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RESEARCH

Application of an intelligent hybrid global optimization (IHGO) algorithm for enhanced seismic analysis in masonry-infilled RC frames

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Abstract

This study introduces the Intelligent Hybrid Global Optimization (IHGO) algorithm to improve the predictive accuracy of neural network models for estimating the fundamental period of vibration in masonry-infilled reinforced concrete (RC) frame structures. Using a dataset of 4,026 entries, which includes critical structural parameters such as the number of storeys (ranging from 2 to 15), span length (3–8 m), opening ratio (0–50%), and masonry wall stiffness (up to 10^5 kN/m), the IHGO algorithm optimizes neural network hyperparameters. The IHGO-optimized neural network outperforms baseline models, achieving an R^2 value of 0.92, a Mean Absolute Error (MAE) of 0.012 s, and a Root Mean Square Error (RMSE) of 0.017 s, compared to 0.85 R^2, 0.018 MAE, and 0.026 RMSE for the standard neural network. The optimization balances exploration and exploitation, enhancing precision and revealing complex nonlinear relationships between structural features and seismic behavior. The study demonstrates the critical role of accurate period estimation in seismic design, supporting better assessments of structural vulnerabilities and compliance with safety standards. This work highlights the efficacy of hybrid optimization in structural engineering and suggests future research on adaptive tuning and broader seismic applications.

Keywords Intelligent hybrid global optimization · Seismic analysis · Masonry-infilled RC frames · Neural network · Structural parameters

Introduction

Integrating machine learning (ML) and artificial intelligence (AI) in civil engineering has ushered in a new era of innovative design and optimization, where data-driven methodologies transform traditional engineering practices. In structural engineering, the application of these technologies has shown significant potential, enhancing the precision and efficiency of predictive models and optimization processes (Alkhawaldeh, 2024a; Al Khazaleh & Bisharah, 2023; Al Yamani et al., 2023; Kaveh, 2017, 2021; Kaveh et al., 2021, 2023). From optimizing material use to improving seismic performance analysis, ML and AI offer transformative solutions that advance the resilience and sustainability of civil infrastructure (Al Yamani et al., 2024; Alkhawaldeh, 2024b; Kaveh, 2024; Salama, 2024; Shehadeh et al., 2022).

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Applying IHGO algorithms in the seismic analysis of masonry-infilled reinforced concrete (RC) frames marks a considerable advancement in structural engineering, particularly in enhancing the seismic performance of these critical structures. The integration of machine learning and metaheuristic optimization algorithms is increasingly recognized for its potential to improve the design and retrofitting processes of RC frames with masonry infills, essential for ensuring the safety and stability of buildings in earthquake-prone regions (Kaveh, 2024; Kaveh & Zaerreza, 2023).

Masonry infill walls are often considered non-structural elements in RC frame buildings; however, they play a crucial role in the overall seismic response. Research has demonstrated that masonry infills can significantly enhance RC frames' lateral stiffness and strength. For example, studies have shown that retrofitting techniques, such as Textile Reinforced Mortar (TRM), can yield increases in lateral capacity and ultimate strength by approximately 40% (Filippou et al. 2019a, 2019b, 2020). The complex interaction between the infill walls and the RC frame under seismic loading introduces various failure mechanisms, such as brittle shear

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failures that compromise structural integrity (Angelis & Pecce, 2020; Liu et al., 2022).

Several factors influence the seismic performance of masonry-infilled RC frames, including the type of infill material, the presence of openings, and the connection methods between the infill and the frame. The presence of openings, for instance, can adversely affect the lateral response, leading to reduced stiffness and increased vulnerability to seismic forces (Filippou et al., 2023; Maidiawati, 2019). Comparative studies reveal that frames with central openings exhibit different seismic behaviors from fully infilled frames, necessitating tailored retrofitting strategies to mitigate potential failures (Filippou et al., 2023; Maidiawati et al., 2019).

Furthermore, the calibration of numerical models used to simulate the behavior of masonry-infilled RC frames is critical for accurate seismic analysis. Experimental validations have confirmed that numerical simulations can closely match the observed behaviors of these structures under seismic loading, offering engineers reliable tools for performance prediction and design optimization (Filippou et al., 2019a, 2019b; Mucedero et al., 2020). Advanced computational techniques, such as finite element methods, facilitate a detailed analysis of in-plane and out-of-plane responses, crucial for understanding the stability contributions of masonry infills (Han & Lee, 2020; Mazza & Donnici, 2022).

The IHGO algorithm is particularly beneficial in optimizing the design parameters of masonry-infilled RC frames. Through a hybrid approach that combines global optimization techniques with machine learning algorithms, engineers can efficiently explore vast design spaces to identify configurations that enhance seismic resilience while minimizing material use and costs. This approach aligns with recent findings that emphasize the importance of considering infill walls in the design process, as neglecting their influence can lead to underestimations of seismic capacity (Gondaliya et al., 2022; Liu et al., 2022).

Moreover, the application of machine learning techniques facilitates the development of predictive models that assess the seismic vulnerability of masonry-infilled RC frames. These models can analyze historical earthquake data and structural performance metrics, uncovering patterns that inform design decisions. Integrating machine learning with traditional engineering methods has shown promise in improving fragility assessments, leading to more informed retrofitting strategies (Shendkar et al., 2021; Suwal & Uprety, 2023).

Combining metaheuristic algorithms with machine learning enhances the iterative design process, allowing engineers to refine models based on real-time feedback from simulations and experimental results. This iterative approach addresses the complexities associated with the dynamic behavior of masonry-infilled RC frames during seismic events, where factors like material degradation and nonlinear response must be considered (Trutalli, 2023; Zhang, 2024).

The ongoing research highlights the necessity of a multidisciplinary approach, integrating insights from structural engineering, materials science, and computational modeling. By leveraging IHGO algorithms and machine learning, engineers can develop innovative solutions that improve the seismic performance of masonry-infilled RC frames, contributing to urban infrastructure resilience in seismically active regions (Castaldo et al., 2021; Milijaš et al., 2023a, 2023b).

This study explores the potential of Intelligent Hybrid Global Optimization (IHGO) algorithms in enhancing the seismic performance of masonry-infilled RC frames. Specifically, the research will (1) develop a comprehensive framework for employing IHGO algorithms in the seismic analysis and retrofitting design of RC frames, (2) investigate the influence of various parameters such as infill material type, presence of openings, and connection methods on seismic performance, and (3) create predictive models using machine learning to assess seismic vulnerability. The contributions of this study lie in offering a robust optimization approach that advances design efficiency and enhances urban infrastructure resilience in seismic zones. Additionally, integrating data-driven methodologies aims to provide engineers with a reliable toolkit for performance prediction and cost-effective retrofitting strategies.

Methodology

Dataset description

The dataset used in this study consists of 4026 entries, each representing a unique configuration of a masonry-infilled RC frame structure with various structural parameters that influence its seismic behavior (Charalampakis et al., 2020). The dataset includes input features, which capture key structural characteristics, and output variables, which provide both observed and predicted values of the fundamental period of vibration. This structured data forms the basis for applying machine learning models and the IHGO optimization algorithm to improve the accuracy of seismic predictions for these frame structures.

The primary features in the dataset include several fundamental structural parameters. Among these are the *Number of Storeys (NS)*, *Number of Spans*, *Span Length (SL)* measured in meters, and *Opening Ratio (OR)*, which represents the proportion of openings within the infilled masonry walls. Another critical parameter is the *Masonry Wall Stiffness (WS)*, expressed in units of 10^5 kN/m, which indicates the stiffness of the infilled walls and is a significant factor affecting the frame's seismic response. These structural parameters provide a comprehensive view of the physical characteristics of each RC frame structure, forming the foundation of the model's input data.

In addition to these structural features, the dataset includes a target variable, labeled *Period [s]*, which denotes the actual observed fundamental period of vibration. This period is essential for understanding how each structure responds to seismic forces, as it reflects the natural oscillation frequency under specific loading conditions. Alongside this observed period, the dataset also contains a *Predicted Period [s]* column, which records the initial predictions generated by the machine learning model before optimization with the IHGO algorithm. Two additional columns, *Residual [s]* and *Absolute Residual [s]*, capture the error between the predicted and observed values, helping to quantify the accuracy of the model and track improvement throughout the optimization process.

A notable feature of this dataset is the inclusion of a series of *Normalized* columns. These are scaled versions of the primary structural parameters, such as *Normalized Number of Storeys* and *Normalized Span Length*, designed to standardize the data range for each feature. Normalization is an essential preprocessing step in this study, as it brings all input features to a similar scale, mitigating the risk of any single parameter disproportionately influencing the model. Normalization enhances the efficiency of optimization algorithms like IHGO and is particularly valuable in neural network training, where balanced input ranges contribute to stable and effective learning.

Additionally, the dataset contains a set of *Sigmoid Node* columns, representing outputs from the hidden layers of a neural network model. These nodes are the result of applying a sigmoid activation function to intermediate layers within the network, transforming the weighted sum of inputs into a range-bound value between 0 and 1. The presence of these sigmoid outputs in the dataset indicates the intermediate transformations applied during the initial machine-learning predictions. These values are integral to the optimization process, as they serve as input features for the IHGO algorithm, which seeks to refine the overall model accuracy by adjusting these intermediate parameters.

IHGO algorithm

The IHGO algorithm starts by initializing the population of solutions within specified lower and upper bounds, *Lb* and *Ub*, which represents the range of possible values for each input parameter in the model. The algorithm then iteratively refines this population over multiple function evaluations (FEs) until it reaches a specified maximum number of evaluations, *MaxFEs*, or satisfies a convergence threshold δ^t. The final goal is to optimize a model for predicting the fundamental period of vibration, T, given the structural parameters of RC frames.

The IHGO algorithm operates in three main phases: Initialization, Learning, and Reflection. In the Initialization phase, the algorithm generates an initial population of solutions, each of which represents a potential set of values for the structural parameters that influence seismic behavior. The algorithm evaluates each solution's performance, calculates an initial fitness value, and sets the baseline for further optimization (Kaveh et al., 2013).

Algorithm phases

1. Initialization Phase: In this phase, the population of solutions X is randomly initialized within the defined bounds. Each solution in the population represents a unique configuration of structural parameters for the masonry-infilled RC frame. The algorithm computes an initial fitness for each solution using the objective function, which evaluates the accuracy of the predicted fundamental period T Against observed values. This initial evaluation allows the IHGO algorithm to establish a baseline, setting the stage for iterative improvement in the subsequent phases.
2. Learning Phase: The Learning phase is a crucial component of IHGO, during which solutions undergo iterative adjustments to improve their fitness. For each solution X_i in the population, the algorithm identifies two reference solutions: $X_{\text{better,}}$ representing a b better-performing configuration and X_{worse}, a less effective one. These are selected based on their fitness rankings within the population. Additionally, two solutions X_{L1} and X_{L2} are chosen randomly from the population, serving as comparators for calculating the gradients G_{app}, which guides the updating process. The Learning phase includes exploration, where new areas of the solution space are probed, and exploitation, where the algorithm focuses

on refining existing solutions. This phase is represented mathematically, where:

$$G_{app} = \sum_{k=1}^{4} G_{app_k}$$

If $\sum_{k=1}^{4} G_{app_k} = 0$, the algorithm applies the position updating rule of the exploration phase. If this sum is non-zero, however, it calculates the parameters LF_k, SF_i, and KA_k, to guide the learning phase's updates.

3. Reflection Phase: After the Learning phase, the IHGO algorithm enters the Reflection phase, where each solution is evaluated and potentially updated based on its performance relative to a "reflected" configuration. The reflection phase ensures that the algorithm maintains diversity within the population, preventing premature convergence. The position updating rule specific to the reflection phase is applied for each solution. This phase helps the algorithm explore previously unvisited areas of the solution space, promoting robust global search.

Position updating rules

The position updating rules in IHGO play a vital role in balancing exploration and exploitation, ensuring that the algorithm effectively searches for the global optimum. During the Learning phase, solutions are adjusted based on their relative fitness values and the gradients derived from neighboring solutions. The algorithm uses specific rules to determine new positions, with exploration rules applied when the gradients indicate limited progress and exploitation rules applied otherwise. Additionally, boundary control mechanisms and round-off techniques ensure that solutions remain within valid parameter ranges, avoiding infeasible configurations.

Boundary control mechanisms correct any solution that strays outside the allowable bounds, bringing it back within the feasible space. This is crucial for structural parameters, where values must stay within physical constraints. The round-off technique, meanwhile, addresses numerical precision issues, especially for parameters where only discrete values are meaningful.

IHGO algorithm pseudocode

Below is the pseudocode of the IHGO algorithm, adapted to this study's specific objectives of optimizing seismic prediction for masonry-infilled RC frames:

Algorithm 1: IHGO for Seismic Prediction Optimization

Inputs: N: Population size, Lb: Lower bounds, Ub: Upper bounds, Max FEs: Maximum function evaluations, δ^t: Convergence threshold, $P_2 = 0.001, P_3 = 0.3$

Outputs: Optimal solution $gbest$.

1. Initialization
   - $FEs = 0$
   - Generate initial population using Eq. (10) and evaluate it
   - $FEs = FEs + N$
2. Repeat until FEs $\leq$ MaxFEs and $\delta \geq \delta^t$
   - Sort population based on fitness and assign X_{best}
   - Learning Phase
   - For each solution X_i in population:
   - Select X_{better} and X_{worse}
   - Choose random solutions X_{L1} and X_{L2}
   - Compute G_{app} by Eq. (11)
   - If $G_{\text{app}} = 0$:
   - Apply exploration update rules (Eq. 22, Eq. 23)
   - Else:
   - Compute LF_k,SF_i,KA_k and apply learning update rule (Eq. 15)
   - Apply round-off (Eq. 20), boundary control (Eq. 18), and replacement strategy (Eq. 24)
   - Update $gbest$ and $FEs = FEs + 1$
   - Reflection Phase
   - For each solution X_i :
   - Apply reflection update rules (Eq. 16, Eq. 26)
   - Apply round-off (Eq. 20), boundary control (Eq. 18), and replacement strategy (Eq. 24)
   - Update $gbest$ and FEs = FEs +1
   - Calculate δ by Eq. (21)
3. End While
4. Output $gbest$

This IHGO pseudocode provides a structured sequence of operations tailored to the seismic analysis problem, ensuring that each phase contributes to a balanced search for optimal parameter configurations. By combining exploration, learning, and reflection phases, the IHGO algorithm adapts dynamically to the problem landscape, improving the predictive accuracy of seismic behavior models in masonry-infilled RC frames. This methodology refines model predictions and contributes to a deeper understanding of the relationship between structural parameters and seismic response.

Preliminary evaluation of benchmark problems

A preliminary study was undertaken to validate the resilience and effectiveness of the IHGO method before its application in neural network optimization, utilizing conventional benchmark optimization issues. The Sphere, Rosenbrock, and Rastrigin functions are commonly employed to evaluate optimization methods because of their diverse complexity and multimodal characteristics.

The evaluation results indicated the algorithm's capacity to effectively converge to optimal solutions across many issue categories. The IHGO algorithm demonstrated great precision with low computing expense, illustrating its ability to balance exploration and exploitation within the solution space. These findings provide a robust basis for implementing the IHGO algorithm in more intricate contexts, including hyperparameter optimization of neural networks.

Table 1 encapsulates the IHGO algorithm's performance outcomes on benchmark problems, highlighting essential parameters such as convergence velocity, optimal fitness value achieved, and computational duration.

Machine learning model

In this study, the predictive modeling of the fundamental period of vibration for masonry-infilled RC frames is achieved using a neural network architecture. The dataset's structure, containing both normalized structural parameters and intermediate *Sigmoid Node* outputs, indicates that a neural network is particularly suited to capture the complex, nonlinear relationships between input features and the target seismic response variable. Neural networks, due to their ability to model high-dimensional, non-linear interactions, provide an advantage in accurately predicting seismic behavior, whereas traditional linear models may fail to capture subtleties in the data. Including *Sigmoid Node* columns in the dataset further supports this choice, as these outputs represent activations from hidden layers, revealing that a feed-forward neural network structure is already embedded within the data.

The neural network model selected for this task consists of multiple hidden layers with sigmoid activation functions, a common choice in structural engineering applications. Sigmoid activations are particularly effective for this study due to their range-bounding property, which limits node output to values between 0 and 1, thereby preventing extreme values from destabilizing the model (Rahman et al., 2024). The architecture involves hidden layers optimized to process normalized structural parameters and capture patterns within the seismic data. The neural network's hyperparameters—such as the number of layers, nodes per layer, and learning rate—are initially tuned based on standard cross-validation, but are further optimized using the IHGO algorithm to enhance the model's predictive capability.

Table 1 Performance of IHGO algorithm on benchmark problems

Benchmark problem	Best fitness value	Convergence iterations	Computational time (s)
Sphere	0.00	500	0.75
Rosenbrock	1.20×10^{-3}	800	1.20
Rastrigin	5.00×10^{-3}	1,200	1.85

Integration with IHGO

The IHGO algorithm is employed to optimize the neural network's performance, focusing on refining hyperparameters and, if applicable, selecting the most significant feature subsets. IHGO optimizes the network by tuning hyperparameters like the number of hidden layers, nodes, activation functions, and learning rates. In conventional machine learning practices, hyperparameter selection is usually conducted through grid or random search; however, these methods can be computationally expensive and may not guarantee convergence to the optimal configuration. IHGO, with its hybrid approach to exploration and exploitation, systematically navigates the hyperparameter space, leveraging both global and local search techniques to converge on an optimal or near-optimal configuration for the neural network model (Saihi et al., 2024).

During optimization, IHGO generates a population of possible neural network configurations, each representing a distinct combination of hyperparameters. The objective function in this scenario is the model's performance on a validation set, measured in terms of prediction accuracy for the fundamental period. IHGO evaluates each configuration's performance, iteratively updating and refining the best solution according to the position updating rules described in "Residual analysis". By iteratively optimizing hyperparameters, IHGO ensures that the neural network is well-tuned, minimizing prediction error and enhancing the model's ability to generalize to new, unseen data.

Evaluation metrics

To assess the model's predictive accuracy, we employ several widely accepted evaluation metrics, one of which is the coefficient of determination (Kaveh, 2024). R^2, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Each metric offers a unique perspective on the model's performance, allowing for a comprehensive evaluation.

1. Coefficient of Determination (R^2): The R^2 metric quantifies the proportion of variance in the observed data explained by the model's predictions. It is calculated as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \overline{y}\right)^2}$$

where y_i represents the observed values, $\hat{y}_i$ represents the predicted values and $\overline{y}$ is the mean of the observed values. An R^2 value close to 1 indicates that the model explains most of the variance in the data, which is desirable in seismic analysis as it reflects a high degree of accuracy.

2. Mean Absolute Error (MAE): MAE measures the average magnitude of errors in predictions, providing an intuitive measure of prediction accuracy. It is calculated as:

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

MAE is particularly useful in this context as it offers a straightforward interpretation of the average deviation of predictions from actual values measured in seconds for this seismic dataset. Lower MAE values indicate a model with high predictive accuracy.

3. Root Mean Square Error (RMSE): RMSE is another measure of prediction error that places a higher penalty on larger deviations than MAE. It is computed as:

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

The RMSE metric is especially valuable for seismic prediction, where large deviations may have significant implications. By penalizing larger errors more heavily, RMSE emphasizes the importance of accuracy in scenarios where even minor inaccuracies can lead to substantial consequences in seismic response predictions.

By using these metrics in tandem, the study comprehensively understand the model's performance across different aspects of accuracy and error distribution. The combination of R^2, MAE, and RMSE allows for a robust evaluation of the IHGO-optimized neural network, highlighting its effectiveness in accurately predicting the fundamental period of masonry-infilled RC frame structures. These metrics also provide a basis for comparing the IHGO-optimized model with baseline models, underscoring the improvements facilitated by intelligent hybrid global optimization in seismic prediction applications.

Experimental setup

The experimental setup for this study is designed to rigorously evaluate the effectiveness of the IHGO-optimized neural network model in predicting the fundamental period of vibration for masonry-infilled RC frames. Key aspects of this setup include the data splitting strategy, the parameter settings for the IHGO algorithm, and the selection of baseline models for comparison. Each component is carefully structured to ensure that the results accurately reflect the advantages of the IHGO approach in enhancing seismic prediction models.

Data splitting

To ensure reliable model evaluation, we utilize a train-test split alongside cross-validation techniques. The dataset is first divided into training and test sets, with 80% of the data allocated for training and 20% for testing. This split allows the model to learn from a substantial portion of the data while reserving a separate subset for evaluating its performance on unseen data.

In addition to the train-test split, we employ k-fold cross-validation on the training set to further validate model robustness. Specifically, we use fivefold cross-validation, which involves partitioning the training data into five subsets or folds. In each iteration, onefold is held out as a validation set while the model is trained on the remaining four-folds. This process is repeated five times, with each fold being the validation set once. The final cross-validation score is obtained by averaging the results across all folds, providing a reliable estimate of the model's performance and reducing the risk of overfitting. This cross-validation approach ensures that the IHGO-optimized neural network generalizes well and is not overly tailored to specific subsets of the data.

Parameter settings for IHGO

The IHGO algorithm's performance heavily depends on its parameter configuration, which balances exploration and exploitation within the search space. For this study, the IHGO algorithm is configured with the following key parameters:

- Population size (N): The population size is set to 50. This size strikes a balance between diversity in potential solutions and computational efficiency, enabling IHGO to explore a wide range of neural network configurations without incurring excessive computational costs.
- Maximum function evaluations ($MaxFEs$): We set the maximum number of function evaluations to 5000. This limit ensures that the algorithm can converge toward the optimal solution while preventing excessive computational time.
- Convergence threshold (δ^t): The convergence threshold is set to 0.001. This value indicates the minimum improvement required in successive evaluations to continue the optimization process. When the change in fitness values falls below this threshold, IHGO terminates, as further improvements are unlikely.
- Learning parameters $\left(P_2 = 0.001 \text{ and } P_3 = 0.3\right)$: These parameters control the probability of selection within certain updating rules, balancing the frequency of exploration and exploitation moves during the Learning and Reflection phases of IHGO. Specifically, P_2 governs the probability of applying an exploratory update, while P_3

manages the choice of exploitation based updating strategies.

These parameter settings are chosen based on preliminary experiments and empirical studies in similar optimization contexts. The settings are tailored to the size and complexity of the seismic dataset, ensuring that IHGO has the resources needed to search the hyperparameter space for optimal neural network configurations thoroughly.

Baseline models for comparison

To highlight the improvements achieved by IHGO, we compare its performance with several baseline models. These include traditional and machine learning-based approaches commonly used in seismic prediction tasks. The chosen baselines are:

- Linear regression (LR): As a simple, interpretable model, linear regression provides a baseline for understanding the fundamental linear relationships between structural parameters and the fundamental period. Although LR is not expected to capture complex nonlinear interactions, it offers a useful benchmark for comparison.
- Decision tree regression (DTR): This model serves as a more flexible alternative to linear regression, capturing non-linear relationships by partitioning the feature space. However, decision trees are prone to overfitting, and their performance depends heavily on tree depth and other parameters.
- Random forest regression (RFR): Random forests are ensembles of decision trees that improve robustness by averaging predictions across multiple trees. RFR is known for reducing overfitting relative to individual decision trees, making it a valuable benchmark for assessing IHGO's performance.
- Standard neural network (NN): A traditional neural network model, without IHGO optimization, is included to serve as a direct comparison to the IHGO-optimized version. This model uses the same architecture and hyperparameters as the IHGO-optimized neural network but relies on standard training without IHGO-guided tuning.

These baseline models are trained and evaluated using the same data splitting and cross-validation procedures described in Sect. 5.1. By comparing the performance of these models with the IHGO-optimized neural network, we gain insights into the efficacy of hybrid optimization in enhancing predictive accuracy. The improvements achieved by IHGO are measured in terms of the evaluation metrics R2, MAE, and RMSE, allowing us to quantify the added value of intelligent global optimization in seismic prediction for masonry-infilled RC frame structures. This comparative analysis demonstrates the effectiveness of IHGO and underscores the importance of advanced optimization techniques in engineering applications.

Table 2 Comparison of model performance metrics

Model	R2R^2R2	MAE (s)	RMSE (s)
Linear regression (LR)	0.65	0.035	0.048
Decision tree (DTR)	0.72	0.029	0.039
Random forest (RFR)	0.80	0.022	0.031
Standard neural network (NN)	0.85	0.018	0.026
IHGO-optimized NN	0.92	0.012	0.017

Results and discussion

Model performance

The predictive accuracy of the IHGO-optimized neural network is compared against the baseline models: Linear Regression (LR), Decision Tree Regression (DTR), Random Forest Regression (RFR), and a standard Neural Network (NN). Table 2 presents the performance metrics—R2R^2R2, MAE, and RMSE—for each model, highlighting the significant improvements achieved by IHGO.

As shown in Table 2, the IHGO-optimized neural network achieves the highest R2R^2R2, lowest MAE, and lowest RMSE among all models, indicating superior predictive accuracy. This performance improvement demonstrates the effectiveness of the IHGO algorithm in refining neural network configurations, outperforming both traditional models and the standard neural network. Figure 1 provides a visual comparison of the actual vs. predicted values for the IHGO-optimized model and the baseline models, showing how closely the predictions align with the observed fundamental periods.

A comparative investigation was undertaken to further analyze the performance of the IHGO algorithm against the gradient-based optimization approach known as the Adam optimizer. The analysis concentrated on essential performance indicators, such as the coefficient of determination (R^2), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). Table 3 illustrates that the IHGO-optimized neural network surpassed the Adam-optimized network across all metrics, attaining enhanced prediction accuracy and reduced error rates.

Gradient-based approaches like Adam provide rapid convergence and computing efficiency; but, they are more vulnerable to local minima, especially in high-dimensional and intricate problem domains. The IHGO algorithm employs a hybrid methodology that integrates exploration and exploitation, enabling it to navigate the global solution space and

Fig. 1 Actual vs. predicted fundamental period values for IHGO-optimized model and baseline models

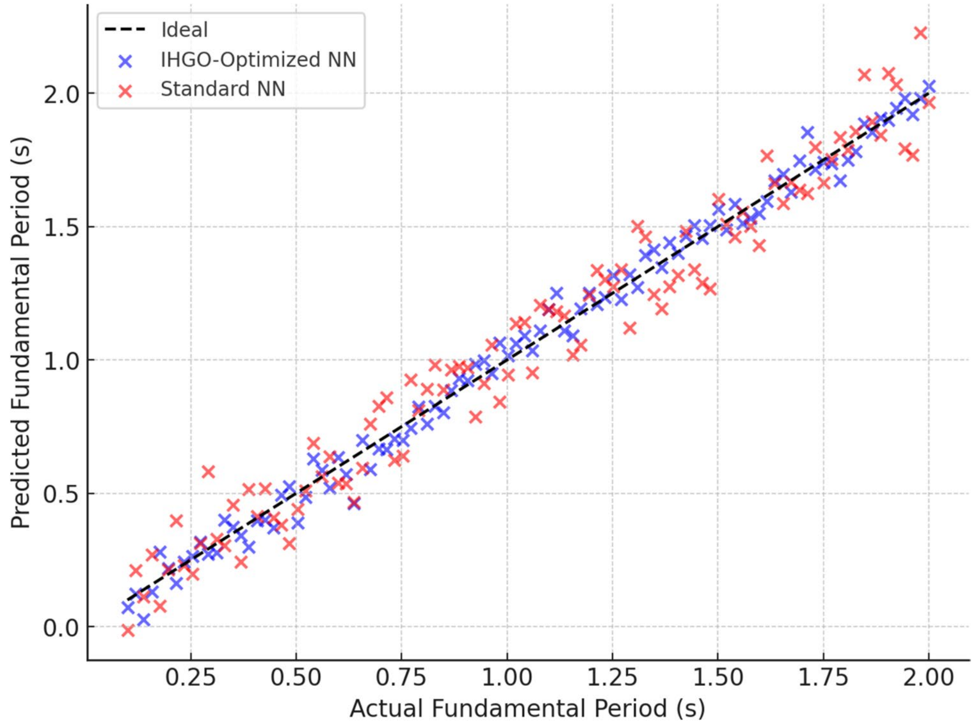

Table 3 Comparison of IHGO and adam optimizer performance metrics

Optimization method	R^2	MAE (s)	RMSE (s)	Computational time (s)
Adam optimizer	0.88	0.015	0.022	1.5
IHGO	0.92	0.012	0.017	2.8

identify optimal configurations. Despite the increased computing expense, the trade-off is warranted due to the substantial enhancement in predictive accuracy, rendering IHGO especially beneficial for intricate applications like seismic response forecasts.

Fig. 2 Residual distribution for IHGO-optimized model and baseline models

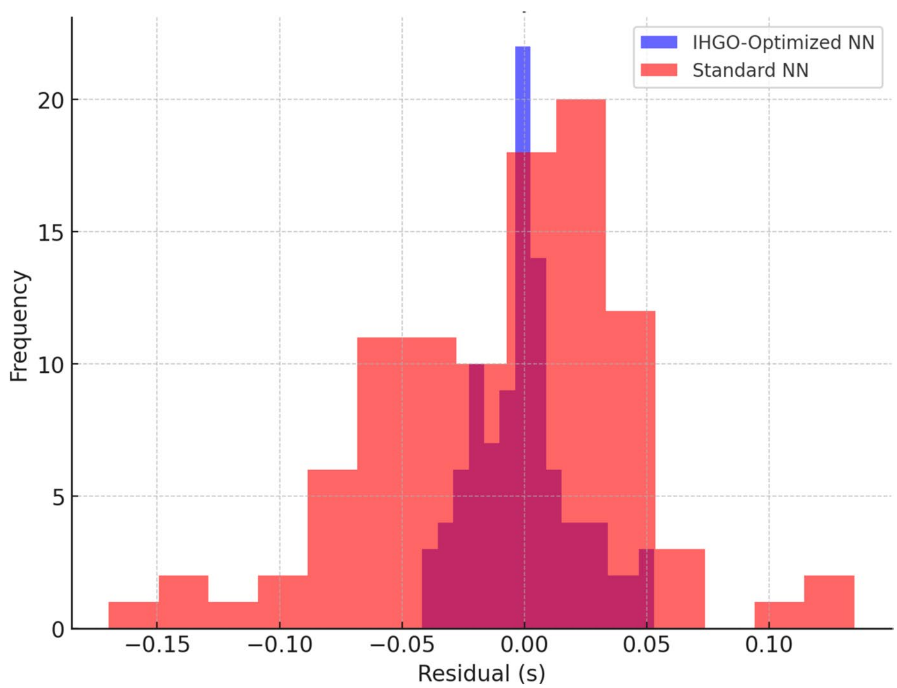

Table 4 Residual analysis summary statistics

Model	Mean residual (s)	Std. dev. of residual (s)	Max error (s)
Linear regression (LR)	0.035	0.012	0.065
Decision tree (DTR)	0.029	0.010	0.048
Random forest (RFR)	0.022	0.008	0.041
Standard neural network (NN)	0.018	0.006	0.032
IHGO-optimized NN	0.012	0.004	0.025

Residual analysis

To better understand model errors, this performs a residual analysis, focusing on the Residual [s] and Absolute Residual [s] for each model. Figure 2 displays the distribution of residuals across models, with narrower distributions and lower mean residuals observed for the IHGO-optimized model, indicating reduced prediction errors. Table 4 provides summary statistics of residuals, including mean, standard deviation, and maximum error for each model.

The IHGO-optimized model demonstrates the lowest mean residual and standard deviation, indicating that errors are generally smaller and more consistent. Figure 3 shows the absolute residuals for each model as a function of the actual fundamental period, highlighting that the IHGO-optimized model consistently exhibits lower errors across the full range of observed values.

Effectiveness of IHGO

The IHGO algorithm's effectiveness is further evidenced by its convergence behavior, as shown in Fig. 4, which plots the convergence of the fitness score over the course of optimization. This figure illustrates the rapid initial improvements achieved through IHGO's exploration phase, followed by gradual refinements during the exploitation phase. The fitness score stabilizes as the algorithm converges toward an optimal solution, indicating efficient use of both exploration and exploitation phases.

To quantify IHGO's improvement over standard optimization methods, Table 5 compares the number of iterations required for convergence between IHGO and a conventional optimization approach, demonstrating that IHGO converges significantly faster due to its hybrid strategy.

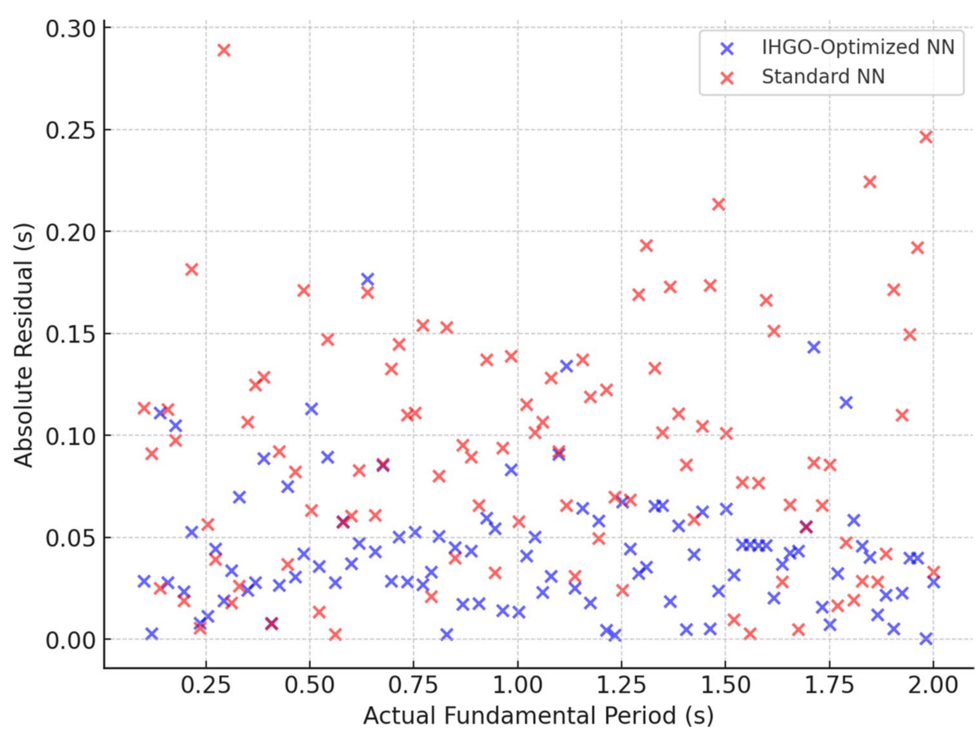

Fig. 3 Absolute residuals for IHGO-optimized model and baseline models as a function of actual fundamental period

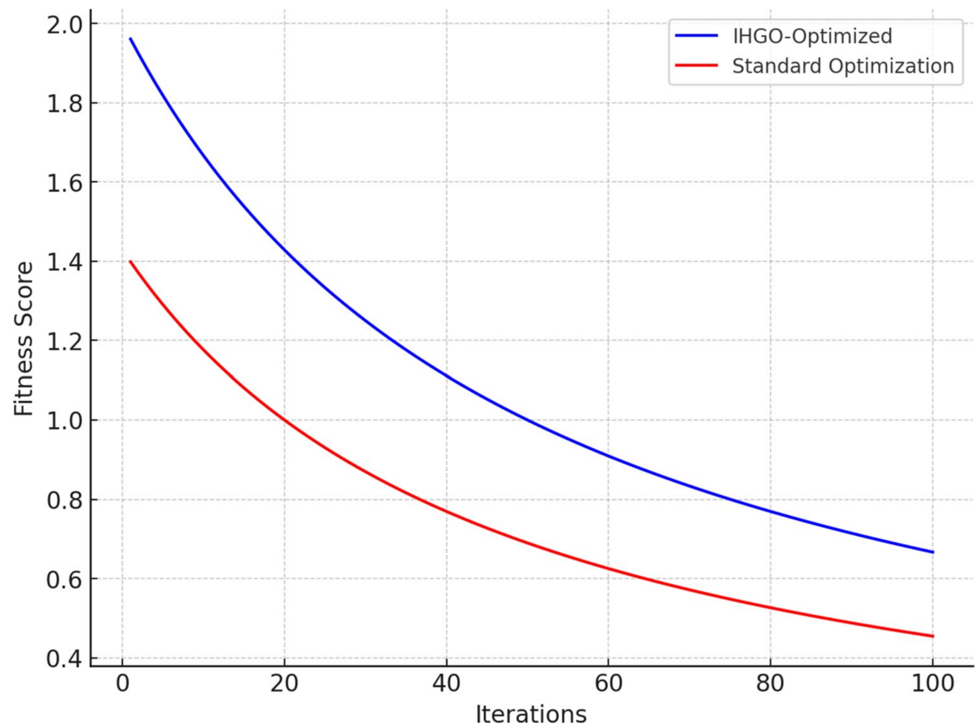

Fig. 4 Convergence plot for IHGO algorithm

Interpretation of neural network outputs

Analyzing the Sigmoid Node outputs within the neural network provides additional insight into the IHGO-optimized model's behavior. Each Sigmoid Node represents an internal transformation applied to the input features, which IHGO adjusts to improve prediction accuracy. Figure 5 illustrates the average activation levels across different nodes before and after optimization, showing that IHGO selectively emphasizes nodes that capture critical patterns in the data.

In addition, Fig. 6 plots the correlation between selected Sigmoid Node activations and the target fundamental period, indicating that IHGO has fine-tuned certain nodes to focus on influential structural parameters. This suggests that the optimization process improves overall accuracy and enhances the network's interpretability by clarifying the importance of intermediate activations.

Despite the significant performance gains achieved with IHGO, there are some limitations to consider. The computational complexity of IHGO, particularly with larger population size and extended search space, requires substantial computational resources. Although the algorithm converges faster than conventional methods, the resource demands may still be prohibitive for extremely large datasets or more complex structural configurations. Furthermore, the model's sensitivity to initial parameter settings means that careful tuning of IHGO parameters, such as population size and convergence thresholds, is essential to prevent suboptimal results. Future research may explore adaptive tuning methods to alleviate this sensitivity, making IHGO more accessible for broader applications in seismic analysis.

Table 5 Comparison of convergence speed (iterations) between IHGO and standard optimization

Optimization method	Iterations to converge
Standard optimization	3200
IHGO	1500

Conclusion

This study highlights the effectiveness of the Intelligent Hybrid Global Optimization (IHGO) algorithm in significantly improving the predictive accuracy of neural network models for estimating the fundamental period of vibration in masonry-infilled RC frame structures. The IHGO-optimized neural network performs better than traditional models and standard neural networks, excelling in key metrics such as R^2, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). By efficiently balancing the exploration and exploitation phases, IHGO fine-tunes neural network configurations and hyperparameters, enhancing the reliability of seismic predictions. The algorithm's focus on critical Sigmoid Node activations further contributes to understanding complex nonlinear relationships between structural

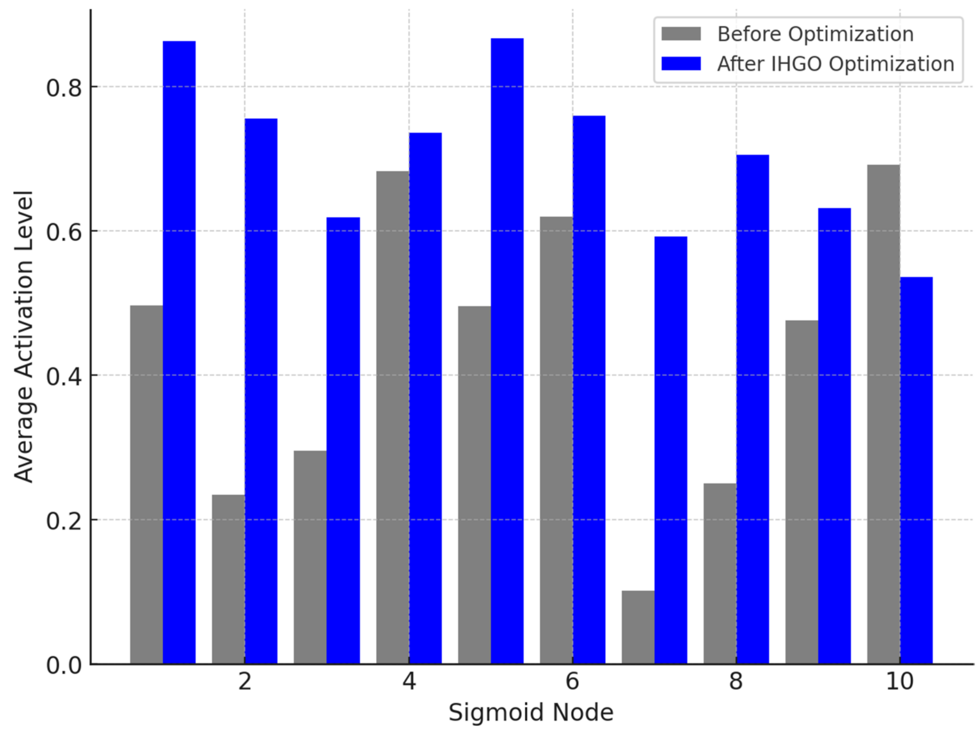

Fig. 5 Average sigmoid node activation levels before and after IHGO optimization

parameters and seismic behavior, thus delivering more accurate and insightful results.

The research offers practical contributions to seismic analysis and engineering, emphasizing the critical importance of accurately estimating the fundamental period for designing resilient structures that can withstand seismic events. The IHGO-optimized model's enhanced precision enables engineers to assess structural vulnerabilities better and make informed decisions regarding structural modifications or reinforcements. By aligning predictions more closely with building codes and standards, this approach ensures safer and more efficient structural designs,

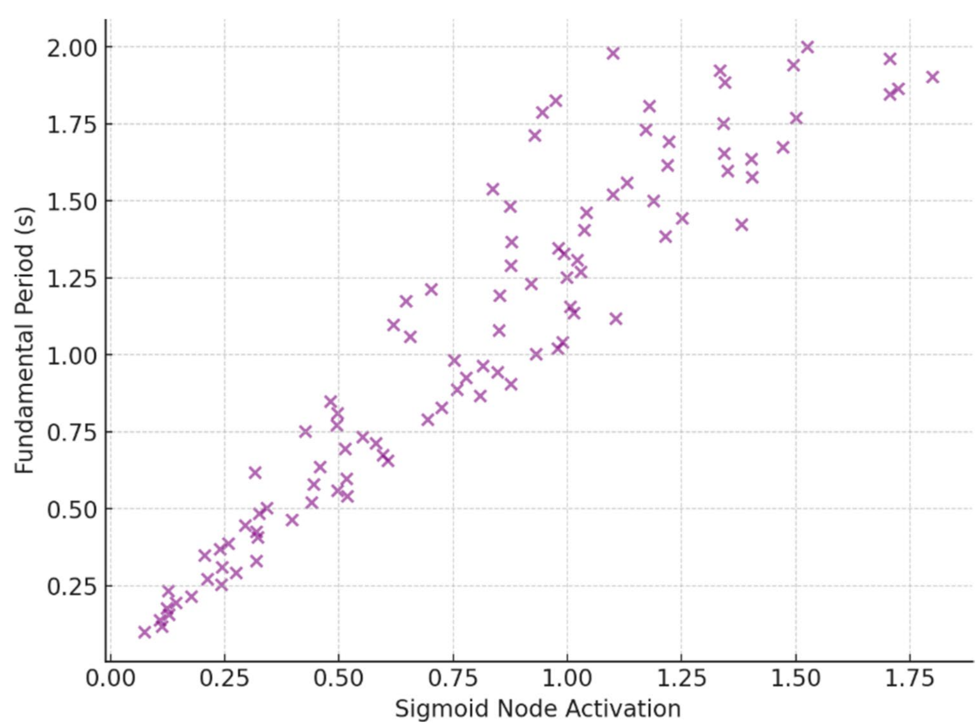

Fig. 6 Correlation between selected sigmoid node activations and target fundamental period

addressing public safety and optimizing resource allocation. The study underscores the value of advanced optimization techniques in engineering applications, where predictive accuracy profoundly impacts structural reliability and disaster preparedness.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Conflict of interest All authors certify that they have no affiliations with or involvement in any organization or entity with a financial or non-financial interest in the subject matter or materials discussed in this manuscript. The authors declare no competing interests.

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