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A SURROGATE APPROACH FOR ACCURATE ESTIMATION OF STRUCTURAL RESPONSE IN STEEL FRAME OPTIMIZATION

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ABSTRACT

Structural design seeks to achieve optimal performance with minimum cost while meeting code requirements. Evaluating optimized designs usually depends on finite element analysis, which is computationally expensive. Recently, surrogate models have been developed to predict structural behavior more efficiently. Among these, Support Vector Machine (SVM) has become a reliable tool in civil engineering. However, the predictive power of SVM is highly dependent on proper parameter tuning. This study introduces the Improved Electric Eel Foraging Optimization Algorithm (I-EEFO) for training SVM to estimate the response of steel frames. Two benchmark structures, a 2-story and a 7-story steel frame, were analyzed, and the results were compared with other metaheuristic algorithms. The proposed method achieved very high accuracy: mean squared errors of 1.11E-13 for the 2-story frame and 2.99E-07 meters for the 7-story frame over 10 runs. The root mean square errors for displacement prediction on test data were 2.67E-07 and 7.23E-04 meters, respectively, confirming reliable estimates. Convergence curves demonstrated that I-EEFO converges faster and more effectively than competing methods. These findings highlight the potential of the proposed approach as a robust and computationally efficient alternative to traditional simulations, offering engineers a practical tool to reduce costs in structural design without compromising accuracy.

Keywords: Electric Eel Foraging Optimization; Structural Design; Metaheuristic algorithm; Machine Learning; Tall Building.

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1. INTRODUCTION

In structural design, controlling the inter-story drift is considered a key criterion for evaluating

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different performance levels. According to the standard of Federal Emergency Management Agency (FEMA), a target displacement is specified for each performance level. Studies such as those by Kaveh et al. [1] and Kaveh and Nasrollahi [2] have focused on optimizing steel moment frames using base shear as the primary criterion[3]. In this approach, the structural capacity curve must be capable of providing the required base shear for various performance levels, without applying any reduction due to the response modification factor [4]. However, considering base shear in the nonlinear range of the structure may not be an appropriate criterion, as part of the energy is dissipated through ductility in this region. Designing structures based solely on base shear without accounting for the response modification factor can lead to uneconomical designs. Therefore, FEMA 265 and FEMA 277 recommend displacement as a more suitable criterion for evaluating structural behavior in the nonlinear range [5].

Performance-based design methods are highly diverse and involve complex constraints and relationships. Numerous studies have been conducted in this area, including the use of predefined or structure-specific target displacements, performance level assessment through damage analysis and structural importance, and performance-based design of concrete and steel structures with concentric bracing systems. Some research has also examined the effects of structural vibration modes and soil-structure interaction. For instance, Hassan et al. emphasized that in displacement-based methods, the structural capacity curve must be capable of achieving the required target displacements [6]. To meet these objectives, the use of a precise simulator—typically developed based on finite element models—is essential. In recent years, the integration of metaheuristic optimization algorithms with linear simulation models has gained attention for the design and performance evaluation of such structures. Gholizadeh et al. demonstrated through a genetic algorithm that in steel frames with semi-rigid connections, structural behavior is highly influenced by building height [7]. Subsequently, Yazdi and Sulong successfully employed a genetic algorithm to optimize connection points and identify more economical cross-sections for eccentrically braced systems [8].

Further research indicates that employing advanced optimization methods can yield up to 10% improvement in design parameters compared to conventional approaches. For instance, integrating target displacement criteria with factored load combinations per FEMA 356 standards has resulted in more economical structural designs. In the optimization of concentrically braced frames (CBFs), significant reductions in base shear forces and story drifts have been observed, accompanied by decreased steel consumption. Kaveh and Talatahari [9], using metaheuristic algorithms and Particle Swarm Optimization (PSO), demonstrated these methods' high potential for structural weight reduction and seismic performance enhancement. These findings corroborate that combining intelligent computational methods with established standards can lead to more efficient and cost-effective designs. Liu et al. conducted a pioneering study on the optimization of steel frames, emphasizing stability criteria and economic considerations [10].

Subsequently, Degertekin et al. investigated multi-story steel frames under biaxial seismic loading [11]. Their study employed an elastic design methodology, with the objective function minimizing construction costs through optimization of various parameters, including the use of semi-rigid connections instead of fully rigid connections.

However, implementing this procedure for structural design requires computationally intensive analyses and significant time investment, which become increasingly problematic

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with larger-scale structures. Consequently, recent years have seen growing attention toward alternative methods for response estimation in the design process. For instance, Gholizadeh and Mohammadi introduced a framework combining Particle Swarm Optimization with Artificial Neural Networks to optimize steel structures while accounting for uncertainties [12]. Further advancing this field, Jafari-Asl et al. employed machine learning techniques such as LSSVM, GRNN, and ELM for structural response prediction and reliability analysis [13]. Due to the importance of the subject, extensive research has been conducted using metaheuristic algorithms and alternative methods for structural design. For a comprehensive study, the reader is referred to [14–17].

The objective of this study is to develop a machine learning based surrogate model for estimating the response of braced steel structures. To this end, Support Vector Machines (SVMs) are employed. Since SVMs have hyperparameters whose optimal values must be determined, we evaluate the effectiveness of the Electric Eel Foraging Optimization Algorithm (I-EEFO) for SVM training and compare it with other algorithms [18].

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2. METHODOLOGY

In general, the optimal design process for steel structures proceeds in two main stages. First, candidate designs generated by the optimization algorithms are subjected to linear static analysis under factored load combinations; member stress checks are performed in accordance with the AISC LRFD provisions, and allowable beam deflections under service loads are verified. Designs that satisfy these criteria advance to a nonlinear pushover analysis to more accurately assess their limit-state behavior. Conversely, designs that fail this preliminary screening are discarded in favor of more promising alternatives. This hybrid workflow reduces the computational burden while enabling solutions that are satisfactory in terms of safety and stability as well as cost-effectiveness. The final-stage pushover analysis further ensures that the selected structures exhibit appropriate performance at limit states under seismic loading. Because the present study focuses exclusively on using a surrogate model in the design process in lieu of full FEM simulations, this section is limited to describing the SVM method and the I-EEFO optimization algorithm.

2.1. Support Vector Machines (SVM)

Given the extensive literature on the theoretical foundations of SVM [19–21], this study provides only a concise overview of ε-SVM (epsilon-SVM) as one variant of SVM. In SVM-based regression, the objective is to estimate the functional relationship between the dependent variable y and the independent variables x. As in other regression approaches, it is assumed that $y = f(x) + noise$. The central challenge is to identify a function f that can accurately predict unseen patterns, even those not encountered during training. This function is obtained by training the SVM on the available data and iteratively minimizing an appropriate loss. In this research, ε-SVM is adopted due to its strong performance on regression tasks. The loss function in this model is the ε-insensitive loss, defined as:

$$\frac{1}{2}\ \mathrm{w}^{\mathrm{T}}\mathrm{w} + C\sum_{i=1}^{N}\xi_i + \mathrm{C}\sum_{i=1}^{N}\xi_i^* \tag{1}$$

The foregoing loss is minimized subject to the following constraints:

$$\begin{gathered} \mathrm{w}^{\mathrm{T}}\phi(x_i) + \mathrm{b} - y_i \leq\ \varepsilon + \xi_i^* \\ y_i - \mathrm{w}^{\mathrm{T}}\phi(x_i) - \mathrm{b} \leq\ \varepsilon + \xi_i^* \\ \xi_i,\ \xi_i^* \geq 0, i = 1. \dots . N \end{gathered} \tag{2}$$

In these expressions, w and w^{T} denote the coefficient vector and its transpose, respectively; C > 0 is the regularization (capacity) parameter; ξ_i and ξ_i^* are slack variables; b is the bias term; N is the number of training samples; and φ(·) is the feature mapping induced by the chosen kernel k(·,·). Because selecting the kernel type, and the parameter C, and the kernel scale (e.g., γ in an RBF kernel) is challenging and time consuming, this study employs optimization algorithms to identify their best combination.

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2.2. Electric Eel Foraging Optimization and improvement (I-EEFO)

Electric eels, native to South America and part of the Gymnotidae family, are remarkable predators known for their ability to generate powerful electrical discharges ranging from 300 to 800 volts. These discharges serve multiple functions, including prey capture, navigation, communication, and defense. Despite their poor eyesight, electric eels emit low-voltage signals (around 10 volts) to sense their surroundings and locate prey with precision. Their electricity is produced by specialized organs containing thousands of electrocytes, which act like biological batteries. Recent studies reveal that electric eels exhibit social hunting behaviors, coordinating in groups to herd fish and deliver synchronized high-voltage strikes. This cooperative strategy has inspired the design of Electric Eel Foraging Optimization (EEFO), reflecting the eels' efficient and adaptive predatory mechanisms [22].

The EEFO algorithm is inspired by the social predation strategies of electric eels, modeling their behaviors such as interaction, resting, migration, and hunting to guide the optimization process. In the interaction phase, each eel represents a candidate solution and engages in collective movement, mimicking the formation of electrified circles used to trap prey. This phase promotes global exploration by updating positions based on differences between individuals and the population center [22].

$$C\ =\ n1\ \times\ B \tag{3}$$

$$n_1\ \sim\ N(0.1) \tag{4}$$

$$B\ =\ [b_1 . b_2 . \cdots b_k . \cdots . b_d] \tag{5}$$

$$g\ =\ randperm(d) \tag{6}$$

$$l = 1. \dots . \left\lceil \frac{T-t}{T} \times r_1 \times (d-2) + 2 \right\rceil \quad (7)$$

Where T is the number of the maximum iterations.

Resting behavior is simulated by projecting an eel's position onto the main diagonal of the normalized search space, establishing a resting area that enhances local search efficiency. The resting behavior can be mathematically represented as follows [22]:

$$v_i(t+1) = R_i(t+1) + n_2 \times (R_i(t+1) round(rand) \times x_i(t)) \quad (8)$$

$$n_2 \sim N(0.1) \quad (9)$$

During hunting, eels coordinate to encircle prey, gradually shrinking the hunting area and updating positions through a curling mechanism that reflects high-voltage strikes.

$$\{X \big| X - xprey(t)\big) \leq \beta 0 \times |x(t) - xprey(t)|\} \quad (10)$$

$$\beta 0 = 2, \left(e - e^{\left(\frac{t}{T}\right)}\right) \quad (11)$$

where β0 represents the initial size of the hunting area.

Migration occurs when eels move from resting zones to hunting areas, modeled by position updates influenced by random factors and prey location.

$$v_i(t+1) = r_5 \times R_i(t+1) + r_6 \times H_r(t+1) - L \times \left(H_r(t+1) - x_i(t)\right) \quad (12)$$

$$H_r(t+1) = x_{prey}(t) + \beta \times \left|x(t) - x_{prey}(t)\right| \quad (13)$$

In this model, H_r represents any position within the hunting area, while r_5 and r_6 are random numbers within the range $(0,1)$.

The transition between exploration and exploitation is governed by an energy factor that decreases over time, allowing the algorithm to shift focus from global search to local refinement. These biologically inspired mechanisms collectively enable EEFO to balance exploration and exploitation effectively, improving optimization performance [22].

$$E(t+1) = 4 \times \sin\left(\frac{1}{t-T}\right) \ln\left(\frac{1}{r_7}\right) \quad (14)$$

where r_7 is a random number within the range (0,1).

In many modern algorithms, random movements are essential for updating the positions of search agents, using a stochastic approach to explore potential solutions along unpredictable paths. This concept of random movement is inspired by well-known physical phenomena such as sound, heat, and light transfer, which led to the development of Brownian motion. Random movements involve a series of unpredictable steps taken for various purposes. In the standard EEFO algorithm, random digits are crucial in the position update process, where the location of a solution candidate is adjusted through random increments. To enhance the effectiveness of I-EEFO, it utilizes the well-known Levy distribution to generate steps, instead of relying on simple random number generation.

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$$Levy(s) = |s|^{-1-\beta} \qquad 0 < \beta \leq 2 \tag{15}$$

$$Levy(s.\gamma.\mu) = \begin{cases} \sqrt{\frac{\gamma}{2\pi}} exp\left[-\frac{\gamma}{2(s-\mu)}\right]\frac{1}{(s-\mu)^{\frac{3}{2}}} & 0 < \mu < 0 \\ 0 & s \leq 0 \end{cases} \tag{16}$$

where μ , β, s, and γ are the scaling parameter, shape factor, distribution factor, and position parameter respectively.

In the I-EEFO, the Levy flight is integrated into the mathematical model of the standard PDO, replacing the traditional random walk with the Levy flight. In Fig. 1, the difference between Levy flight and classic Brownian steps are demonstrated.

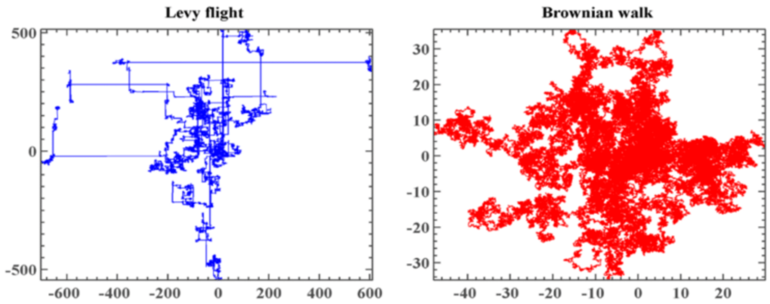

Figure 1: Difference between Levy flight and classic Brownian steps

Figure1 Alt Text: The image shows the difference between Levy flight and Brownian motion steps. The left side depicts the Levy flight path (with blue points), which features larger random steps, while the right side shows the Brownian motion path (with red points), which has smaller steps and more limited dispersion.

2.3. Proposed hybrid method (SVM-IEEFO)

One of the main challenges in structural analyses is the connection between analysis software and MATLAB code. While calling explicit objective functions and constraints in MATLAB is straightforward, there is often no explicit function available for analyzing many structural problems. In these cases, for each design option created by the search particles in each iteration, it is necessary to transfer the problem variables (including geometric, material, or load parameters) from MATLAB code to the structural analysis model, followed by modeling and analysis. For instance, in optimizing a structure with 20 search particles over 50 iterations, 1,000 objective function calls are needed, requiring the creation of new geometry in Abaqus and the adjustment of boundary conditions and loading. This process is particularly challenging and sometimes impossible for complex models.

To address this issue, this research proposes using advanced machine learning models as a substitute for defining objective functions and constraints. This way, there is no need to connect MATLAB code with the finite element analysis software, and the objective functions can be directly entered into MATLAB. This approach aids in predicting the structural response during the optimization process without the need for simulation. Initially, random samples for design parameters are generated, and the structural behavior for these samples is calculated. Subsequently, the structural response for other samples is estimated using trained machine

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learning models, significantly reducing computational costs. Additionally, the IEEFO method is utilized to determine SVM parameters and enhance prediction accuracy. The pseudocode for the proposed framework is presented in Algorithm 1.

Algorithm 1

Step 1: Generate initial design samples $X = [x_1 . x_2 . , , , . x_n]$.
Step 2: For each xi in X:
  a. Run FEA to compute response y_1 (e.g., stress, displacement).
  b. Store $(x_i . y_i)$ in training dataset D.
Step 3: Train SVM on D, optimizing hyperparameters via I-EEFO.
Step 4: Define optimization problem in MATLAB:
  Objective: min $f(x) = MSE_{SVM}(x)$
Step 5: Predicted test samples by using trained SVM in previous step.
Step 6: Analysis the obtained results.

3. EVALUATION PARAMETERS

To evaluate alternative approaches, various aspects have been reported, with the most common being the use of statistical metrics such as the Root Mean Squared Error (RMSE), the Mean Squared Error (MSE), the Mean Absolute Percentage Error (MAPE), the Nash-Sutcliffe Efficiency (NSE), and the coefficient of determination (R2) for estimated data during the testing phase (see Table 1). Additionally, to assess the performance of evolutionary algorithms, this study utilizes the mean and standard deviation of the objective function value defined as MSE for 10 independent runs of the algorithms. Table 1 shows the formulation of the aforementioned parameters. For more information regarding these and other statistical parameters, the reader is referred to [23,24].

Table 1: Equations of evaluation parameters.

Parameter	Equation	
$RMSE$	$\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_{mea}^{i} - y_{pre}^{i}\right)^2}$	
MSE	$\frac{1}{n}\sum_{i=1}^{n}\left(y_{mea}^{i} - y_{pre}^{i}\right)^2$	
NSE	$1 - \frac{\sum_{i=1}^{n}\left(y_{mea}^{i} - y_{pre}^{i}\right)^2}{\sum_{i=1}^{n}\left(y_{mea}^{i} - y_{exp}^{avg}\right)^2}$	$-\infty \leq NSE \leq 1$
$MAPE$	$\frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_{mea}^{i} - y_{pre}^{i}}{y_{mea}^{i}}\right)$	
R^2	$1 - \frac{\sum_{i=1}^{n}\left(y_{mea}^{i} - y_{pre}^{i}\right)^2}{\sum_{i=1}^{n}\left(y_{mea}^{avg} - y_{pre}^{i}\right)^2}$	

where, y_{mea}^{i} and y_{pre}^{i} denote the measured and the predicted values, respectively, and n is the number of measurements. y_{mea}^{avg} and y_{pre}^{avg} are the corresponding average values of the measured and predicted parameters, respectively.

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4. RESULTS AND DISCUSSION

This section presents the modeling results of two steel structures employing SVM-based surrogate models optimized with the I-EEFO (Improved-EEFO) metaheuristic algorithm. The performance of the proposed I-EEFO-SVM framework is validated and compared against other metaheuristic algorithms, including, Particle Swarm Optimization (PSO) [20], Grey Wolf Optimizer (GWO) [25], Whale Optimization Algorithm (WOA) [26], Standard EEFO, and the gradient-based Adam algorithm. Since the efficacy of metaheuristic algorithms depends on optimal parameter tuning, all algorithms were configured according to their original reference values, as recommended by Arcuri and Fraser [27]. Table 2 summarizes the optimized parameters for each algorithm. Notably, the I-EEFO, EEFO, and Adam algorithms require no tunable parameters.

Table 2: Setting parameters of the selected metaheuristic algorithms.

Algorithm	Parameter	Value
PSO	Inertia weight	0.85
	C1	0.43
	C2	0.02
GWO	α	$Linearly\ dicreased\ from\ 2\ to\ 0$
WOA	p	Between 0 and 1

The dataset obtained from finite element analysis was partitioned into training (70%), validation (10%), and test (20%) subsets using random sampling. All optimization algorithms were configured with an initial population size of 3 and terminated after 6 iterations. To account for random sampling variability, we conducted 10 independent trials for each algorithm configuration.

4.1. Case study I

The first structure is a two-story, single-span steel frame braced with 8-shaped buckling-restrained braces. The frame was modeled in Abaqus according to the specifications in Table 3, and 500 different scenarios were generated by varying the cross-sectional properties of all structural members. The objective of this case study is to estimate the roof displacement of the second story using machine learning (ML) instead of performing additional Abaqus simulations. Fig. 2 illustrates the frame schematic and its deformed shapes under the baseline configuration and two additional scenarios. As shown, variations in member cross-sections significantly affect the frame's displacement response.

Table 3: Initial Section Properties of the Two-Story Frame

	Type	Dimension (mm)
Columns	I-Shape	500x400x15x10
Beams	I-Shape	400x400x20x20
Braces	Box-Uniform	200x150x12x12
	Elasticity modulus (MPa)	Poisson’s ratio
Steel fy50	199948	0.3

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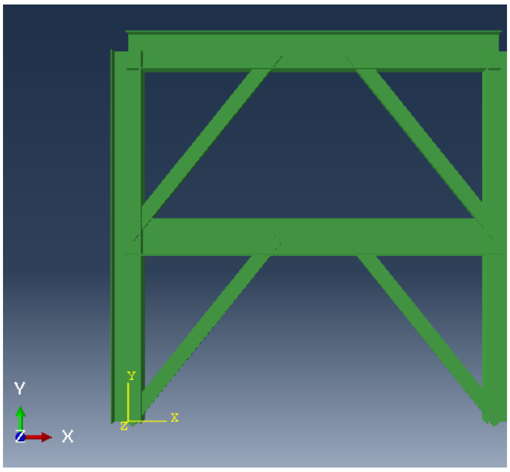
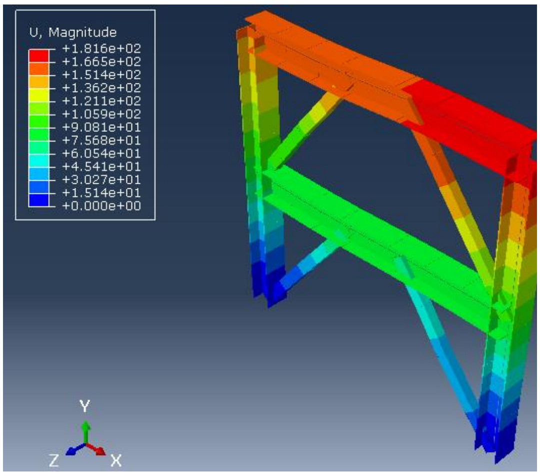
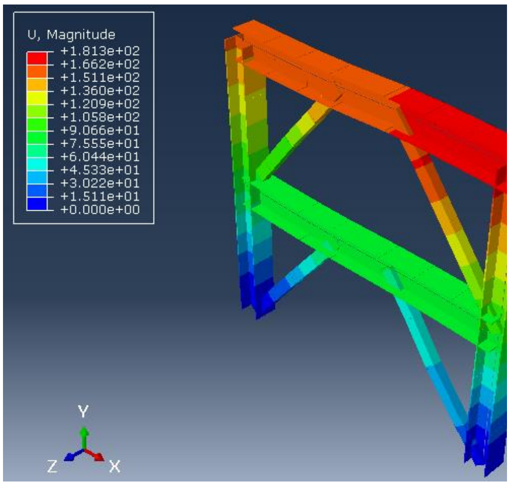


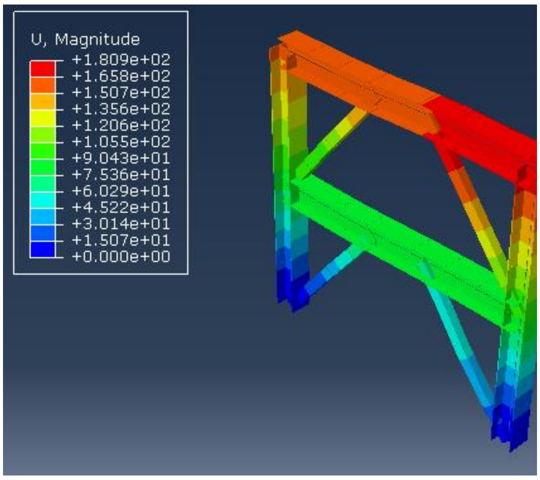
(a) Modeling process in Abaqus



(b) Results for basic scenario



(c) Results for a new scenario



(d) Results for a new scenario

Figure 2: Schematic of studied steel frame I.

Figure 2 illustrates the modeling process of a steel frame in Abaqus and the results showing the distribution of stress across four different scenarios. Part a shows the modeling process in Abaqus with the stress distribution. Part b presents the stress distribution for the baseline scenario. Part c shows the stress distribution for a new scenario, while part d illustrates the stress distribution for another scenario. Variations in the cross-sectional properties of the structural members lead to significant changes in the stress distribution.

Following the generation of 500 random scenarios incorporating cross-sectional properties, applied loads, and elastic modulus values, the corresponding moment of inertia for each member was calculated. ABAQUS simulations were then performed for each dataset to compute second-story displacements. The resulting data was used to train, validate, and evaluate the developed machine learning models.

The mean squared error (MSE) was adopted as the objective function for SVM training, with each model executed 10 times. As shown in Table 4, the proposed I-EEFO algorithm achieved the lowest mean and standard deviation of MSE values compared to other metaheuristics (PSO, GWO, WOA, EEFO, and Adam). Notably, all algorithms demonstrated highly competitive performance, with minimal differences in their mean and standard deviation values, indicating their overall effectiveness in SVM training.

Furthermore, the best-performing runs of all algorithms yielded nearly identical objective function values, suggesting marginal differences between models. Fig 3 presents the convergence curves for each algorithm's best run. The I-EEFO algorithm converged to its optimal solution in the first iteration, while EEFO, GWO, and Adam required two iterations, and PSO needed three iterations. These results demonstrate the superior efficiency of I-EEFO in training SVM models for structural response prediction.

Table 4: Results of the SVM-based model for the two-story frame in training process.

Parameters	Algorithm					
	PSO	GWO	WOA	I-EEFO	EEFO	Adam
Average	2.1E-13	3.19E-13	1.69E-13	**1.11E-13**	1.87E-13	1.74E-13
SD	1.49E-13	2.83E-13	1.23E-13	5.08E-14	7.51E-14	8.39E-14
Best	7.93E-14	9.01E-14	7.93E-14	7.93E-14	7.93E-14	7.93E-14

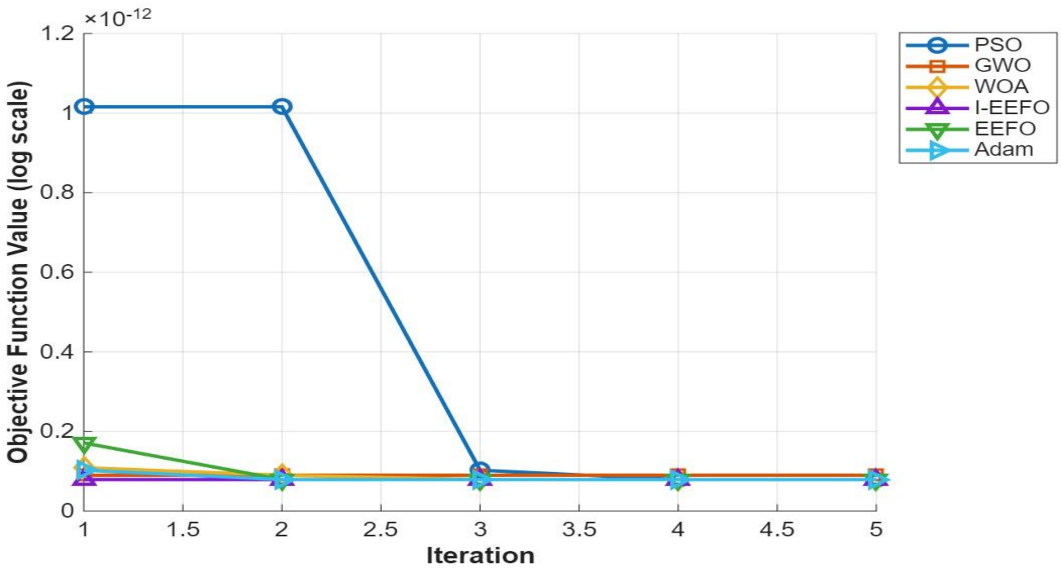


Figure 3: Convergence curves of algorithms for training of SVM for case I.

Figure 3 presents the convergence curves of various algorithms used for training the Support Vector Machine (SVM) model in Case I. The plot shows the objective function values (log scale) over the number of iterations for different algorithms: PSO, GWO, WOA, I-EEFO, EFOO, and Adam. The curves indicate that the I-EEFO and EFOO algorithms outperform the others in terms of faster convergence.

Table 5 presents the optimal SVM model parameters (decision variables) obtained by each

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algorithm in their best execution. Notably, all algorithms selected the Polynomial kernel function as optimal. The Box Constraint parameter was consistently 2 across all models, while the Kernel Scale value was 5 for all cases - except for I-EEFO, where this configuration yielded superior performance.

The reliability assessment metrics for the optimized SVM models on test data are shown in Table 6. All algorithm-trained models demonstrated satisfactory performance, with the I-EEFO-optimized SVM achieving the lowest Mean Percentage Absolute error (MPA = -2.85×10^{-1}%). The GWO-based model showed marginally higher error compared to others. Fig 4 further confirms excellent agreement between predicted and numerically simulated results, displaying the best-performing run from each algorithm's 10 executions.

These results collectively demonstrate that the machine learning approach can effectively serve as an alternative to conventional optimization methods, as evidenced by its accurate prediction of the braced two-story frame's structural response.

Table 5: Design variables for the SVM model in training for the two-story frame.

		Algorithm					
		PSO	GWO	WOA	I-EEFO	EEFO	Adam
Variables	Kernel	Polynomial	Polynomial	Polynomial	Polynomial	Polynomial	Polynomial
	Kernel scale	5	5	5	6	5	5
	Box Constraint	2	2	2	2	2	2

Table 6: Results of the SVM-based model for the two-story frame in test phase.

Parameter	**Algorithm**					
	PSO	GWO	WOA	I-EEFO	EEFO	Adam
RMSE (m)	2.67E-07	3.03E-07	2.67E-07	2.67E-07	2.67E-07	2.67E-07
MAE (m)	2.00E-07	2.36E-07	2.00E-07	2.00E-07	2.00E-07	2.00E-07
MPE (%)	3.71E-01	3.71E-01	3.71E-01	-2.85E-01	3.71E-01	3.71E-01
NSE	9.88E-01	9.85E-01	9.88E-01	9.88E-01	9.88E-01	9.88E-01

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Figure 4 illustrates the comparison between predicted and simulated frame displacement values obtained using the SVM model under six optimization algorithms: PSO, GWO, WOA, I-EEFO, EFOO, and Adam. Each subplot shows the predicted displacement plotted against the observed values, along with the corresponding coefficient of determination (R^2). All models demonstrate high prediction accuracy with R^2 values close to 0.99, indicating strong agreement between the simulated and predicted results.

4.1. Case study II

The second steel frame used to evaluate the effectiveness of the proposed approach is a 7-story, three-bay structure, with the second bay featuring cross-bracing. Fig 5 schematically illustrates this frame, and the specifications of its members are similar to those in Table 3. This structure is subjected to a lateral force of 70 kN at each floor and has 150 variables affecting the system response, considering the cross-sections and moments of inertia of all members.

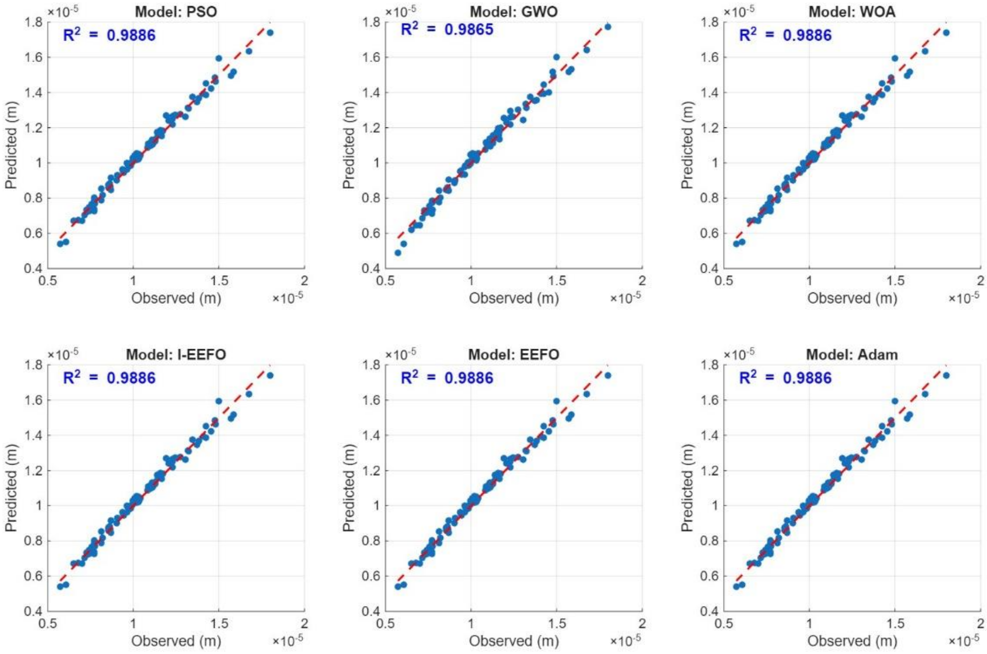

Figure 4: Predicted versus simulated values of frame displacement by SVM.

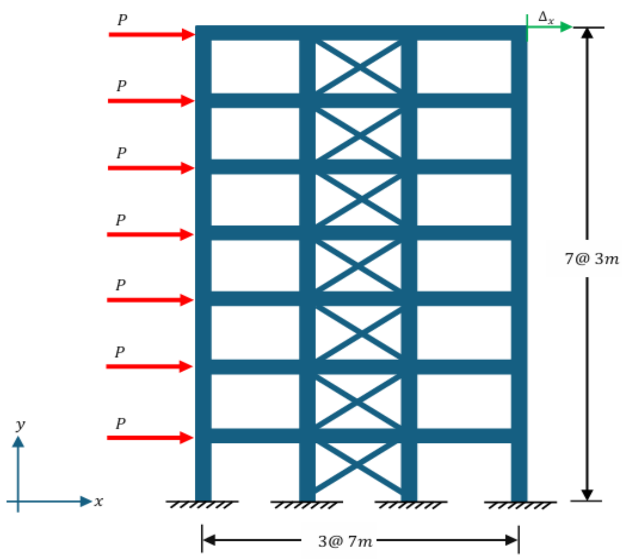

Figure 5: Schematic of second case study.

Figure 5 presents the schematic of the second case study, consisting of a seven-story, three-

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bay steel frame. Each story has a height of 3 meters, and each bay spans 7 meters. Lateral loads (P) are applied at each floor level, and the lateral displacement (Δ) is indicated at the top of the frame. Cross-bracing is incorporated within the frame to enhance lateral stiffness and resistance.

Table 7 shows the MSE values (objective function) for each execution of the algorithm, along with the mean and standard deviation of the responses. As can be seen, all the developed models based on SVM and metaheuristic algorithms have achieved better accuracy than the Adam-based SVM model. Notably, the lowest value of the objective function corresponds to the I-EEFO algorithm, which is equal to 2.95E-07. Additionally, the lowest mean value is also associated with this algorithm, equal to 2.99E-07. Meanwhile, the WOA algorithm has achieved the lowest standard deviation of 2.21E07, indicating its robustness in finding solutions.

Fig. 6 illustrates the convergence graph of the selected metaheuristic algorithms during the training process of the SVM for estimating the structural response of the 10-story building, based on the best response obtained across 10 executions. As evident, the EEFO and GWO algorithms converged in the first iteration, providing their obtained response as the final answer. This indicates an inappropriate balance between the exploration phases of these algorithms, leading them to not seek suitable responses in subsequent iterations. Adam reached the optimal response in the second iteration, while PSO found it in the third. In contrast, the enhanced I-EEFO version, in the third iteration, managed to provide the best response by suitably searching for and finding the lowest objective function value among the algorithms, demonstrating the positive impact of the approach used to improve EEFO.

Table 7: Results of the SVM-based model for the 7-story frame in training process.

No. Run	Algorithm					
	PSO	GWO	WOA	I-EEFO	EEFO	Adam
Average	4.10E-07	3.01E-07	3.01E-07	**2.99E-07**	4.01E-07	4.59E-07
SD	2.33E-07	5.09E-09	**2.21E-09**	4.73E-09	2.13E-07	2.38E-07
Best	2.98E-07	2.98E-07	2.98E-07	**2.95E-07**	2.98E-07	2.99E-07

Figure 6 illustrates the convergence curves of different algorithms used for training the SVM model in Case II. The x-axis represents the number of iterations, while the y-axis shows the objective function value on a logarithmic scale. The compared algorithms include PSO, GWO, WOA, I-EEFO, EFOO, and Adam. The results indicate that the I-EEFO algorithm achieves the fastest and most stable convergence compared to the other methods.

Table 8 presents the values of the decision variables, or in other words, the parameters of the SVM model provided by the optimization algorithms. As indicated, the kernel function of the SVM model was chosen as Gaussian by all algorithms, highlighting the high flexibility of this kernel in handling high-dimensional problems and complex relationships for simulation. The Kernel scale values vary among the algorithms, ranging from 9 to 27, with the lowest and highest values belonging to I-EEFO and WOA, respectively. Interestingly, the Box Constraint parameter values are uniformly set to 3 across all algorithms, indicating that the parameter influencing the results is the Kernel scale.

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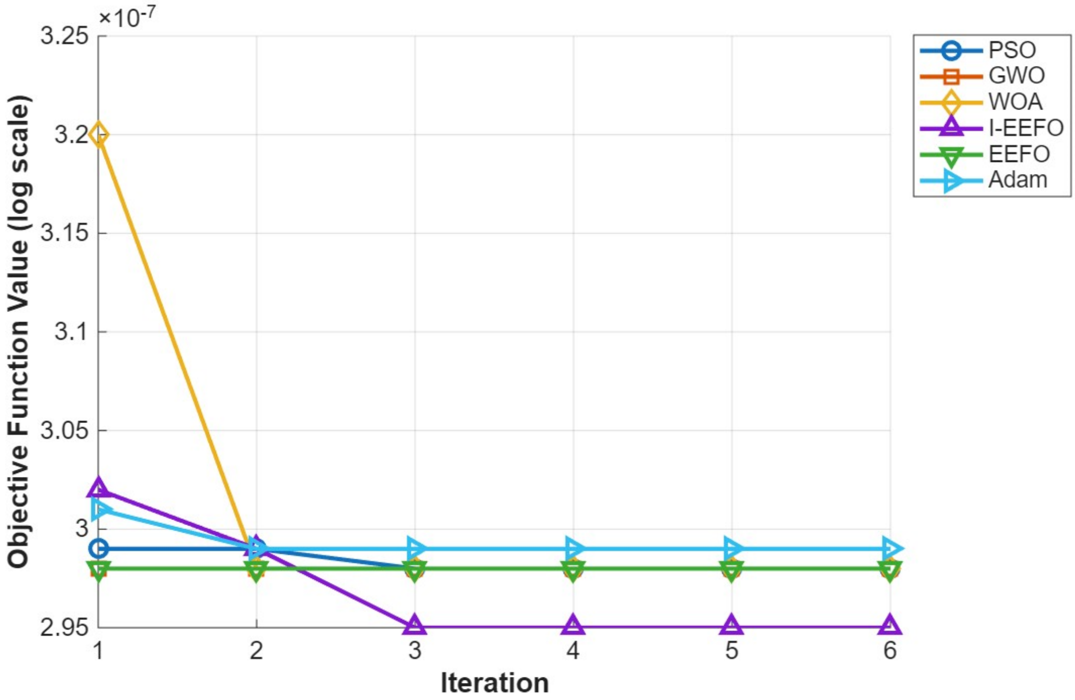

Figure 6: Convergence curves of algorithms for training of SVM for case II.

Table 8: Design variables for the SVM model in training for the two-story frame.

		Algorithm					
		PSO	GWO	WOA	I-EEFO	EEFO	Adam
Variables	Kernel	Gaussian	Gaussian	Gaussian	Gaussian	Gaussian	Gaussian
	Kernel scale	19	19	27	9	13	12
	Box Constraint	3	3	3	3	3	3

Table 9 presents the statistical parameters calculated for the test data, based on the predicted roof displacements of the 10-story structure by the SVM model using optimization algorithms. As indicated, the RMSE and MAE parameters, which represent the model's error, have the lowest values for the I-EEFO algorithm, suggesting that the predicted values from the SVM model developed by this algorithm are considerably more accurate. The MPE parameter, which indicates the mean percentage error, is very small for all models, around 1%. However, it is negative for all models, indicating an overestimation of the roof displacement compared to the actual value. Nevertheless, the I-EEFO algorithm provides the lowest MPE and the highest NSE. To demonstrate the superior efficiency of soft computing methods in estimating the structural response of tall buildings, Fig 7 shows the correlation between the predicted data and the data obtained from simulation. The high R^2 values for the models, with the maximum being 0.9833 for the I-EEFO-based SVM model, are also presented.

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Table 9: Results of the SVM-based model for the 7-story frame in test phase.

Parameters	Algorithm					
	PSO	GWO	WOA	I-EEFO	EEFO	Adam
RMSE (m)	0.000732	0.000732	0.000732	0.000723	0.000733	0.000732
MAE (m)	0.000564	0.000564	0.000564	0.000555	0.000565	0.000564
MPE (%)	-0.454985	-0.454985	-0.457313	-0.405115	-0.458443	-0.457445
NSE	0.981102	0.981102	0.981112	0.981566	0.981050	0.981089

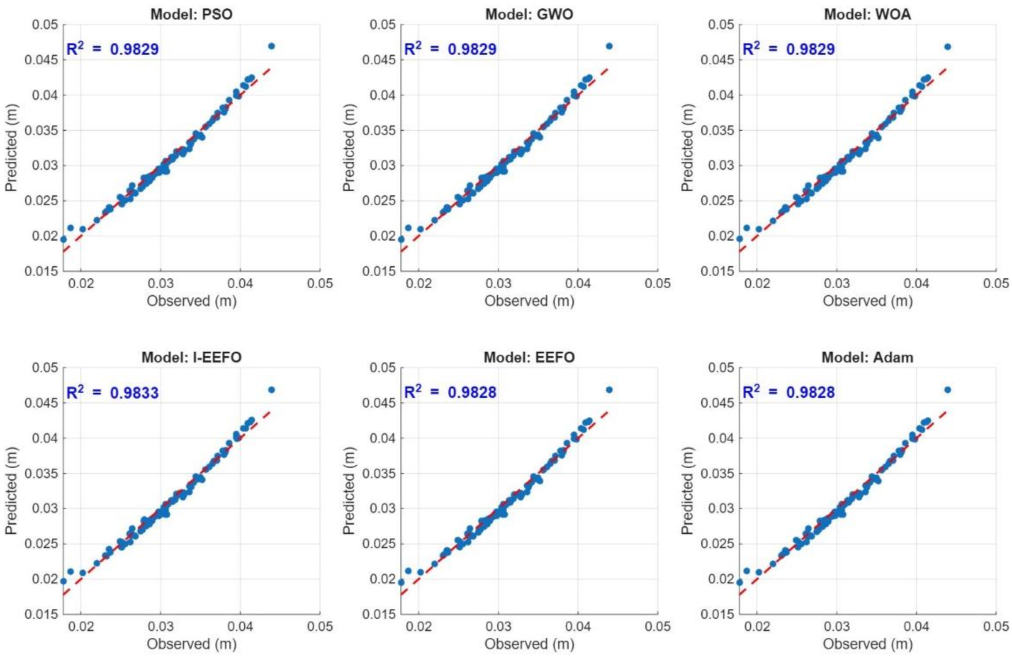

Figure 7: Predicted versus simulated values of frame displacement by SVM.

Figure 7 compares the predicted and simulated frame displacement values obtained using the SVM model in Case II. Six subplots correspond to the optimization algorithms PSO, GWO, WOA, I-EEFO, EFOO, and Adam. Each subplot shows the predicted displacement versus the observed values, along with the coefficient of determination (R^2). All models demonstrate high prediction accuracy, with R^2 values close to or above 0.98, indicating strong agreement between the simulated and predicted results.

The analysis of the results obtained from the above examples indicates that using an alternative approach instead of simulating structures and estimating their responses through machine learning methods provides an accurate response that can significantly reduce the computational time for structural analysis. Furthermore, the use of optimization algorithms can accurately select the parameters of the machine learning model, leading to precise estimations of its responses.

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5. CONCLUSION

This research aims to evaluate the effectiveness of the SVM method and metaheuristic algorithms for estimating the dynamic response of frame structures equipped with braces under lateral forces. The main goal is to reduce the substantial costs associated with dynamic analyses of such structures during the design process or reliability assessment, which typically use finite element models. To this end, five metaheuristic algorithms, including GWO, WOA, PSO, EEFO, and I-EEFO, along with a gradient-based algorithm called Adam, were employed to optimize the tuning parameters of the SVM for enhancing the accuracy of dynamic response estimations. The key findings of this research are:

1. The proposed approach for estimating the dynamic response of structures was highly accurate, with the best response obtained by the I-EEFO SVM model for both studied structures, showing RMSE values of 2.67E-07 and 0.000723 meters for the two-story and ten-story structures, respectively, which are negligible.
2. For both studied structures, the results indicate the high efficiency of metaheuristic algorithms in training SVM compared to the Adam gradient method in terms of accurate responses and rapid convergence, leading to more precise answers during the testing phase.
3. The responses obtained from I-EEFO were the best, demonstrating the effectiveness of the approach used to enhance EEFO. The correlation coefficients for the test data generated by the SVM model using this algorithm were higher than those of other models, with values of 0.9886 and 0.9833 for the two case studies.

As evident, the proposed approach can serve as an alternative model in the design and optimization of structures, as well as in assessing their reliability under uncertainty to reduce computational costs. For future studies, it is recommended to utilize the proposed approach alongside structural optimization and compare it with other machine learning models.

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