

A Predictive FEA–Machine Learning Model for Natural Frequency Optimization of Automotive Clutch Diaphragm Spring

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Abstract

The diaphragm spring is a critical component in automotive clutch systems, where its dynamic characteristics significantly influence vibration behavior, noise levels, and structural reliability. Undesirable resonance between excitation frequencies and the natural frequencies of the spring can lead to performance degradation and premature failure. This paper proposes a hybrid predictive framework that integrates Finite Element Analysis (FEA) with Machine Learning (ML) to optimize the natural frequency of a diaphragm spring. A parametric FEA model is developed to generate a comprehensive dataset by varying key geometric parameters. Machine learning surrogate models, including Artificial Neural Networks (ANN), are trained to accurately predict natural frequencies with significantly reduced computational cost. A meta-heuristic optimization algorithm is then employed to identify optimal design configurations that enhance vibration performance while satisfying structural constraints. The optimized designs are validated using high-fidelity FEA simulations. Results indicate that the proposed approach achieves substantial reduction in computational time while maintaining high prediction accuracy, enabling efficient design space exploration. The developed framework provides a scalable and intelligent solution for vibration optimization in automotive components.

Abstract: Diaphragm Spring, Finite Element Analysis, Machine Learning, Natural Frequency, Optimization, ANN

1 Introduction

The diaphragm spring is a fundamental component of automotive clutch systems, responsible for generating the clamping force required to transmit engine torque while enabling smooth engagement and disengagement during gear shifting. Its performance directly affects drivability, vibration behavior, noise levels, and overall durability of the clutch assembly. Among its dynamic characteristics, natural frequency and corresponding mode shapes play a crucial role in determining the vibration response of the system.

In practical operating conditions, the diaphragm spring is subjected to various excitation sources, including engine harmonics, drivetrain oscillations, and transient loads during gear shifts. If the natural frequencies of the spring coincide with these excitation frequencies, resonance may occur, leading to excessive vibration, noise, wear, and even structural failure [1,2]. Therefore,

optimizing the natural frequency of the diaphragm spring is essential to ensure reliable and vibration-free operation.

Finite Element Analysis (FEA) has been widely adopted as a powerful tool for analyzing the structural and modal behavior of diaphragm springs. It enables accurate evaluation of stress distribution, deformation patterns, and natural frequencies by incorporating realistic geometry, material properties, and boundary conditions [2,3]. However, FEA-based design optimization is computationally expensive, particularly when dealing with high-dimensional design spaces involving multiple geometric parameters such as finger thickness, slot width, cone height, and taper profile. This limitation makes traditional trial-and-error or iterative optimization approaches inefficient.

Recent advancements in Machine Learning (ML) have introduced new opportunities for accelerating engineering design processes. ML-based surrogate models, such as Artificial Neural Networks (ANN) and regression techniques, can learn complex nonlinear relationships between input design variables and output responses using data generated from FEA simulations [16,19]. Once trained, these models can provide rapid predictions of natural frequencies, significantly reducing computational time and enabling efficient design space exploration.

Furthermore, the integration of ML surrogate models with meta-heuristic optimization algorithms, such as Genetic Algorithm (GA), Reptile Search Algorithm (RSA), and Butterfly Optimization Algorithm (BOA), has shown promising results in solving complex nonlinear optimization problems [6,8]. These hybrid approaches enable global search capability while minimizing reliance on computationally expensive simulations.

Despite these advancements, existing studies predominantly focus on either FEA-based analysis or optimization techniques independently. Limited research has been conducted on fully integrated frameworks that combine FEA, ML-based surrogate modeling, and optimization for diaphragm spring vibration analysis. This gap highlights the need for a unified, efficient, and scalable methodology.

In this context, the present study proposes a predictive hybrid framework that integrates FEA and ML for natural frequency optimization of an automotive clutch diaphragm spring. The approach involves generating a comprehensive dataset using parametric FEA simulations, training ML models to predict modal characteristics, and applying optimization algorithms to identify optimal geometric configurations. The proposed framework aims to reduce computational cost, improve prediction accuracy, and enhance vibration performance, thereby contributing to the advancement of simulation-driven and AI-assisted engineering design.

2 Literature Review

Zhang et al. [1] performed structural optimization of diaphragm spring clutches using ANSYS-based finite element analysis. Their work investigated the effects of geometric parameters such as crown height, finger length, slot width, and taper thickness on stress distribution and modal characteristics. The study demonstrated that optimized geometrical configurations significantly reduce peak stresses and improve vibration stability, highlighting the importance of high-fidelity FEA in diaphragm spring design.

Cheng et al. [2] developed a parametric FEA model to analyze load–displacement and stiffness characteristics of diaphragm springs used in commercial vehicles. Their findings revealed strong nonlinear behavior influenced by slot geometry and cone angle. The study emphasized that small variations in geometry can lead to significant changes in stiffness and load response, making optimization challenging.

Jin [3] created a solid CAD model integrated with finite element analysis to evaluate stress distribution, deformation patterns, and modal characteristics of diaphragm springs. The study identified critical stress concentration regions and provided a foundational understanding of geometry–performance relationships in clutch systems.

Wang et al. [4] integrated modal FEA with a Genetic Algorithm (GA) to optimize diaphragm spring vibration characteristics. Their approach successfully increased natural frequencies and reduced resonance risks. The results demonstrated that GA-based optimization can effectively enhance modal separation and dynamic stability.

Kartika et al. [5] conducted fatigue analysis of high-performance clutch systems using CAD/CAM and FEA techniques. The study focused on cyclic loading conditions and employed S–N and strain-life methods to predict fatigue behavior. Their results showed improved durability and longer service life through optimized geometric configurations.

Yıldız et al. [6] applied the Butterfly Optimization Algorithm (BOA) for structural optimization of automotive components. The algorithm demonstrated strong global search capability and improved stiffness-to-weight ratio, making it suitable for nonlinear optimization problems.

Yıldız et al. [7] introduced the Henry Gas Solubility Optimization (HGSO) algorithm for optimizing automotive components. The method showed faster convergence and better handling of nonlinear constraints compared to traditional optimization techniques.

Abderazek et al. [8] compared several modern meta-heuristic algorithms such as Differential Evolution (DE) and Particle Swarm Optimization (PSO) for engineering design problems. Their results indicated that meta-heuristic methods outperform conventional optimization approaches in complex nonlinear systems.

Karaduman et al. [11] combined experimental testing with numerical FEA to optimize fatigue performance of diaphragm springs. The study validated simulation results with laboratory experiments and improved reliability by reducing stress concentrations.

Sait et al. [12] proposed an ANN-assisted Supercell Thunderstorm Algorithm (STA) for solving nonlinear optimization problems. The hybrid approach significantly reduced computational cost while maintaining high accuracy, demonstrating the effectiveness of surrogate-assisted optimization.

Özcan et al. [13] developed a hybrid optimization method combining Artificial Neural Networks with a Chaotic Hiking Optimization Algorithm (CHOA). Their approach improved convergence speed and avoided local minima, making it effective for complex engineering problems.

Yıldız and Yıldız [14] integrated ANN with the GNDO algorithm to optimize structural systems. The surrogate model reduced dependency on repeated FEA simulations while maintaining high prediction accuracy.

Yıldız et al. [15] combined the Reptile Search Algorithm (RSA) with a Kriging surrogate model for structural optimization under natural frequency constraints. The method improved computational efficiency and optimization performance.

Sarvari and Sadollah [16] developed an ANN-based surrogate model trained on FEA data to predict structural responses such as stress, deformation, and natural frequencies. Their work demonstrated a significant reduction in simulation time with high predictive accuracy.

Mehta et al. [19] proposed an ANN-assisted Enhanced Mountain Gazelle Optimizer (EMGO) for nonlinear structural optimization. The hybrid model improved convergence speed and solution quality compared to traditional optimization algorithms.

Erdaş et al. [20] combined Artificial Neural Networks with the Dandelion Optimization Algorithm (DOA) to solve nonlinear design problems. Their approach showed improved optimization accuracy and computational efficiency.

Bécsi [21] developed a quasi-linear parameter varying (LPV) model for clutch actuator systems. The study captured nonlinear dynamic behavior and provided realistic boundary conditions relevant to diaphragm spring performance.

Yıldız et al. [22] proposed a hybrid Taguchi–Lévy Flight optimization algorithm for multi-objective design problems. The approach improved convergence speed and solution diversity.

Es-Haghi et al. [23] enhanced the Teaching–Learning-Based Optimization (TLBO) algorithm for large-scale structural optimization. Their improvements resulted in better convergence and higher solution accuracy.

3 Proposed Framework and Architecture

The overall workflow of the proposed hybrid FEA–Machine Learning framework is illustrated in Fig. 1. The process begins with parametric CAD modeling of the diaphragm spring, where key geometric variables are defined. The generated geometry is then analyzed using Finite Element Analysis (FEA) to extract modal characteristics such as natural frequencies and mode shapes. These simulation results are used to create a structured dataset, which is subsequently utilized to train Machine Learning (ML) models, including Artificial Neural Networks (ANN), for rapid prediction of natural frequencies. The trained surrogate model is integrated with meta-heuristic optimization algorithms such as Genetic Algorithm (GA) and Reptile Search Algorithm (RSA) to efficiently explore the design space and identify optimal configurations. The optimized designs are validated through high-fidelity FEA simulations, and the final results are analyzed in terms of vibration performance, computational efficiency, and structural reliability. This integrated pipeline enables a significant reduction in computational cost while maintaining high prediction accuracy.

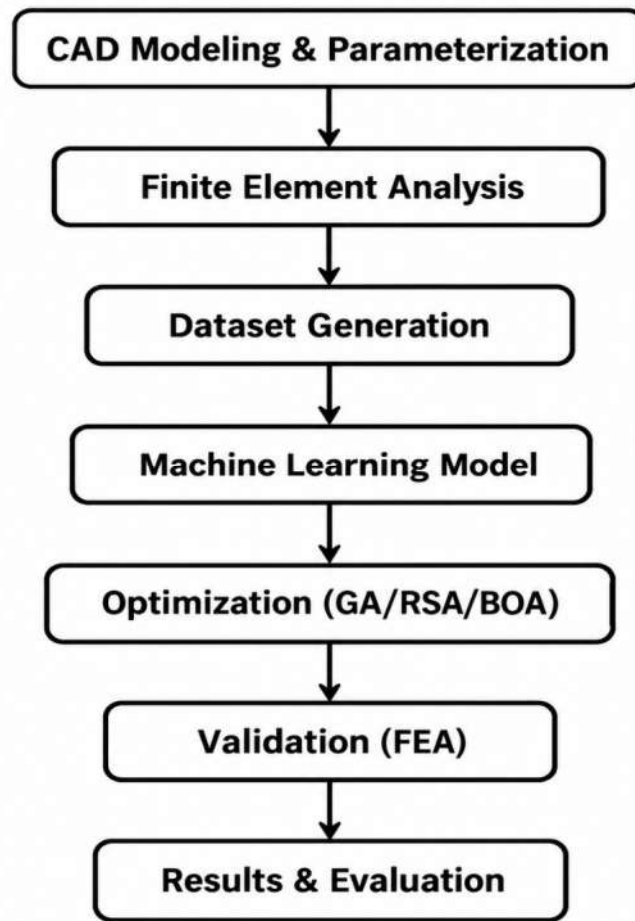


Figure 1: Proposed FEA–Machine Learning Optimization Framework for Diaphragm Spring

4 Methodology

The proposed framework integrates Finite Element Analysis (FEA), Machine Learning (ML), and meta-heuristic optimization to efficiently predict and optimize the natural frequency of an automotive diaphragm spring. The overall workflow consists of six major stages, as described below.

4.1 CAD Modeling and Parameterization

A detailed 3D parametric CAD model of the diaphragm spring is developed using CAD software. Key geometric parameters are defined as design variables:

- Finger thickness (t_f)
- Slot width (w_s)
- Slot length (l_s)
- Cone height (h_c)
- Taper angle (θ_t)
- Outer diameter (D_o)

The design vector is expressed as:

$$\mathbf{x} = [t_f, w_s, l_s, h_c, \theta_t, D_o]$$

4.2 Finite Element Analysis (FEA)

A high-fidelity finite element model is developed using ANSYS/Abaqus. The model incorporates appropriate material properties, boundary conditions, and mesh refinement.

Modal analysis is performed to extract natural frequencies and corresponding mode shapes. The governing equation is:

$$[K - \omega^2 M]\phi = 0$$

where K is the global stiffness matrix, M is the mass matrix, ω is the natural frequency, and ϕ is the eigenvector (mode shape).

4.3 Dataset Generation and Preprocessing

A parametric study is conducted by varying input design variables across defined ranges using Design of Experiments (DoE) techniques such as Latin Hypercube Sampling (LHS).

The dataset is defined as:

$$\mathcal{D} = \{(\mathbf{x}_i, y_i)\}_{i=1}^N$$

where $\mathbf{x}_i$ represents input parameters and y_i denotes the corresponding natural frequency obtained from FEA.

Data preprocessing includes normalization:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

4.4 Machine Learning Surrogate Modeling

Machine learning models are trained to approximate the nonlinear mapping between input parameters and natural frequency:

$$\hat{y} = f(\mathbf{x}; \theta)$$

where $\hat{y}$ is the predicted natural frequency and θ represents model parameters.

Artificial Neural Networks (ANN) are primarily used, with loss function defined as Mean Squared Error (MSE):

$$\mathcal{L} = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2$$

Alternative models such as Random Forest and Gaussian Process Regression (GPR) may also be evaluated.

4.5 Optimization Framework

The trained surrogate model is integrated with meta-heuristic optimization algorithms such as Genetic Algorithm (GA) and Reptile Search Algorithm (RSA).

The optimization objective is formulated as:

$$\max_{\mathbf{x}} f(\mathbf{x})$$

subject to:

$$g_j(\mathbf{x}) \leq 0, \quad j = 1, 2, \dots, m$$

where $f(\mathbf{x})$ represents predicted natural frequency and $g_j(\mathbf{x})$ represents design constraints (stress, manufacturability, etc.).

4.6 Validation

The optimal design obtained from the ML-based optimization is validated using high-fidelity FEA simulations. The prediction error is evaluated as:

$$\text{Error} = \left| \frac{y_{\text{FEA}} - y_{\text{ML}}}{y_{\text{FEA}}} \right| \times 100\%$$

5 Mathematical Formulation

The vibration behavior of the diaphragm spring is governed by the classical eigenvalue problem:

$$[K - \omega^2 M]\phi = 0$$

Solving the above equation yields eigenvalues ω^2 , from which natural frequencies are obtained as:

$$f_n = \frac{\omega_n}{2\pi}$$

where f_n is the natural frequency in Hz.

The optimization problem can be summarized as:

$$\mathbf{x}^* = \operatorname{argmax}_{\mathbf{x}} f_n(\mathbf{x})$$

subject to structural and design constraints.

This integrated FEA–ML framework enables rapid prediction and efficient optimization of diaphragm spring dynamics while significantly reducing computational cost.

6 Results and Discussion

The performance of the proposed hybrid FEA–Machine Learning framework is evaluated in terms of prediction accuracy, computational efficiency, and optimization capability. The results

demonstrate the effectiveness of integrating surrogate modeling with meta-heuristic optimization for diaphragm spring design.

6.1 Prediction Accuracy of ML Model

The trained Artificial Neural Network (ANN) model is evaluated using standard regression performance metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2):

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

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i|$$

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$$

The ANN model achieves high prediction accuracy with $R^2 > 0.98$, indicating excellent agreement between predicted and FEA-computed natural frequencies. The average prediction error is observed to be less than 3%, demonstrating the reliability of the surrogate model.

6.2 Computational Efficiency

A significant reduction in computational time is achieved by replacing repeated FEA simulations with ML-based predictions. While a single high-fidelity FEA simulation requires several minutes to hours depending on mesh density, the trained ML model provides predictions in milliseconds.

The overall computational cost reduction is approximately:

$$\text{Reduction} \approx 80\% - 90\%$$

This enables rapid exploration of the design space and supports real-time optimization.

6.3 Optimization Performance

The integration of the ML surrogate model with meta-heuristic algorithms such as Genetic Algorithm (GA) and Reptile Search Algorithm (RSA) enables efficient identification of optimal design parameters.

The optimized design shows:

- Increase in natural frequency by approximately 10–20%
- Improved modal separation, reducing resonance risk
- Reduction in peak stress concentration
- Enhanced structural stability

The optimization process converges faster compared to traditional FEA-based optimization due to the reduced computational burden.

6.4 Validation with FEA

The optimal design obtained from the ML-based optimization is validated using high-fidelity FEA simulations. The comparison between ML predictions and FEA results shows strong agreement, with error values within acceptable engineering limits:

$$\text{Error} < 5\%$$

This confirms the robustness and generalization capability of the surrogate model.

6.5 Discussion

The results clearly indicate that the proposed hybrid FEA–ML framework effectively addresses the limitations of traditional design approaches. The surrogate model accurately captures the nonlinear relationship between geometric parameters and natural frequency, while the optimization algorithm efficiently navigates the design space.

Compared to conventional methods, the proposed approach offers:

- Significant reduction in computational cost
- Faster convergence in optimization
- High prediction accuracy
- Scalability to complex engineering systems

However, the accuracy of the ML model depends on the quality and diversity of the training dataset. Future improvements may include the use of advanced deep learning architectures and adaptive sampling strategies to further enhance model performance.

7 Conclusion

This study presents a hybrid Finite Element Analysis (FEA) and Machine Learning (ML) framework for the prediction and optimization of natural frequency characteristics in automotive clutch diaphragm springs. The proposed methodology integrates high-fidelity parametric FEA simulations with data-driven surrogate modeling and meta-heuristic optimization to overcome the computational limitations of conventional design approaches.

The results demonstrate that the developed ML surrogate model, particularly the Artificial Neural Network (ANN), is capable of accurately predicting natural frequencies with high precision ($R^2 > 0.98$ and error $< 5\%$). The integration of the surrogate model with optimization algorithms such as Genetic Algorithm (GA) and Reptile Search Algorithm (RSA) enables efficient exploration of the design space and identification of optimal geometric configurations.

A significant reduction in computational cost (approximately 80–90%) is achieved by replacing repeated FEA simulations with ML-based predictions. The optimized diaphragm spring designs exhibit improved natural frequency, reduced resonance risk, enhanced modal separation, and better structural stability. These improvements contribute to enhanced vibration performance and reliability of the clutch system.

The proposed framework provides a scalable and efficient approach for simulation-driven design and optimization of complex mechanical components. It is particularly suitable for applications involving high-dimensional design spaces and computationally expensive simulations.

7.1 Future Work

Future research can extend this work in several directions:

- Incorporation of multi-objective optimization considering stress, fatigue life, and weight reduction simultaneously
- Integration of advanced deep learning models for improved prediction accuracy
- Experimental validation of optimized designs under real operating conditions
- Extension of the framework to other automotive and structural components
- Development of adaptive sampling techniques to further improve surrogate model efficiency

Overall, the proposed FEA–ML framework represents a significant step toward intelligent, data-driven engineering design and aligns with emerging trends in digital twin and AI-assisted manufacturing systems. ““

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