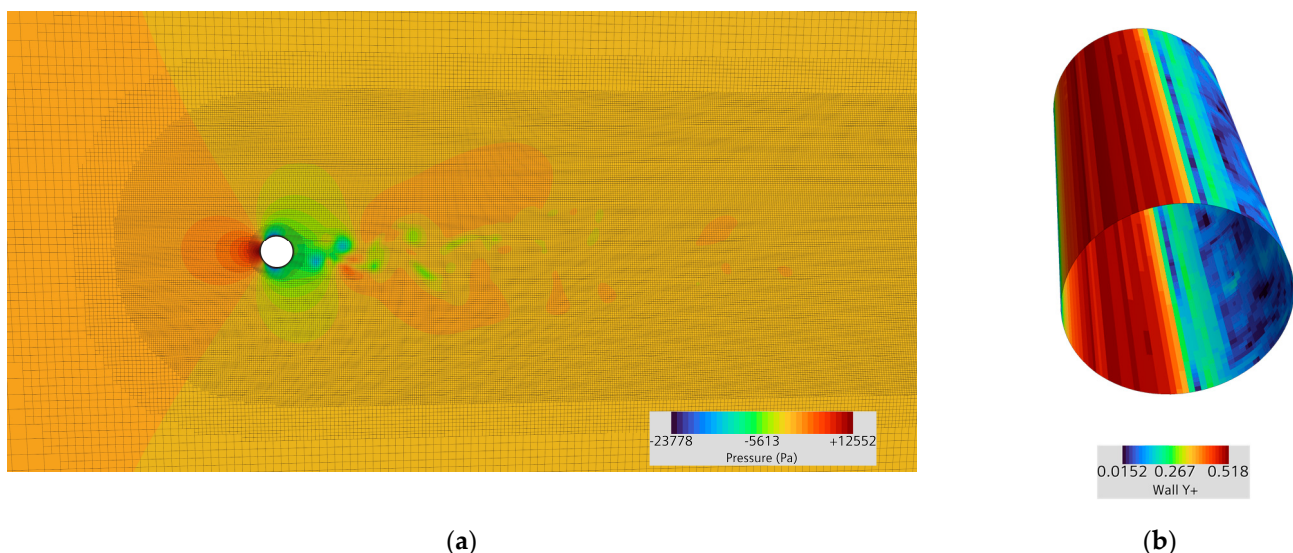
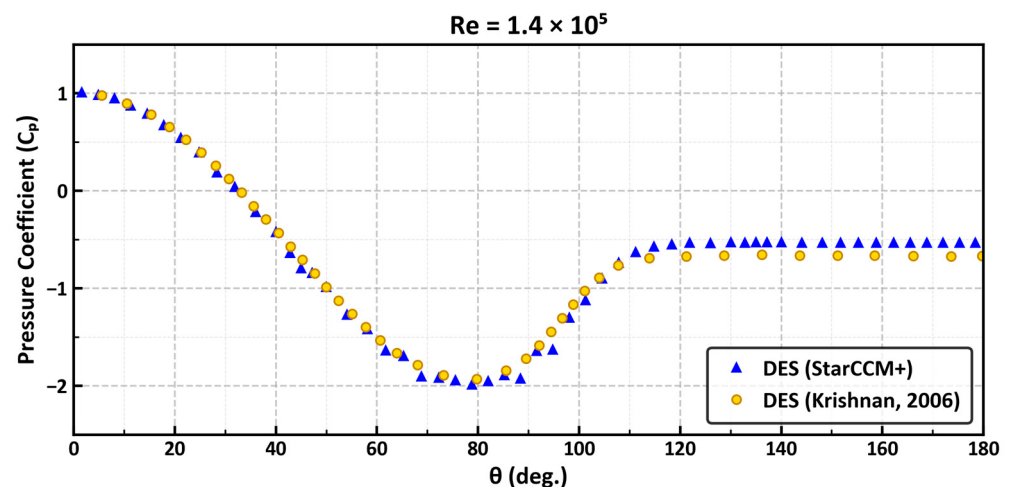


Figure 2. Refined mesh and near-wall resolution around the cylinder: (a) Pressure distribution and mesh refinement in the turbulent wake region; (b) Distribution of wall distance confirming $Y^+ \leq 1$ along the cylinder surface.

Table 2. Numerical setup for CFD simulation and hydroacoustic analysis, including mesh characteristics, CFD solver configurations, and acoustic solver settings.

Category	Parameter	Values/Setting
Mesh	Y^+	1
	Number of prism layers	30
	Total cell count	2.8~3.2 M
CFD solver	Flow method	Segregated flow
	Working fluid	Incompressible (Water)
	Formulation option	Detached Eddy Simulation
	Turbulence model	k- ω SST Detached Eddy
	Time solver	Implicit unsteady
	Time step (s)	2.5×10^{-5}
	Maximum inner iteration	10
Acoustic solver	Solution end time (s)	0.1
	FW-H formulation	Farassat 1A
	Amplitude function	Sound Pressure Level (SPL)
	Frequency function	Octave bands

To confirm the suitability of the present simulation, the pressure coefficient (C_p) distribution along the cylinder surface was compared with reference data [15]. As illustrated in Figure 3, the results show close agreement with the reference dataset. Both the separation point and the overall pressure distribution exhibit a similar trend, thereby validating the reliability of the current CFD setup.

**Figure 3.** Comparison of surface pressure coefficient (C_p) distributions at $Re = 140,000$ with reference data from Krishnan et al. [15].

2.2. Ffowcs-Williams Hawkins

Flow-induced noise at observer locations was predicted using the FW-H Equation, which extends Lighthill's acoustic analogy to account for solid boundaries. The FW-H Equation has been extensively applied in aeroacoustics to model radiated noise from unsteady flows. It evaluates the sound generated by a source at distance r from an observer, incorporating the Doppler-corrected effective distance term $r|1 - M_r|$, and is expressed as:

$$4\pi p'(x, t) = \frac{\partial}{\partial t} \int_S \left[\frac{Q(y, \tau)}{r|1 - M_r|} \right] dS(y) - \frac{\partial}{\partial x_i} \int_S \left[\frac{F_i(y, \tau)}{r|1 - M_r|} \right] dS(y) + \frac{\partial^2}{\partial x_i \partial x_j} \int_V \left[\frac{T_{ij}(y, \tau)}{r|1 - M_r|} \right] dy. \quad (1)$$

where x and y denote the observer and source positions, respectively, and the retarded time is defined as $\tau = t - r/c_0$. The three source terms are given by

$$Q(y, \tau) = [\rho(u'_i + U_i) - \rho_0 U_i] \hat{n}_i. \quad (2)$$

$$F_i(y, \tau) = [\rho u'_i(u'_j + U_j) + p \delta_{ij}] \hat{n}_i. \quad (3)$$

$$T_{ij}(y, \tau) = \rho u'_i u'_j + [(p - p_0) - c_0^2(\rho - \rho_0)] \delta_{ij}. \quad (4)$$

Here, u'_i and U_i represent the fluctuating and mean velocity components, respectively, while p and p_0 corresponds to the instantaneous and mean pressures. The constants c_0 and ρ_0 are the ambient sound speed and density of the medium. The first term represents monopole (thickness) noise, the second corresponds to dipole (loading) noise, and the third accounts for quadrupole (turbulent) noise associated with turbulence in the flow field, expressed by the Lighthill stress tensor T_{ij} .

For the present fixed submerged cylinder, the monopole contribution vanishes because the surface-normal velocity is zero. Quadrupole effects are negligible at the moderate flow velocities considered. Consequently, this study focuses on dipole noise, using unsteady surface pressure data on the cylinder as input for acoustic prediction at the observer locations. For this purpose, Farassat's Formulation 1A, which provides an analytical time-domain surface solution of the FW-H Equation for thickness and loading noise, was employed [16,17]. Its governing expression is:

$$4\pi p'_L(x, t) = \frac{1}{c_0} \int_{f=0} \left[\frac{\dot{L}_r}{r(1 - M_r)^2} \right]_{ret} dS + \int_{f=0} \left[\frac{L_r - L_M}{r^2(1 - M_r)^2} \right]_{ret} dS + \frac{1}{c_0} \int_{f=0} \left[\frac{L_r (r\dot{M}_r + c_0(M_r - M^2))}{r(1 - M_r)^3} \right]_{ret} dS. \quad (5)$$

where

$$L_r = P_{ij} \hat{n}_j + \rho u_i (u_n - v_n) \quad (6)$$

and $L_r = L_i r_i$ represents the surface loading in the radiation direction. $L_m = L_i M_i$ denotes the projection of the surface loading along the Mach vector. The overdot symbol ($\dot{\cdot}$) denotes the time derivative, representing the temporal variation in the corresponding quantity. These equations enable accurate prediction of the loading noise, p'_L , from unsteady aerodynamic forces. The resulting acoustic data were used to train the DNN-based flow-induced noise prediction framework.

The acoustic data for DNN training were obtained from the FW-H Farassat 1A acoustic model implemented in STAR-CCM+, which computes unsteady sound pressure levels at observer locations using surface pressure and shear stress distributions on the cylinder. Because this model directly solves the FW-H formulation with time-accurate CFD coupling, the resulting acoustic dataset is physically consistent with the flow field and suitable for deep-learning-based prediction.

3. SPL Prediction Using Deep Neural Network

3.1. Deep Neural Network

A DNN is a deep learning architecture based on Artificial Neural Network (ANN) structures with multiple hidden layers between the input and output. Each hidden layer contains interconnected nodes with trainable weights, and learning is achieved through forward and backward propagation. During training, network parameters are iteratively updated to minimize the prediction error.

In forward propagation, the output of each layer is computed by applying a weight matrix $W^{(l)}$ to the previous layer output $h^{(l-1)}$, adding a bias vector $b^{(l)}$, and applying an activation function g :

$$h^{(l)} = g\left(W^{(l)}h^{(l-1)} + b^{(l)}\right), \quad (7)$$

This process continues across all hidden layers until the output layer is reached. The deviation between predicted and reference values is quantified by a loss function L , and weights are updated to minimize this error using an optimization algorithm. The update rule is expressed as:

$$W^{(l)} \leftarrow W^{(l)} - \eta \left(\frac{\partial L}{\partial W^{(l)}} \right), \quad (8)$$

where η denotes the learning rate, which controls the step size during parameter updates. A small value of η results in slow convergence, whereas an excessively large value may lead to divergence or oscillation. With repeated iterations and an appropriately chosen learning rate, the DNN is able to learn complex nonlinear mappings between input features and output responses.

3.2. DNN Model Architecture

In this study, DNN was designed to predict flow-induced noise around cylinders using design parameters, receiver coordinates, and center frequencies as inputs. The predicted output was the SPL at designated receiver positions. A multilayer perceptron (MLP) with four hidden layers was employed to capture nonlinear acoustic responses effectively. As shown in Figure 4, the network maps the composite inputs to broadband SPL predictions across the target frequency bands. This configuration provided a compact yet expressive regression model suitable for efficient inference, and the overall architecture is summarized in Table 3.

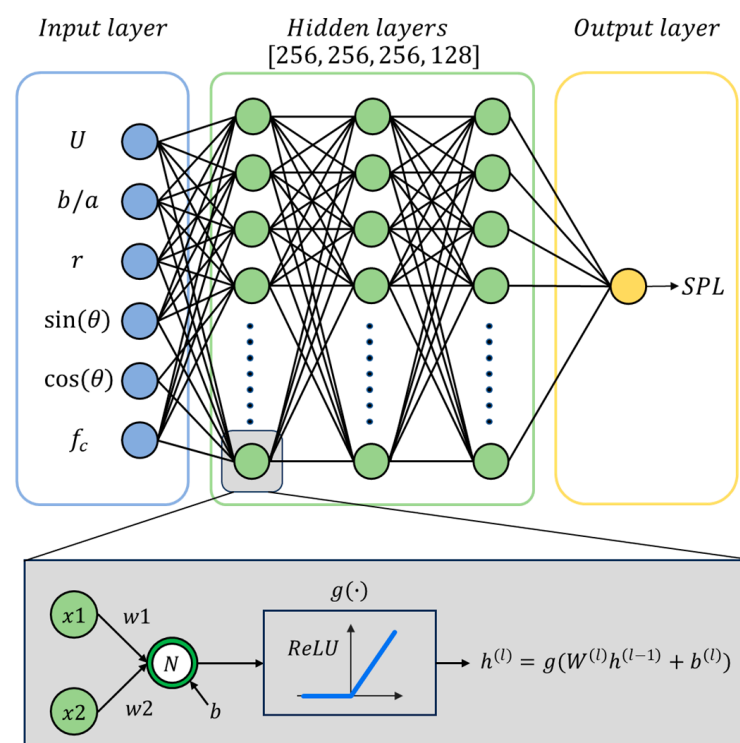


Figure 4. Architecture of the DNN model developed for predicting SPLs.

Table 3. Hyperparameters and training setting of the SPL prediction model.

Category	Parameter	Values/Setting
Model structure	Input features	Inlet velocity (U)
		Aspect ratio (b/a)
		Receiver position (r, θ)
		Octave central frequency
	Output	SPLs
		[256, 256, 256, 124] nodes
		ReLU
Training setup	Epochs	2000
	Batch size	512
	Optimizer	Adam
	Loss function	MSE
Learning strategy	Learning rate schedule	Cosine annealing with warm-up steps
	Maximum learning rate	0.001
	Minimum learning rate	1×10^{-6}
	Warm-up steps	5000
	Early stopping	Patience = 50, tolerance = 1×10^{-4}
Data preprocessing	Feature scaling method	Standardization
	Angular variable treatment	$\theta \rightarrow \sin/\cos$
	Octave band filtering	Below 5000 Hz
	Data split (train/validation/test)	0.70/0.15/0.15
Evaluation metrics	Error metrics	RMSE
	Model Explanatory Power	R_{adj}^2
System environment	GPU	NVIDIA TITAN Xp
	PyTorch	v2.6.0
	CUDA	v12.6
	CPU	Ryzen 9 7950X3D
	RAM	64 GB

The hyperparameters of the model were selected based on widely used configurations in MLP frameworks. The rectified linear unit (ReLU) was applied as the activation function, the mean squared error (MSE) as the loss function, and adaptive moment estimation (Adam) as the optimizer for weight updates. These settings are summarized in Table 3. The dataset was divided into training, validation, and test subsets in the ratio 0.70:0.15:0.15. The loss function was defined as:

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2, \quad (9)$$

where y_i represents the reference value and $\hat{y}_i$ denotes the predicted value for the i -th sample. This formulation provided a consistent basis for evaluating predictive accuracy during model training.

The learning strategy was designed to balance convergence speed and generalization capability. A cosine annealing schedule with warm-up steps was applied to control the learning rate, ranging from a maximum of 0.001 to a minimum of 1×10^{-6} . A warm-up period of 5000 steps prevented unstable parameter updates during the initial iterations. Early stopping was applied with a patience of 50 epochs and a tolerance of 1×10^{-4} on the validation loss. This strategy reduced overfitting while maintaining training efficiency over 2000 epochs. A batch size of 512 was used to leverage parallel computation effectively while ensuring stable gradient updates.

Data preprocessing was conducted to standardize feature representations and improve numerical conditioning. Continuous variables were normalized to zero mean and unit

variance. The angular design variable θ was encoded using $\sin \theta$ and $\cos \theta$ to eliminate discontinuities at 0° and 360° and to enforce rotational periodicity. Octave Band Analysis was restricted to center frequencies below 5000 Hz, since the dominant acoustic components generated by cylinders are concentrated in the low-frequency range. These preprocessing steps established a reliable pipeline that facilitated stable convergence of the DNN.

Model performance was assessed using the root mean squared error (RMSE) on the held-out test set. RMSE provided a direct measure in decibels, representing average SPL discrepancies across receivers and frequency bands. Lower RMSE values indicated improved agreement with reference data, and this metric was consistently used to evaluate alternative hyperparameter settings and learning schedules. The performance results are presented in Section 4, together with validation against the CFD-based acoustic data. The overall training workflow of the DNN, including data preprocessing, model training, and validation procedures, is illustrated in Figure 5 to provide a concise overview of the learning process.

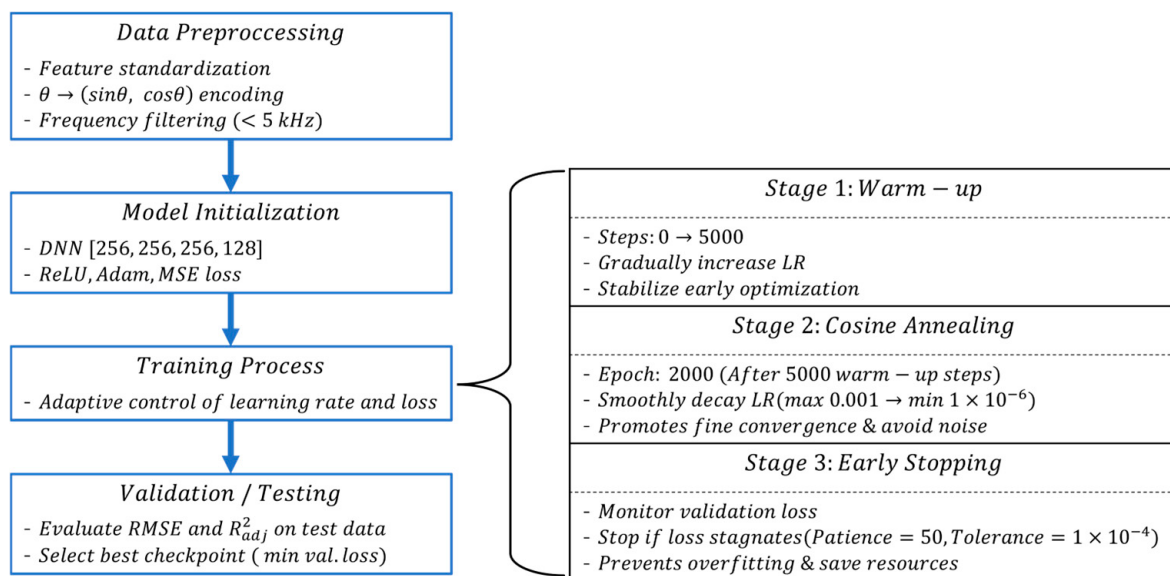


Figure 5. Workflow of the DNN training and validation process, showing sequential stages including data preprocessing, model initialization, adaptive learning-rate scheduling, and performance evaluation.

3.3. Data Integration

In deep learning frameworks, predictive accuracy generally improves as the amount of training data increases, although larger datasets also require longer training times. In this study, the interpolation performance of the proposed model was examined by progressively enlarging the radial spacing interval (Δr) and angular spacing interval ($\Delta \theta$) from a baseline of $\Delta r = 0.5$ m and $\Delta \theta = 10^\circ$. As summarized in Table 4, five interval values for each parameter were combined to construct datasets for training and evaluation. Increasing the interval size reduced the number of training samples, which under conventional epoch-based training would correspond to fewer effective iterations for smaller datasets. To compensate for this imbalance, training was performed on an iteration basis, where the total number of iterations was defined as:

$$\text{Total iterations} = \frac{\text{Number of training samples}}{\text{Batch size}} \times \text{Epochs} \quad (10)$$

Table 4. Receiver spacing intervals for interpolation performance evaluation.

Spacing Type	Values
Radial spacing Δr (m)	0.5 ¹ , 1.0, 2.0, 3.0, 4.5
Angular spacing $\Delta \theta$ (deg.)	10 ¹ , 20, 30, 60, 90

¹ Baseline case used for reference in performance evaluation.

For interpolation evaluation, test datasets were selected exclusively from samples not included in training, ensuring that the model was assessed under genuinely unseen interpolation conditions. As the radial and angular intervals (Δr , $\Delta \theta$) increased, a simple ratio-based data split produced large variations in the number of test samples. To ensure fair comparison across models, the test set size was fixed to that of the baseline case, and an equal number of samples was used for all conditions.

4. DNN Prediction Results

4.1. Baseline DNN Prediction Results

The predictive capability of the proposed DNN framework was evaluated using the hyperparameter settings summarized in Table 3. After training, the model was tested on an independent dataset. For regression tasks such as SPL prediction, performance was assessed using prediction error and the coefficient of determination. Prediction error was measured by the RMSE between the predicted SPL values and the reference CFD data, defined as:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}, \quad (11)$$

where y_i is the reference value and $\hat{y}_i$ is the predicted value for the i -th sample.

The explanatory power of the trained model was quantified using the coefficient of determination, R^2 , which measures the proportion of variance explained in the dataset:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} = \frac{\sum_{i=1}^n (\hat{y}_i - \bar{y})^2}{\sum_{i=1}^n (y_i - \bar{y})^2}, \quad (12)$$

where $\bar{y}$ represents the mean of the reference values. Since R^2 generally increases with the number of independent variables, the adjusted coefficient of determination, R_{adj}^2 , was also computed to account for the number of samples n and input features k :

$$R_{adj}^2 = 1 - \left[\frac{(1 - R^2)(n - 1)}{n - k - 1} \right], \quad (13)$$

The baseline prediction results are illustrated in Figure 6a. With an adjusted R^2 of 0.9999, the DNN demonstrated excellent predictive performance, explaining more than 99% of the variation in the dataset. In addition, the low test RMSE of 0.1587 confirmed the high predictive accuracy for flow-induced noise around cylinders. As shown in Figure 6b, the error distribution histogram indicates that most predictions deviate from the reference data by less than 1%.

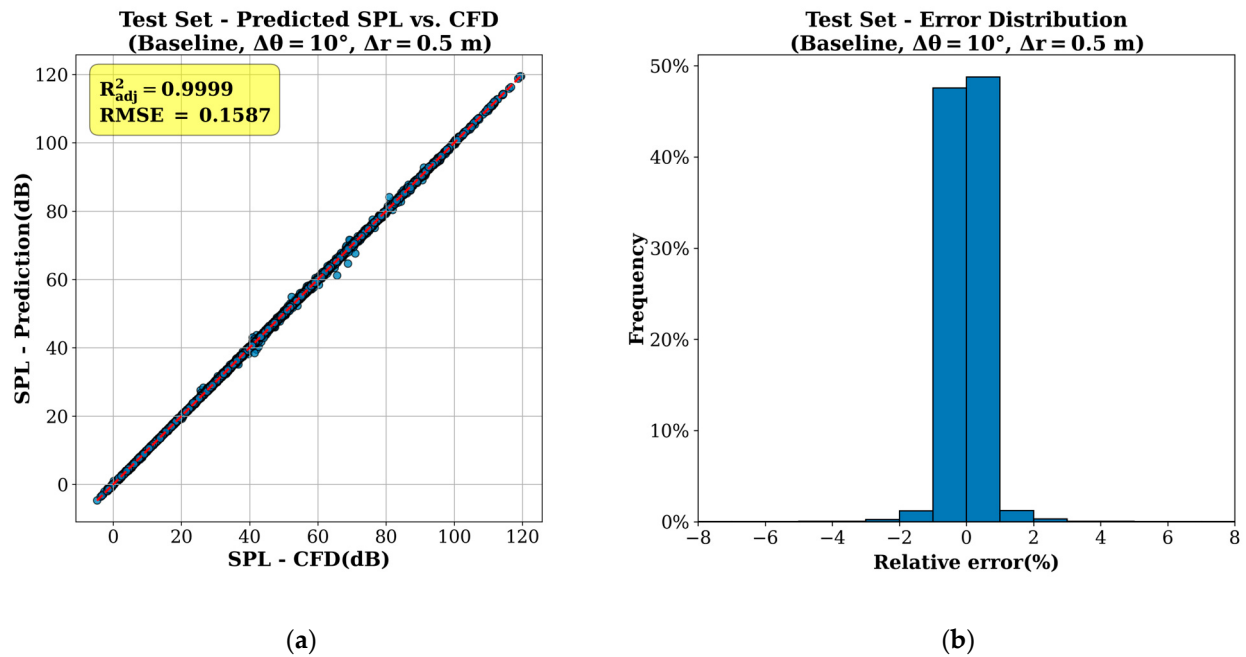


Figure 6. Prediction performance of the DNN model: (a) Comparison between the predicted SPLs and CFD results in the test set; (b) Distribution of relative prediction errors.

4.2. Integrated Data Prediction

The baseline model exhibited high predictive accuracy, which enabled interpolation tests to be conducted by systematically varying the angular and radial spacing intervals. As summarized in Table 4, five interval values were defined for each parameter, and their combinations were evaluated. Each interpolation case was trained using a filtered dataset and tested with independent samples excluded from training.

The effect of radial spacing is illustrated in Figure 7, where five prediction cases under the baseline angular spacing were compared. As radial spacing increased, R^2_{adj} consistently decreased and RMSE increased, reflecting reduced predictive accuracy. The effect of angular spacing is presented in Figure 8, while the complete distributions of R^2_{adj} and RMSE across all interval combinations are summarized as heatmaps in Figure 9a,b.

Interpolation Performance as a Function of Radial Spacing (Δr) (at $\Delta\theta = 10^\circ$ (Baseline))

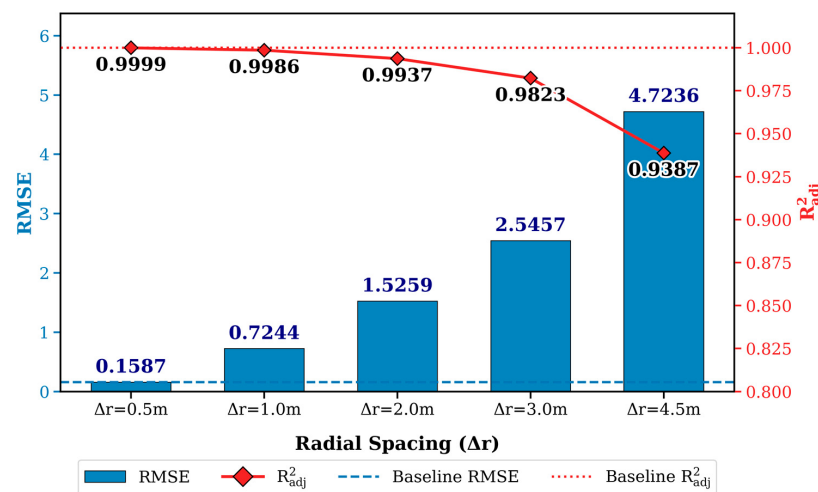


Figure 7. Effect of radial receiver spacing (Δr) on model performance: evaluation using R^2 and RMSE relative to the baseline case.

**Interpolation Performance as a Function of Angular Spacing ($\Delta\theta$)
(at $\Delta r=0.5\text{m}$ (Baseline))**

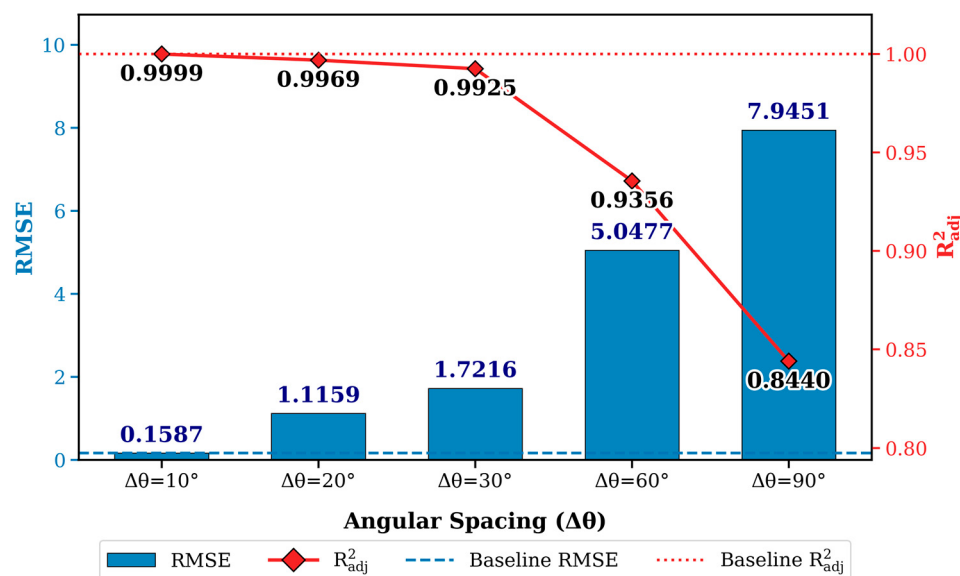


Figure 8. Effect of angular receiver spacing ($\Delta\theta$) on model performance: evaluation using R^2 and RMSE relative to the baseline case.

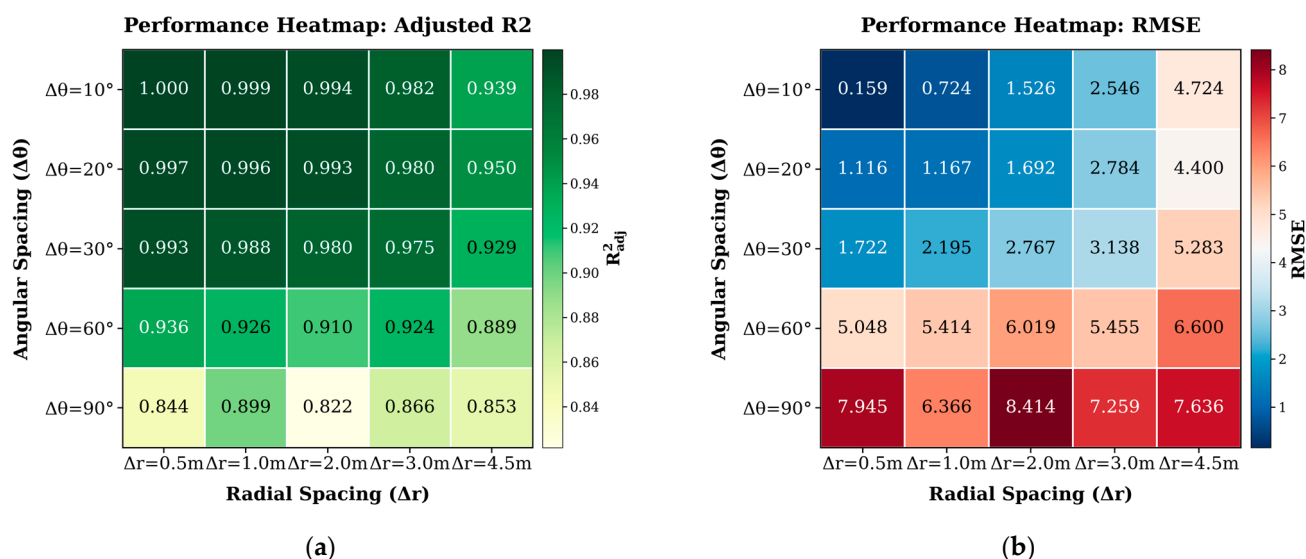


Figure 9. Comparison of performance metrics for all combinations of angular ($\Delta\theta$) and radial (Δr) receiver spacing: (a) R^2_{adj} , where lower values correspond reduced predictive performance with coarser spacing; (b) RMSE, where higher values correspond to increased prediction errors with coarser spacing.

Although both radial and angular spacing led to performance degradation, the extent of reduction differed between the two parameters. For radial spacing, a reduction was evident at $r = 3.0\text{ m}$, where R^2_{adj} decreased from 0.9823 to 0.9382 and RMSE increased from 2.5457 to 4.7236. For angular spacing, degradation was observed at $\Delta\theta = 60^\circ$, with R^2_{adj} decreasing from 0.9925 to 0.9356 and RMSE increasing from 1.7216 to 5.0477.

In the Farassat 1A formulation, the acoustic pressure exhibits an approximate inverse proportionality to distance ($1/r$) due to geometrical spreading. The angular response is governed by the orientation of the surface loading vector relative to the observer direction. As the observer angle θ varies, the inner product ($L_i r_i$) and the associated Doppler correction term ($1 - M_r$) produce pronounced directivity in the radiated sound field. This effect

causes sharper variations in sound pressure with respect to angle than with distance. The degradation observed at larger $\Delta\theta$ arises from the complex dipole radiation pattern of the cylinder, where both the phase and amplitude of acoustic waves vary rapidly in the circumferential direction. These directional characteristics are effectively captured by the DNN, demonstrating the model's capability to reproduce the directivity features inherent in the FW–H acoustic source formulation.

5. Conclusions

This study developed a DNN-based framework to predict flow-induced noise generated around a circular cylinder. The training dataset was derived from CFD simulations employing the DES turbulence model, with cylinder aspect ratio and flow velocity defined as the principal design variables. Acoustic signals were extracted from polar-distributed receiver locations using Farassat's Formulation 1A of the FW–H Equation.

The proposed DNN model accurately predicted the SPL as a function of geometry, receiver position, and octave band frequency. The model achieved high predictive accuracy while maintaining superior computational efficiency. Interpolation analyses verified that the predicted acoustic fields were consistent with the theoretical behavior of the FW–H formulation, in which the SPL decays approximately with $1/r$ in the radial direction and exhibits stronger angular variation due to source directivity effects.

The present study primarily focused on developing a data-driven framework for acoustic prediction, while CFD validation was conducted only to ensure the reliability of the training data. The validation relied on internally generated FW–H datasets under incompressible flow conditions, where the design space was restricted to a two-dimensional circular cross-section with fixed spanwise geometry. Further investigation is required to determine whether the inverse-distance attenuation ($1/r$) relationship observed in the current configuration remains valid in three-dimensional spherical coordinates. To enhance the physical consistency of the framework, future research will employ independent CFD cases to assess the correspondence between DNN-predicted acoustic responses and the underlying flow-field dynamics.

In addition, the framework will be extended to complex marine geometries such as hydrofoils, propellers, and submarine hulls, supporting practical applications in submarine acoustic stealth optimization and real-time noise prediction under variable operating conditions. To address the geometric limitations of a single DNN model, the framework will be further expanded into a hybrid architecture that integrates the DNN with geometry-aware networks, such as CNN or GNN, enabling accurate representation of intricate marine structures. Through these extensions and validations, the proposed method aims to establish a robust and physically consistent foundation for flow-induced noise prediction in practical marine engineering applications.

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