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A hybrid machine learning and particle swarm system for configuring holes on cantilever beams to achieve desired natural frequencies

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ABSTRACT

In this paper, a hybrid machine learning/optimization system is developed to identify the optimal configuration of holes on a cantilever beam to achieve a desired natural frequency. Based on a design of experiments, 100 configurations are selected from the vast possible combinations of placing five holes on a 5x21 matrix grid over the beam. The natural frequencies for these configurations are obtained using frequency analysis in COMSOL. A dataset containing the hole configurations and their corresponding normalized first natural frequency is constructed to build a machine-learning model using the LightGBM method. The particle swarm optimization algorithm is employed to find the optimal hole configuration that yields the desired natural frequency. The results demonstrate the success of the developed hybrid system, as the machine learning model accurately predicts both the training and testing data. Additionally, the optimization algorithm successfully identifies hole configurations that closely match the desired natural frequency in various test cases, validating the system's effectiveness.

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1. Introduction

Structural engineering faces an ongoing difficulty in altering the inherent frequencies of structures to avoid unwanted occurrences like resonance and dynamic fatigue. The natural frequency, an inherent property of a structure, determines how it reacts to external pressures and vibrations from the environment [1, 2]. Resonance occurs when the natural frequency of a structure aligns with the

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frequency of external forces. This alignment can potentially cause significant damage or catastrophic collapse [3, 4]. Therefore, it is crucial to control and adjust the inherent frequency of a structure to maximize its dynamic performance [5, 6]. Structural alterations offer a pragmatic method for altering the natural periodicity of structures. Modifications to the form and physical characteristics of a structure can substantially impact its inherent frequency. This technology is highly advantageous for constructing structures with both a lightweight structure and exceptional performance. Cantilever beams are frequently employed in many engineering endeavors, such as building bridges, towers, and skyscrapers and developing industrial and mechanical machinery [7, 8]. Consequently, they are a vital subject of examination in the domain of natural frequency tuning.

This topic is unquestionably vital in numerous sectors. Accurate adjustment of the inherent frequencies of aircraft structural elements is crucial in the aerospace industry to prevent failures caused by dynamic fatigue [9]. Modifying the inherent frequencies of different parts in a car can decrease noise and vibrations, resulting in improved comfort for passengers and increased economy of the vehicle in the automotive sector [10]. In the architectural design and construction of skyscrapers, manipulating the natural frequency can effectively mitigate problems arising from vibrations induced by wind or seismic events [11].

An extensive examination has been done to alter structures' natural frequencies, particularly cantilever beams, by applying different approaches. Wang and Cheng [12] presented a new method for altering natural frequencies by using structural patches in their research. They showed that changing the natural frequencies to desired levels is possible by adjusting the thickness and placement of these patches on the main structure. Their research revealed that this technique has the potential to alter many natural frequencies at the same time, hence reducing the necessity for intricate conventional optimization searches. Al-Ashtari, Hunstig, Hemsel, and Sextro [13] created and assessed a piezoelectric device that can change its resonance frequency to gather energy. This is accomplished by altering the magnetic attraction force between two permanent magnets. Empirical and computational evidence has definitively shown that this technique may increase the natural frequency of the harvester by over 70%, allowing precise adjustments to be made while it is in use. Alshabat [14] proposed a methodical technique to modify the inherent frequency of buildings composed of different materials. They accomplished this with Evolutionary Algorithms. The EA CPPN-NEAT approach optimized many natural frequencies without requiring external vibration dampers. The study demonstrated that modifying the material composition of an existing building can provide the intended frequency responses. Cheney et al. [15] presented an automated method for vibrational design and natural frequency tuning of multi-material structures using Evolutionary Algorithms. They used the EA CPPN-NEAT approach to tune multiple natural frequencies without external vibration absorbers, demonstrating that changing the type of material within an existing structure can achieve desirable frequency responses. Alshabat and Naghshineh [16] investigated the enhancement of beam natural frequencies by creating cylindrical dimples on the beam's surface under different boundary conditions. The findings revealed that this method could decrease the natural frequencies of simple and free-free beams while increasing the frequencies of clamped beams. The experimental and simulation results showed good agreement.

Karadag and Topaloglu [17] proposed a self-tuning, smart vibration energy harvester that automatically maintains its natural frequency in resonance with environmental vibrations. Their results showed that this method increased energy efficiency to 83.4% and improved the fractional bandwidth of the harvester from 4% to 10%, while the piezoelectric motor consumed only 2.4%

of the harvested energy. Kayıran and Yaman [18] examined the effect of enhanced lattice structures on the natural frequency of parts fabricated using SLA. The results indicated that compliance optimization could significantly influence the fundamental natural frequency, affirming the need for multi-objective optimization to extend the lifespan of parts under vibration. Wang et al. [19] presented an electromagnetic vibration absorber with adjustable negative stiffness for controlling vibrations at variable frequencies. Their results showed that by adjusting the coil current, the natural frequency of the absorber could be effectively reduced, achieving vibration control effects of up to 62.1%, especially when the natural frequency decreased from 9 Hz to 7.2 Hz. Chen and Fan [20] explored the use of internal resonance in vibration-based energy harvesters, which convert unwanted environmental vibrations into electrical energy. Their findings indicated that exploiting nonlinear modal coupling and phenomena such as double-jump and saturation could broaden the operational bandwidth and enhance the performance of these devices. Li et al. [21] introduced a novel method for creating low modal density bands based on natural frequency tuning in periodic structures. The findings showed that this method increased the low modal density bandwidth by 17.4% compared to phononic crystals and enabled more precise and efficient tuning.

In recent decades, the use of artificial intelligence (AI), particularly machine learning algorithms, has seen significant advancements in structural engineering. One of the main challenges in this field is accurately predicting the natural frequencies of structures, particularly cantilever beams, which play a key role in dynamic structural analysis by providing crucial insights into their stability and dynamic response [22, 23]. Traditionally, natural frequencies are computed using numerical methods like Finite Element Analysis (FEA), which, while precise, are often time-consuming and computationally intensive. In contrast, machine learning can significantly accelerate this process, offering high accuracy and lower computational cost. Machine learning proves especially valuable when experimental data or simulation results are limited [24, 25]. By training machine learning models on available data, complex relationships between structural parameters such as beam dimensions, material properties, boundary conditions, and natural frequencies can be extracted and predicted [26]. This approach not only reduces costs and time associated with complex simulations but also allows for the efficient analysis of numerous scenarios.

In recent years, numerous studies have investigated the use of machine learning algorithms for predicting the natural frequency of structures, particularly cantilever beams, focusing on damage detection. For example, Gillich et al. [27] evaluated damage in prismatic cantilever beams using shifts in natural frequency and two machine learning methods, Random Forest and Artificial Neural Network. Their results demonstrated that these methods could accurately estimate the location and severity of cracks with less than 0.6% error. Paridie et al. [28] employed Neural Networks to predict the effects of preload location and magnitude on the natural frequencies of prestressed cantilever beams. By comparing the neural network results with those from finite element analysis, they showed that the neural network could accurately predict natural frequencies under various conditions. Vu et al. [29] used machine learning algorithms, including Artificial Neural Networks, Extreme Gradient Boosting, and Random Forest, to predict the location, width, and depth of cracks in steel beams. Their findings showed that changes in natural frequency could be used with high accuracy for damage detection and that machine learning models performed well in combination with FEM and FDD methods. Khalkar et al. [30] focused on detecting and predicting crack depth and location in cantilever beams using regression and machine learning models. Artificial Neural Network and Random Forest models were developed using numerical

and experimental data, demonstrating that these models could accurately predict crack locations and depths using two-point static deviations. Zhang et al. [31] presented a new surrogate-based method for crack identification in cantilever beams based on changes in natural frequencies. They utilized a Radial Point Interpolation Method and a database generated from FEA. The genetic algorithm accurately identified crack location and length, with a maximum relative error of 0.5% for numerical analysis and 2.5% for experimental analysis.

Several studies also focus on designing energy-efficient machine-learning models and algorithms tailored for lightweight and high-performance structures. These developments are part of a broader trend toward integrating machine learning and artificial intelligence into engineering applications [32-35]. As demonstrated by these studies, structural modifications and machine learning-based techniques offer promising avenues for optimizing the natural frequency of structures. Structural modifications provide a direct method for tuning natural frequencies by adjusting a structure's mass and stiffness properties. Machine learning techniques, on the other hand, offer a more flexible approach, enabling accurate predictions based on data-driven models. Combining these two approaches makes it possible to significantly improve the design and performance of engineering structures, such as cantilever beams while minimizing costs and computational requirements.

A thorough literature review shows that substantial research has been conducted on tuning the natural frequency of structures, particularly cantilever beams. Moreover, recent advancements have seen the application of artificial intelligence, especially machine learning algorithms, in predicting natural frequencies. However, no systematic study has yet explored tuning these frequencies through varying hole configurations. Thus, the unique contribution and innovation of this work lie in the development of a hybrid system that combines the Light Gradient Boosting Machine (**LightGBM**) learning model with the **Particle Swarm Optimization (PSO)** algorithm to determine optimal hole configurations on a cantilever beam for precise natural frequency tuning. As stated, the main objective of the present study is to determine the locations of the holes to achieve a specific natural frequency. However, a logical correlation between the hole locations and the natural frequency has not been established in this study.

2. Methodology

2.1. Frequency analysis and dataset generation

Five different holes are created in cantilever beams to tune the natural frequency to a desired value. The positions of these five holes on the beams, as shown in Figure 2, are configured in a 5x21 matrix array. Given the numerous possible locations for creating these five holes, there are 96,560,646 possible configurations. Producing this many samples to achieve frequency tuning is not feasible. Therefore, in this study, we selected 100 different samples based on a design of experimental approach. The choice of 100 samples, though small, was practical given computational constraints. This sample size suffices for training the LightGBM model, which effectively handles limited data. The model's strong generalization capability is evident from the close alignment of predictions with actual values. Frequency analysis was then conducted on each sample in COMSOL, and the first eight natural frequencies were extracted. The mode shapes obtained from the frequency analysis in COMSOL for one of the samples are illustrated in Figure 1.

The resulting dataset includes five input variables, each representing the row and column positions of a hole. The output of the dataset is the first natural frequency of each sample, which is the

primary focus for frequency tuning in this research. It should be noted that the input variables can only take integer values (ranging from 1 to 5 for rows and 1 to 21 for columns). Additionally, the output (the natural frequency values) was normalized between 0 and 1 for better performance of the machine learning system. Figure 2 provides a graphical representation of a portion of the generated dataset. In this figure, the positions of the holes are indicated by red circles, and the normalized frequency for each sample is displayed on the right.

2.2. Explanation of LightGBM

LightGBM is a machine learning algorithm developed for regression and classification tasks based on the Gradient Boosting framework. It is designed to optimize performance and reduce processing time, particularly for large and complex datasets [36]. LightGBM achieves its efficiency through innovative techniques like constructing decision trees leaf-wise rather than level-wise [37]. In standard Gradient Boosting, trees are typically built level by level; however, LightGBM builds trees leaf by leaf, which reduces errors and speeds up the learning process [38].

Additionally, LightGBM employs methods like Gradient-based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB). These techniques help reduce the number of samples and input features without sacrificing accuracy, thereby accelerating the training process [39]. This makes LightGBM especially effective in regression problems, where the goal is to predict a numerical value. It often outperforms algorithms like Random Forest and XGBoost in terms of efficiency and accuracy. In regression, the primary objective is minimizing the Mean Squared Error (MSE) by gradually boosting weaker models [40]. Key parameters used in LightGBM for Python implementations include `num_leaves`, `learning_rate`, `n_estimators`, and `max_depth`. `num_leaves` determines the number of leaves in each decision tree and is critical for model configuration. `Learning_rate` controls the speed at which the model is updated. `N_estimators` defines the total number of boosting iterations (trees) and `max_depth` sets the maximum depth of trees. Other parameters, like `min_data_in_leaf`, specify the minimum number of samples in each leaf, helping to manage overfitting.

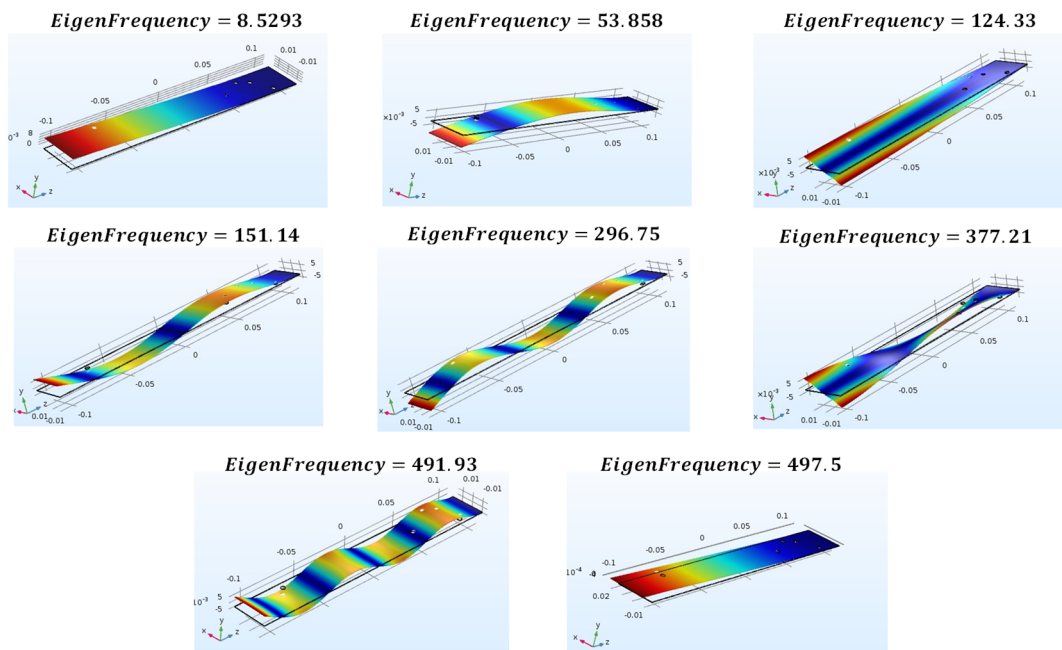


Figure 1. Frequency mode shapes for a selected sample.

2.3. Explanation of PSO

Particle swarm optimization is a population-based optimization algorithm inspired by the social behavior of birds or fish. In PSO, a group of particles represents potential solutions within the search space. Each particle adjusts its position based on its current state and the best-known positions discovered by itself and its peers. The algorithm combines local search (based on each particle's individual experiences) and global search (based on the collective experience of all particles) to converge to an optimal solution.

Each particle in PSO has two main attributes: position and velocity, which are updated iteratively using simple mathematical functions to move towards the best solutions found. One of the key advantages of PSO is its simplicity and ease of implementation. It is particularly effective in finding near-optimal solutions in complex, high-dimensional problems. The parameters commonly used in PSO with Python include `num_particles`, `inertia_weight`, `cognitive_coefficient`, and `social_coefficient`. `Num_particles` denotes the number of particles in the swarm. `Inertia_weight` controls the influence of a particle's previous velocity. `Cognitive_coefficient` reflects the particle's trust in its own experience, and `social_coefficient` indicates the particle's trust in the swarm's collective experience.

2.4. Hybrid hole configuration algorithm

This section describes the working mechanism of the hybrid hole configuration algorithm designed to tune the natural frequency of a cantilever beam to a specific value. The LightGBM machine learning model is first trained using the generated dataset, which is split into 70% training and 30% test data. The model's inputs are the positions of the holes, and its output is the normalized frequency for each sample. After building the machine learning model, the PSO optimization algorithm is employed to find the optimal positions for the holes, targeting a desired normalized frequency.

The objective function in the PSO algorithm measures the difference between the machine learning model's output and the desired normalized frequency. Consequently, the optimization algorithm searches for the best configuration that minimizes the objective function, effectively tuning the machine learning model's output frequency to the desired value. In this context, the optimization variables are the hole configurations in the model. In essence, PSO adjusts the positions of the holes in the cantilever beam to align the machine learning model's output frequency with the desired target. Figure 3 illustrates the schematic of the hole configuration algorithm. Table 1 lists the parameters utilized for the LightGBM and PSO algorithms, along with detailed descriptions of each parameter.

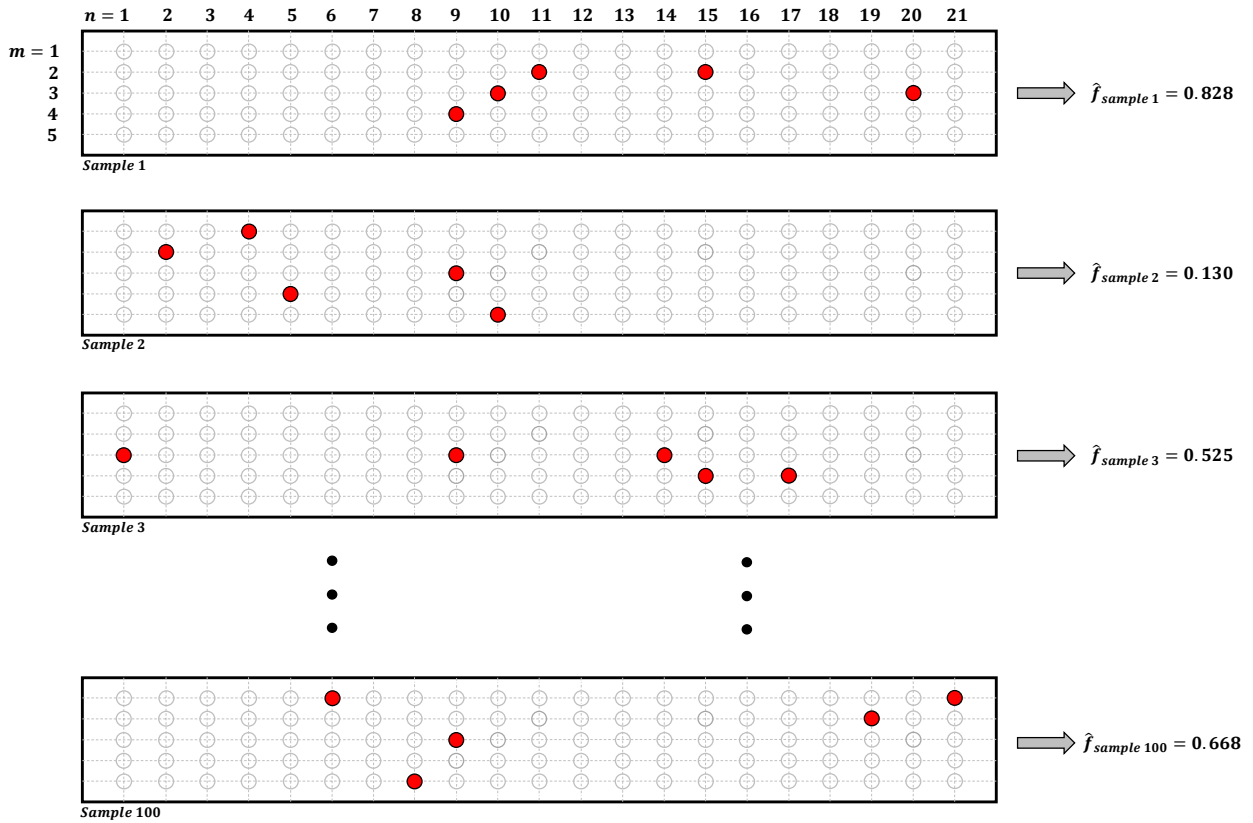


Figure 2. A graphical representation of a portion of the generated dataset.

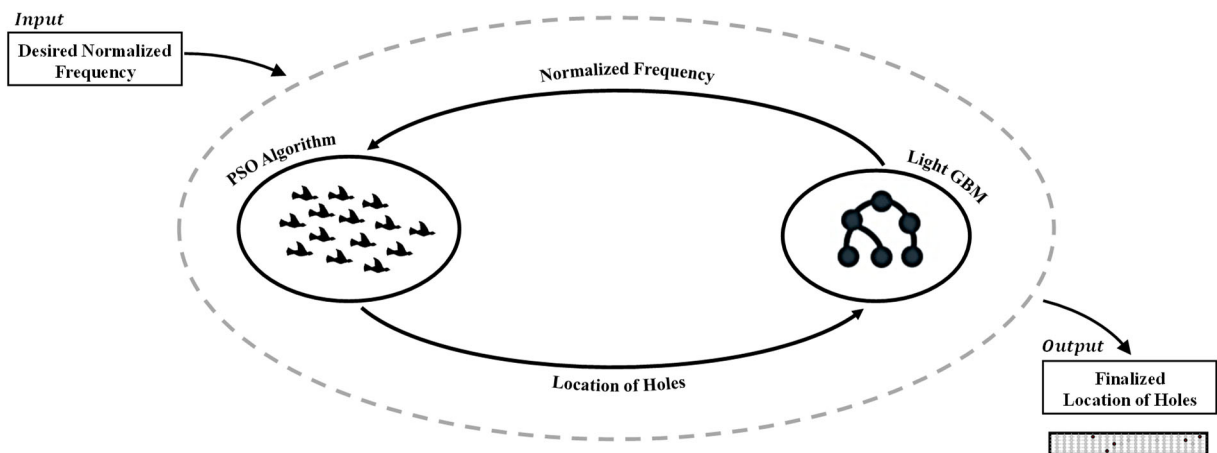


Figure 3. The hole configuration determination algorithm, including the machine learning model and the optimization algorithm.

Table 1. Configuration of LightGBM and PSO algorithm parameters used in the study.

Algorithm	Parameter	Value	Description
LightGBM	n_estimators	1000	Number of boosting iterations.
	learning_rate	0.5	Step size shrinkage to prevent overfitting.
	objective	regression	Defines the learning task and loss function.
	num_leaves	31	Maximum number of leaves per tree.
	max_depth	-1 (default)	Maximum depth of a tree (-1 means no limit).
	min_data_in_leaf	20	Minimum number of samples required in a leaf node.
PSO	maxiter	100	Maximum number of iterations.
	swarm_size	20	Number of particles in the swarm.
	omega	0.1	Inertia weight controlling the velocity.
	phip	0.1	The coefficient for personal best influence.
	phig	0.1	The coefficient for global best influence.

3. Discussion and results

Figure 4 presents a scatter plot for predicting the normalized frequency using the LightGBM method. In this plot, the training and testing data are displayed separately. The horizontal axis represents the actual frequency values, while the vertical axis shows the predicted values. A blue dashed line represents the A=P line, the ideal line where predicted and actual values perfectly match. The green triangles indicate the training data points, and the pink diamonds represent the test data points. This plot demonstrates that the machine learning model performed well in predicting the normalized frequency. Most points are closely aligned with the A=P line (A represents the actual frequency values, while P denotes the predicted frequency values obtained using the machine learning algorithm), indicating high accuracy of the training and test datasets. However, some test points (pink diamonds) deviate from the ideal line, suggesting a slight decrease in model accuracy when predicting the test data compared to the training data. Overall, the distribution of points around the ideal line appears appropriate, indicating that the model can effectively generalize and predict normalized frequencies for new data. Outliers in the LightGBM model’s predictions are expected in complex design spaces. Most test points align with the ideal A=P line, showing effective generalization. The few deviations reflect inherent complexities, with minimal impact on robustness due to the PSO algorithm optimizing the global solution.

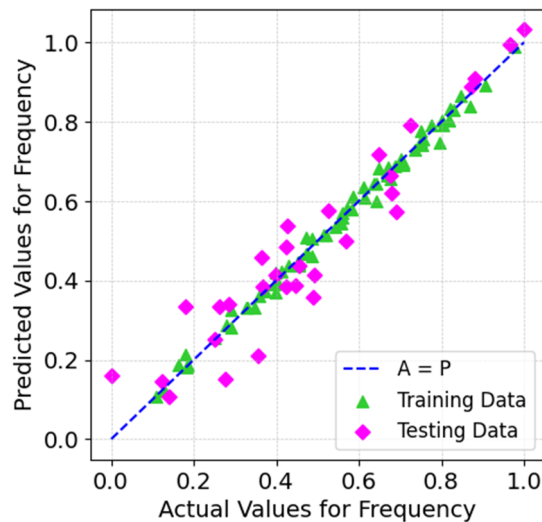


Figure 4. Predicted values of normalized frequency using the LightGBM model for training and test data, compared with actual values.

Figure 5 shows a comparison plot for predicting the normalized frequency using the LightGBM method. In this plot, the actual and predicted training and test data values are separately displayed based on the sample numbers. The horizontal axis shows the sample numbers, while the vertical axis represents the normalized frequency. Green triangles indicate the predicted values for the training data and are compared with the actual values represented by the gray line. Similarly, the orange diamonds correspond to the predicted values for the test data and are compared with the actual values shown by the blue line. This plot indicates that the LightGBM model performed excellently in predicting the normalized frequency for the training data, as the green triangles are closely aligned with the gray line and follow similar fluctuations. For the test data, the orange diamonds also follow the trend of the actual values, although some discrepancies are observed. Despite this, the LightGBM model has provided relatively accurate predictions for both datasets.

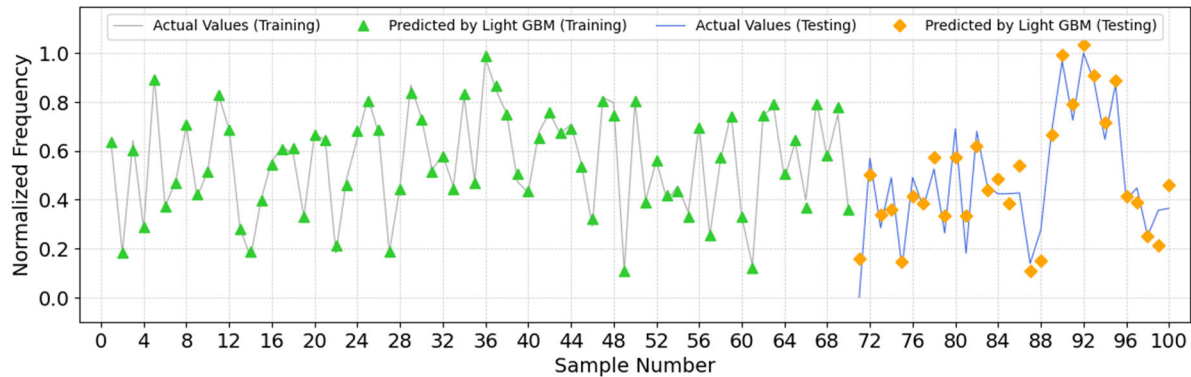


Figure 5. Predicted versus actual values for all samples.

Figure 6 illustrates a histogram of the machine learning model's errors in predicting the normalized frequency for all training and test samples. In this histogram, the horizontal axis represents the error magnitude, and the vertical axis shows the error density. A black curve displays a normal distribution fitted to these data. This histogram reveals that most model errors are close to zero, indicating high model accuracy in predicting the normalized frequency. The error distribution is nearly normal around the center (zero), suggesting that the model has performed in a balanced manner, with few significant outliers. Although a few larger errors are observed in the ranges of -0.15 and 0.15 , these are rare and do not substantially impact the model's overall performance. This histogram indicates that the LightGBM model has accurately predicted the normalized frequency, with most errors being small and close to zero.

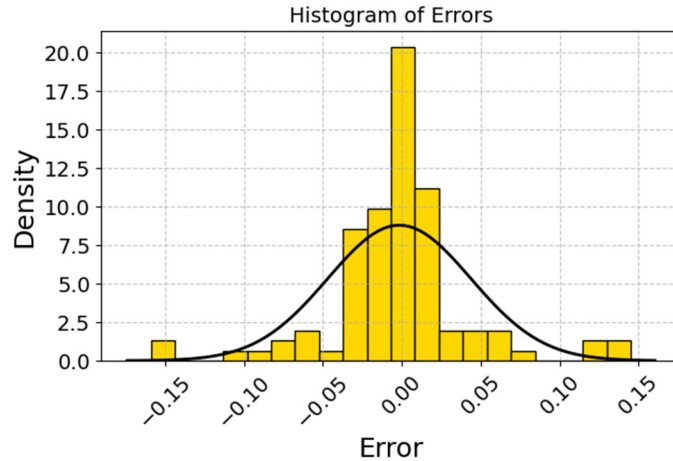


Figure 6. Histogram of the LightGBM model's errors in predicting the normalized frequency.

Figure 7 presents a box plot of the residuals for the LightGBM machine-learning model used to predict the normalized frequency. The residuals are relatively small and well-centered in the training phase, with a few outliers indicating minor errors. These residuals suggest that the model has achieved reasonably accurate predictions during the training phase. In the test phase, the residuals show more dispersion, with a larger box and a wider range. This increased spread is because the model has only been trained on the training data and has not seen the test data before. According to the analysis conducted so far, it can be concluded that the machine learning model has performed successfully in the critical test phase. The accuracy of the machine learning algorithm on the test data is lower than on the training data. This is a common phenomenon in machine learning, as the model is trained on the training data but does not encounter the test data during the learning process. This study aimed to fine-tune the hyperparameters to achieve near-optimal accuracy on the test data, ensuring a well-balanced model that avoids overfitting and underfitting.

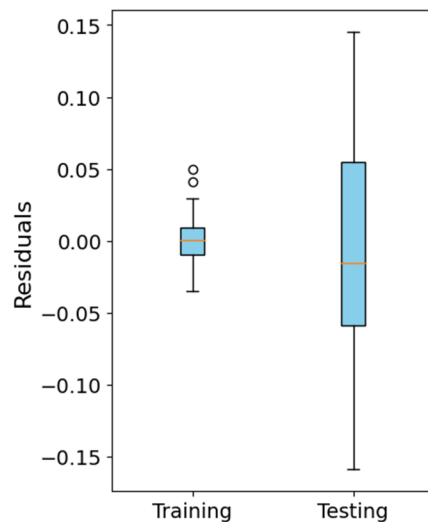


Figure 7. Box plot of residuals for training and test phases in predicting normalized frequency using the LightGBM model.

Figure 8 illustrates the plot of the best loss value over iterations for optimizing the positions of five holes in the cantilever beam, aiming to maintain the beam's natural frequency at 0.5. This plot corresponds to the PSO optimization algorithm, which gradually improves the inputs to determine the optimal hole positions. This plot shows that during the initial iterations (approximately up to 5 iterations), the best loss value rapidly decreases from around 0.005 to about 0.002. This sudden drop indicates a swift improvement in the algorithm's performance during the early optimization stages. After this rapid decrease, between iterations 5 and 30, the best loss value remains steady, indicating a plateau phase in the optimization process. However, around iteration 30, another sudden decrease occurs, bringing the loss value close to zero, which suggests proximity to the optimal solution. After this point, the algorithm successfully reaches a stable point, indicating the completion of optimization and achieving optimal positions for the holes. The obtained hole positions and the final normalized frequency value are also depicted in the figure. The PSO algorithm parameters, including a swarm size of 20 and inertia weight of 0.1, were selected to balance convergence speed and solution accuracy. The observed convergence within 30 iterations and solution stability confirm the robustness and effectiveness of the chosen parameters. Figures 9 and 10 show similar plots for normalized frequencies of 0.3 and 0.7, respectively. The designed system demonstrates excellent performance in determining the hole positions in the cantilever beam for any desired frequency value.

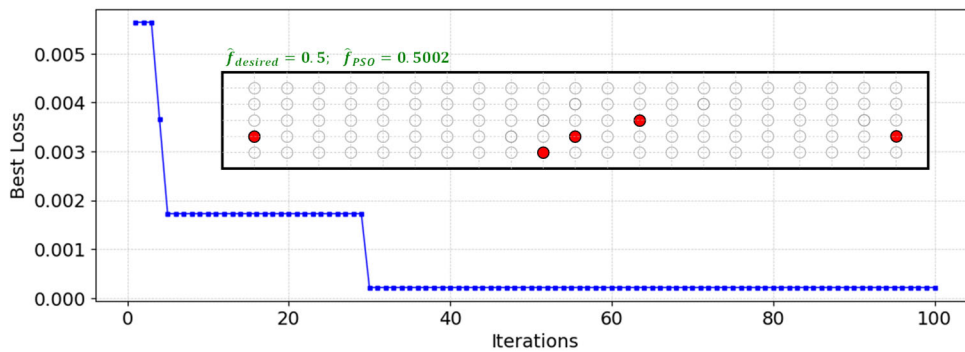


Figure 8. Best loss value over iterations for optimizing hole positions in the beam for a normalized frequency of 0.5.

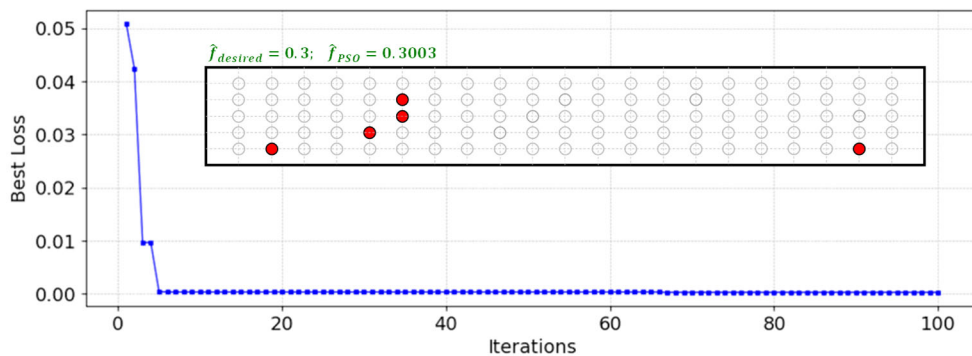


Figure 9. Best loss value over iterations for optimizing hole positions in the beam for a normalized frequency of 0.3.

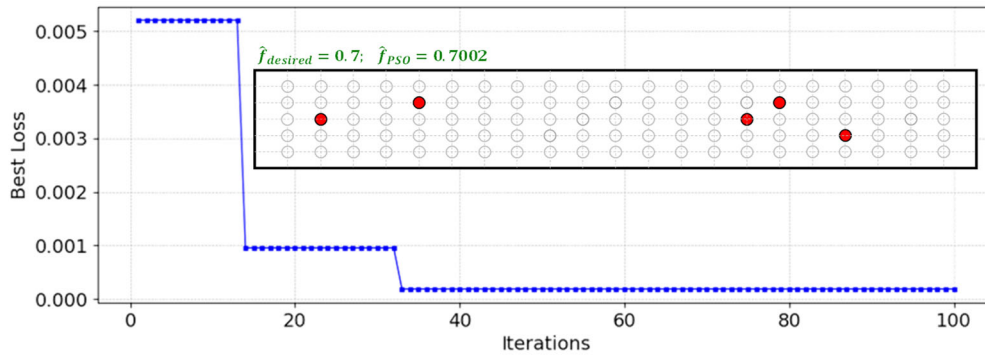


Figure 10. Best loss value over iterations for optimizing hole positions in the beam for a normalized frequency of 0.7.

4. Conclusion

This study developed a hybrid machine learning/optimization system to identify an appropriate configuration of holes on a cantilever beam to achieve a specific natural frequency. The machine learning model was initially trained using data obtained from finite element modeling. The key findings of this research are as follows: The **LightGBM** machine learning algorithm performed exceptionally well in predicting normalized frequencies for the training data, with predicted values closely matching the actual data and following similar trends. For the test data, the predictions also followed the actual values closely, although some discrepancies were observed. Despite these differences, the **LightGBM** model provided relatively accurate predictions for both the training and test datasets, demonstrating its strong generalization capability in predicting normalized frequencies for new data.

The majority of the model's errors were found to be near zero, indicating the high accuracy of the model in predicting normalized frequencies. The error distribution was approximately normal around the center (zero), suggesting that the model performed balanced without significant anomalies or large outliers. The residuals were small and well-centered, with only a few outliers indicating minor errors. These residuals confirm that the model made its predictions with relatively high precision. Additionally, the **PSO** optimization algorithm effectively identified the appropriate hole configuration to tune the natural frequency. The hybrid system demonstrated its ability to reach an optimal configuration within a desired frequency range through multiple examples.

This study demonstrates a proof of concept for tuning a single natural frequency, with the methodology extendable to multi-frequency tuning. The hybrid LightGBM-PSO approach, capable of optimizing multiple objectives, offers a solid foundation for scaling to more complex problems. The system's success in single-frequency tuning highlights its potential for multi-frequency scenarios, ensuring adaptability without fundamental changes.

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