Response Prediction Analysis Of RC Frame Structures Using Support Vector Machine Algorithm

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To more accurately predict the structural response under seismic actions, this paper takes two reinforced concrete frame structures with 9- and 11-stories as examples and utilizes the Support vector machine (SVM) algorithm to analyze the efficiency of 6 scalar and 15 vector intensity measures (IMs) in predicting the response of RC frame structures. The time required to determine hyperparameters using a grid search optimization algorithm is also provided. The results show that when using scalar IMs for prediction, SI can better predict the structural response of 9-story structure, $S_a(T)$ can better predict the structural response of 11-story structure, and the hyperparameters of the model can be determined in a relatively short time. When using vector IMs for prediction, the best vector IMs for prediction is $[PGV, S_a(T)]$, and the determination coefficient R^2 of the training and testing sets reaches 0.96 or above, with the standard deviation (β) below 0.3 . Compared with the best prediction results based on scalar IMs, the β is significantly reduced, both by more than 20%. This conclusion provides a theoretical basis for quantitatively evaluating the degree of structural damage caused by seismic motion.

Keywords: Support vector machine; grid search optimization; intensity measures; structural response; prediction model

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1. Introduction

Performance-Based Earthquake Engineering (PBEE) [1–3] aims to quantify the structural damage risk and seismic performance caused by future earthquakes. In recent years, it has gained significant attention and is considered an important method for seismic assessment of existing buildings and the design of new structures [4–6]. As Chandrikka [7] highlights, structural failure modes during seismic events have pushed towards research on different materials and techniques for more resilient buildings. This research analysis can help avoid the economic and environmental costs associated with building failures, as shown by Afzali [8]. When predicting the seismic response of structures, typically linear or logarithmic methods are employed to establish predictive models for the relationship between intensity measures (IMs) and structural response [9–11]. The efficiency and sufficiency of IMs in predicting structural responses are analyzed [12, 13]. In the study of IMs, PGV and PGA are widely used due to their simplicity in calculation and applicability. For stiff structures with lower natural vibration periods, PGA is known to exhibit relatively high correlation with structural response. However, for medium- to long-period structures, PGV becomes more important and demonstrates higher correlation [14, 15]. $S_a(T)$ has consistently been considered a good IM to predict structural response and is adopted in design spectra in many countries [16–18]. It is often used as a parameter for amplitude scaling in incremental dynamic analysis (IDA). However, when structures undergo nonlinear response, the model for predicting structural response based on IMs changes, leading to increased uncertainty in the response

[19]. Therefore, some experts have investigated the establishment of vector IMs to enhance the ability to predict structural responses [20–22]. Ebrahimian et al. [23] have simultaneously analyzed scalar and vector IMs, revealing that vector IMs containing PGA or $S_a(T)$ can efficiently represent the max floor acceleration (MFA) and maximum inter-story drift ratio (MIDR).

Additionally, some experts have utilized support vector machine (SVM) algorithm to build prediction models for IMs and structural responses [24, 25]. Xu et al. [24] applied the probabilistic support vector machines (PSVM) in this paper for the system fragility analysis of existing highway bridges structures. Zhou et al. [25] introduced the method of SVM to improve the computational efficiency of estimating structural response. Therefore, this paper mainly studied the dynamic response analysis of medium-story reinforced concrete frame structures based on the SVM method. This paper first selected 6 scalar IMs and 15 vector IMs that reflect amplitude, duration, and spectral characteristics. Then, two representative reinforced concrete frame structures of 9-story and 11-story are established. Lastly, the efficiency of IMs in predicting structural responses are analyzed by using the SVM algorithm.

2. Selection of ground motion records and IMs

In this study, a dataset of 1000 horizontal ground motion records were selected from the Pacific Earthquake Engineering Research (PEER) database for analysis. All ground motion records were sourced from different stations, and the distribution of earthquake magnitude and epicentral distances for the selected earthquake events is illustrated in Fig. 1. Earthquake magnitude and epicentral distance play crucial roles in determining the seismic hazard and potential damage to structures. As the earthquake magnitude increases, so does its destructive capacity, resulting in greater seismic risk for structures. Therefore, most of the ground motion records selected in this paper with a magnitude greater than 5. Under the conditions of significant earthquake events, the selected range of epicentral distances is broad, extending up to 400km. For earthquakes 6 scalar IMs were selected in this study, as shown in Table 1. These IMs were chosen for their ability to reflect amplitude, duration, and spectrum characteristics of ground motions, and they were used to characterize the structural response. These IMs are commonly employed for predicting structural responses, with PGA and PGV often used as measures of ground motion intensity [26]. $S_a(T)$ is utilized in many national building codes and standards, and duration-based IMs are used in conjunction with other IMs to predict structural response.

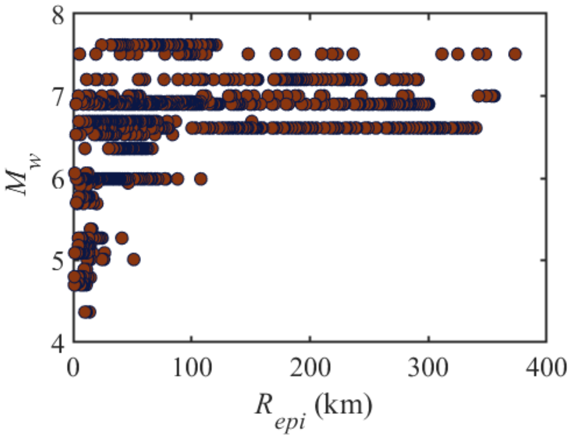


Fig. 1. Distribution of earthquake magnitude and epicentral distance.

Furthermore, this study also analysis the efficiency of 15 vector IMs. The prediction capabilities of these vector IMs in relation to structural response were analyzed. The distribution histograms of these 6 scalar IMs are depicted in Fig. 2.

3. Establishment of structural models

To analyze the correlation between different IMs and structural responses, two representative reinforced concrete frame structures of 9-story and 11-story were separately established for analysis. The design and construction of the structural models were based on the relevant research findings of Chang [27] and Lai [28]. The natural vibration periods of these two structures were 1.18 s and 1.93 s, respectively. They were designed for a seismic design intensity of 7 degrees and categorized as type II site conditions. The structures utilized an improved IK three-linear hysteresis model, with a concrete strength grade of C30. The roof live load was 0.4 $\mathrm{kN/m^2}$. The elevations of both structures are shown in Fig. 3, and the rebar designs for columns and beams are detailed in Tables 2 and 3. The main reinforcement for the components was Grade III steel, and the stirrups were Grade I steel. The calculation of structural dynamic responses was performed using the IDARC_2D software. During the calculations, it was assumed that the stiffness of the floor plan was infinitely large. Stiffness degradation coefficient α, strength degradation coefficient k, and pinching effect coefficient γ were employed to comprehensively describe the hysteresis behavior of the components. For the calculations, this study employed $\alpha = 2.0, k = 0.1$, and $\gamma = 0.1$, indicating that the elastic-plastic hysteresis model of reinforced concrete structures has the characteristics of moderate stiffness degradation,

Table 1. Selected intensity measures in this paper.

Scalar IMs	Vector IMs
Peak ground acceleration (PGA)	$[PGA, PGV]$; $[PGA, PGD]$; $[PGA, D_s]$; $[PGA, S_a(T)]$; $[PGA, SI]$; $[PGV, PGD]$; $[PGV, D_s]$; $[PGV, S_a(T)]$; $[PGV, SI]$; $[PGD, D_s]$; $[PGD, S_a(T)]$; $[PGD, SI]$; $[D_s, S_a(T)]$; $[D_s, SI]$;
Peak ground velocity (PGV)	
Peak ground displacement (PGD)	
Significant time (D_s)	
First order acceleration response spectrum $(S_a(T))$	
Housner spectral intensity (SI)	

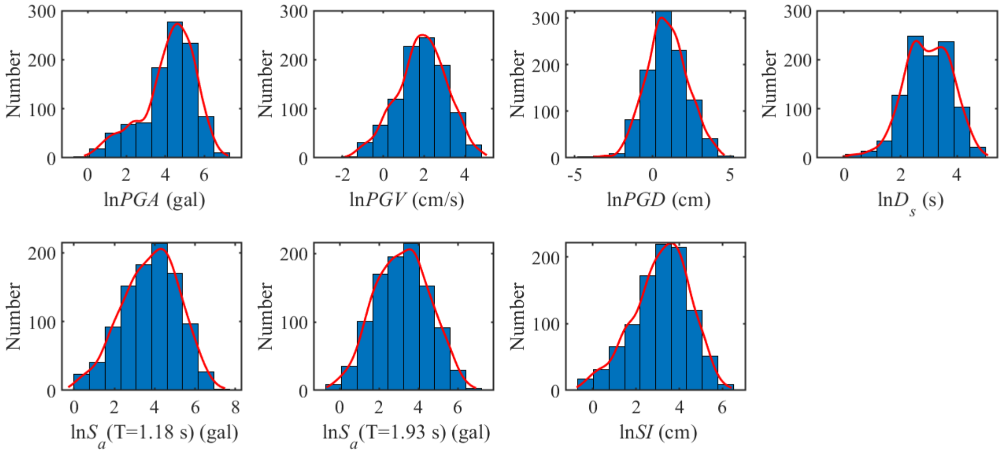


Fig. 2. Histogram distribution of ground motion IMs.

moderate strength degradation, and significant pinching effect [29]. The concentrated plasticity is considered in this paper.

4. The principle of SVM algorithm

The SVM algorithm, introduced by Cortes and Vapnik in 1995 , has since evolved and expanded. Vapnik later proposed the ε-SVR algorithm, introducing an ε-insensitive loss function [30] and applying SVM to regression prediction models. The fundamental principle of SVM involves mapping input data into a high-dimensional feature space through the use of a kernel function, thereby transforming non-linear problems into linear ones. This algorithm offers advantages such as good generalization performance, suitability for small datasets, and high-dimensional feature spaces.

In SVM, the process begins by mapping the input data X into an m-dimensional feature space using a fixed (non-linear) mapping. Subsequently, a linear model is constructed in this feature space, as shown in Eq. (1) [31]:

$$f(X,\omega)=\sum_{k=1}^{m}\omega_k\phi_k(X)+b \tag{1}$$

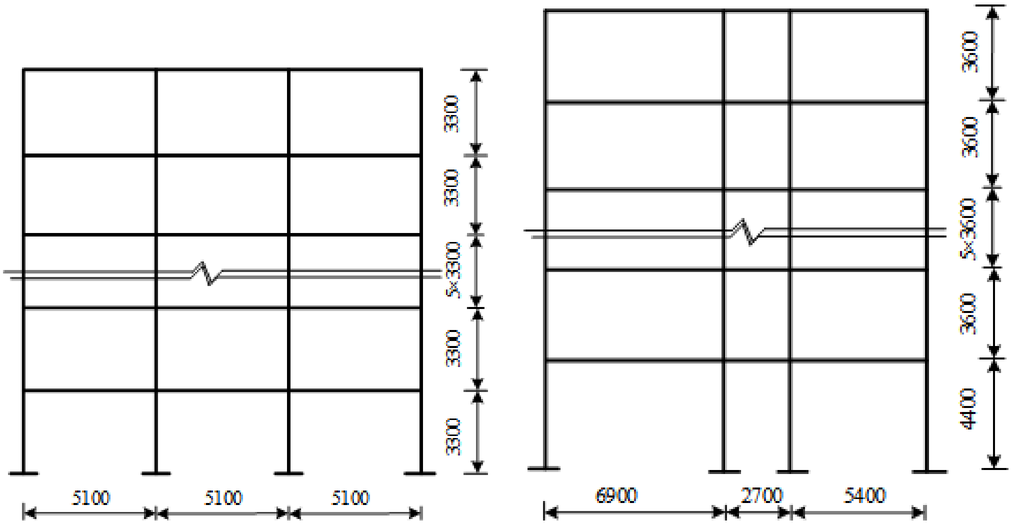
where " m " represents the total number of dimensions in the feature space, " k " denotes a k-dimensional space, " ω_k " signifies the weight coefficients in the k dimensional space, and it represents a set of non-linear transformations, while " b " stands for the bias term.

The SVM algorithm employed in this paper utilizes a novel loss function known as the ϵ-Insensitive Loss Function to minimize empirical risk, defined as shown in Eq. (2):

$$L_\varepsilon(Y,f(X,\omega))=\begin{cases}0 & \text{if} \quad |Y-f(X,\omega)|\le\varepsilon\\ |Y-f(X,\omega)|-\varepsilon & \quad\;\; |Y-f(X,\omega)|>\varepsilon\end{cases} \tag{2}$$

where " Y " represents the predicted values of the training outputs, " ε " stands for the permissible error, signifying the approximation precision of the training data points. In a high-dimensional feature space, support vector regression (SVR) uses the ε insensitive loss to perform linear regression in the high-dimensional feature space. Essentially, it is an optimization problem that can be expressed as the minimization of the function represented by Eq. (3).

$$\begin{gathered}\min\frac{1}{2}\|w\|^2+C\sum_{i=1}^{n}\left(\xi_i-\xi_i^*\right)\\ \text{S.T.}\left\{\begin{array}{c}y_i-f\left(x_i,w\right)-b\le\varepsilon-\xi_i^*\\ f\left(x_i,w\right)+b-y_i\le\varepsilon+\xi_i\\ \xi_i,\xi_i^*\ge 0\end{array}\right.\end{gathered} \tag{3}$$



(a) 9-story (b) 11-story

Fig. 3. Elevation view of two structural models.

Table 2. Beam cross-sectional dimensions and reinforcement parameters for two structures.

Structural model	Story	Edge beam	Middle beam	Edge beam main reinforcement (mm^2) / Stirrup	Middle beam main reinforcement (mm^2) / Stirrup
9-story	1	500×250	500×250	$1296/\phi8@100$	$710/\phi i8@200$
	$2-6$	500×250	500×250	$1015/\phi8@100$	$710/\phi8@200$
	$7-9$	500×250	500×250	$833/\phi8@100$	$710/\phi8@200$
11 -story	$1-4$	600×250	400×250	$1610/\phi8@100$	$1964/\phi8@100$
	$5-6$	600×250	400×250	$1610/\phi8@100$	$1964/\phi8@100$
	$7-10$	600×250	400×250	$1256/\phi8@100$	$1256/\phi8@100$
	11	600×250	400×250	$942/\phi8@100$	$942/\phi8@100$

Table 3. Column cross-sectional dimensions and reinforcement parameters for two structures.

Structural model	Story	Edge column	Middle column	Edge column main reinforcement (mm^2) / Stirrup	Middle column main reinforcement (mm^2) / Stirrup
9-story	1	550×550	550×550	$2733/\phi8@100$	$2733/\phi8@100$
	$2-9$	500×500	500×500	$2035/\phi8@100$	$2035/\phi8@100$
11 -story	$1-6$	600×600	600×600	$3807/\phi10@100$	$3807/\phi10@100$
	$7-11$	550×550	550×550	$3411/\phi10@100$	$3411/\phi10@100$

By minimizing $\frac{1}{2}\|\omega\|^2$ to reduce the complexity of the model, where C is the regularization parameter used to adjust the model complexity and training error. This optimization formula can be transformed into a dual problem, and its solution in Eq. (4)

$$f(x)=\sum_{i=1}^{n}\left(a_i-a_i^*\right)k\left(x_i,x\right)+b \tag{4}$$

where dual variables are constrained, $0 \leq a_{\mathrm{i}}, a_{\mathrm{i}}{}^* \leq \mathrm{C}$; the kernel function $k\left(x_i,x\right)$ is a symmetric function that satisfies the Mercer condition.

In this case, the Support Vector Machine (SVM) employs a radial basis function (RBF) kernel as the kernel function. The selection of the regularization parameter " C ", the RBF parameter " γ " and the permissible error " ε " has a significant impact on the prediction of structural responses, representing the approximation precision of the training data points. To find the best parameters, this study employs a grid search optimization approach [32]. The grid search method involves systematically evaluating all possible parameter values by grouping them. Based on empirical considerations, the approximate ranges for the two parameters are typically set at $[-10,10]$, with a step size of 0.5 . Subsequently, it calculates the potential optimal parameter values within each grid. The optimization process involves observing the values of the coefficient of determination (R^2) and the standard deviation (β) on the training and testing sets to determine whether the results are optimal. This approach aims to identify the best parameters. The experimental machine configuration includes a 64-bit operating system, 16GB of memory, an Intel(R) Core(TM) i7-8700 CPU @ 3.20GHz, and a running environment on Windows 10 Professional. The algorithm is implemented using Matlab2021a. Furthermore, this study uses the standard deviation (β) and the determination coefficient (R^2) as criteria to assess which IMs perform better in predicting structural responses.

5. Prediction results analysis

5.1. Analysis of structural response prediction based on scalar IMs

To determine the optimal IMs for predicting the response of structures, this study used the SVM algorithm with 6 scalar IMs to predict the structural responses. The maximum inter-story displacement ratio (MIDR) is mainly used as the criterion to evaluate the damage state of structures. The obtained prediction model hyperparameters are shown in Table 4. The calculation results are shown in Fig. 4.

It can be concluded that for the 9-story structure, the most efficient IM is SI. The R^2 for both the test set and training set calculated using SVM method are 0.94 , with β of 0.33 and 0.32 , respectively. In addition, $S_a(T)$ and PGV have relatively good predictive effects on the response of the 9-story structure, with a larger R^2 and less dispersion. Similarly, when analyzing the 11-story structure, the most efficient IM is $S_a(T)$. The R^2 for both the test set and training set calculated using SVM method are 0.94 and 0.93 , with β of 0.33 and 0.35 , respectively. In addition, SI and PGV have relatively good predictive effects on the response of 11-story structure. However, when establishing prediction models for the D_s and the response of 9-story and 11-story structures, the D_s is a poor indicator of structural response due to its low R^2 and high β. Therefore, when using scalar IMs to predict the structural response, $PGV, S_a(T)$, and SI demonstrate strong prediction capabilities. Furthermore, Fig. 5 illustrates the time required for SVM model parameter optimization based on scalar IMs. When establishing prediction models by using $PGV, S_a(T)$, and SI, the time for hyperparameter optimization is minimized.

Table 4. Model Scalar -parameters for predicting structural response based on scalar IMs.

IMs	9 -story			11-story		
	C	γ	ε	C	γ	ε
PGA	-1.0	2.5	0.0638	-1.5	5.5	0.0730
PGV	0.0	3.0	0.0159	4.0	3.5	0.0189
PGD	6.0	3.0	0.0752	3.5	2.5	0.0631
D_s	-2.5	0.5	0.1480	-2.5	4.0	0.1357
$S_a(T)$	3.0	1.5	0.0103	1.5	4.5	0.0108
SI	1.0	1.5	0.0100	-0.5	0.0	0.0186

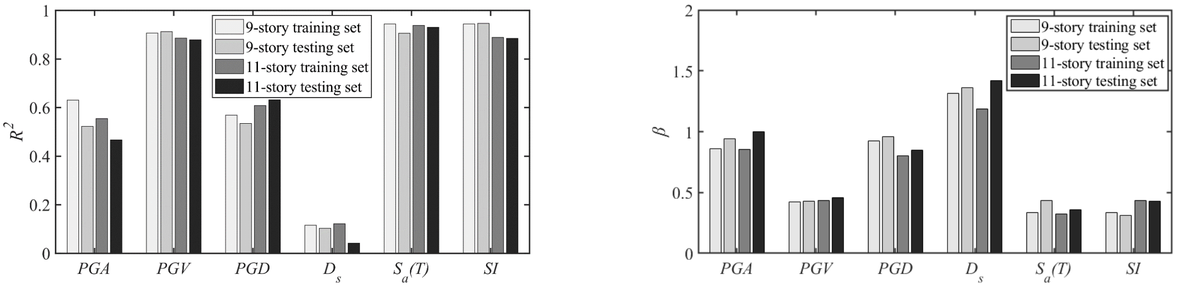
5.2. Analysis of structural response prediction based on vector IMs

It is challenging to fully predict actual structural responses based on scalar IMs. Therefore, this study employed the SVM algorithm to analyze the efficiency of predicting structural responses using vector IMs. The computed hyperparameters are presented in Table 5, and the calculation results are shown in Fig. 6. The time required for calculating SVM predictive model hyperparameters based on vector IMs is shown in Fig. 7.

Table 5. Model hyper-parameters for predicting structural response based on vector Ims.

IMs^2	9-storye.			11-storye.		
	C	γ	ε	C	γ	ε
$[PGA, PGV]$	1.5	0.5	0.0125	2.0	0.5	0.0128
$[PGA, PGD]$	2.0	0.5	0.0296	2.0	1.5	0.0297
$[PGA, D_s]$	-1.5	4.0	0.0531	0.0	4.0	0.0547
$[PGA, S_a(T)]$	4.5	2.0	0.0099	-0.5	1.5	0.0088
$[PGA, SI]$	2.5	0.5	0.0078	0.5	0.5	0.0128
$[PGV, PGD]$	0.5	1.0	0.0129	1.5	2.5	0.0132
$[PGV, D_s]$	1.5	1.0	0.0143	0.5	1.5	0.0144
$[PGV, S_a(T)]$	-0.5	2.0	0.0064	0.0	2.5	0.0061
$[PGV, SI]$	2.0	0.5	0.0083	4.5	2.0	0.0150
$[PGD, D_s]$	-0.5	1.5	0.0413	0.0	3.5	0.0338
$[PGD, S_a(T)]$	6.5	1.5	0.0077	2.0	2.0	0.0084
$[PGD, SI]$	1.5	0.5	0.0072	2.0	-0.5	0.0094
$[D_s, S_a(T)]$	-1.0	0.5	0.0111	2.0	1.0	0.0095
$[D_s, SI]$	1.0	0.0	0.0091	1.5	2.5	0.0126
$[S_a(I), SI]$	-0.5	2.5	0.0063	1.5	3.0	0.0078

From the calculation results in Figure 6, it can be concluded that when predicting the response of the 9-story and 11-story structures, when the vector IMs includes PGV, $S_a(T)$, and SI, the calculated R^2 is relatively large, β is relatively small and has a good predictive effect on structural response, and its predictive effect is better than that of scalar IMs. The best efficient IM among them is $[PGV, S_a(T)]$. The R^2 is maximum, and the β value is the smallest. When predicting the response of the 9-story structure, the R^2 of both the training and testing sets is 0.97 , and the β values are 0.25 and 0.23 , respectively. Compared



(a) R^2 (b) β

Fig. 4. Efficiency analysis of scalar intensity measures and structural responses ((a) R^2, (b) β).

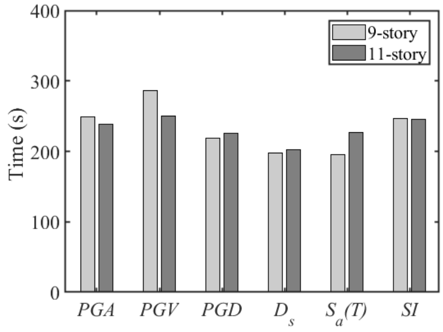
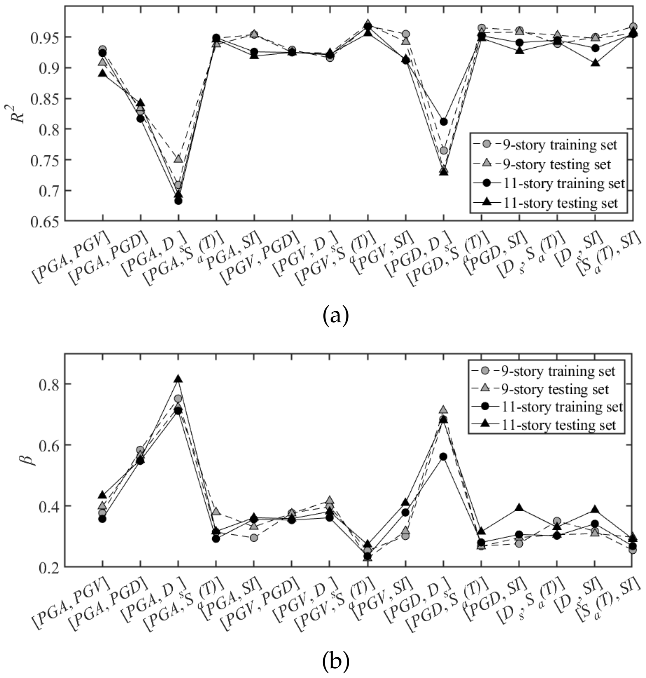


Fig. 5. Time consumption to calculate scalar-parameters of SVM prediction model based on.



(a)

(b)

Fig. 6. Efficiency analysis of scalar IMs and structural responses ((a) R^2, (b) β).

with using only SI to predict structural response, the standard deviation is reduced by 24% and 28%. The use of vector IMs greatly reduces the discreteness of predicting structural response. When analyzing the response of the

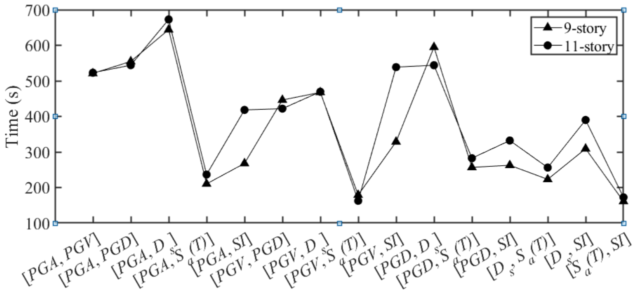


Fig. 7. Time consumption to calculate hyper-parameters of SVM prediction model based on.

11-story structure, the R^2 values for the training and testing sets were 0.97 and 0.96 , and the β values are 0.24 and 0.27 , respectively. Compared to using only $S_a(T)$, the standard deviation was reduced by 27% and 23%. Based on the calculation results of these two structures, it can be concluded that the prediction of structural response based on vector IMs greatly reduces discreteness.

Additionally, as shown in Fig. 7, the time required for hyperparameter optimization when establishing SVM prediction models based on $[PGV, S_a(T)]$ is the shortest. The average optimization time is approximately 171 seconds, while the average optimization time for scalar Intensity measures PGV and $S_a(T)$ is around 240 seconds. Consequently, it is evident that using vector IMs for predicting structural responses yields the best results and the shortest optimization time.

6. Conclusion

In this study, two representative RC frame structures of 9-story and 11-story structures were used as examples. The efficiency of predicting the response of RC frame structures was analyzed using the Support Vector Machine (SVM) algorithm, Structural response prediction models were established by considering 6 scalar IMs and 15 vector IMs., and model hyperparameters were determined. The following conclusions were drawn from the analysis:

1. For scalar IMs, the SI is the optimal IM to predict the structural responses of the 9-story, and the $S_a(T)$ is the optimal IM to predict the structural responses of the 11story. The determination coefficients of the test set and training set calculated using SVM method reach above 0.90 , with the β values of below 0.40.

2. For vector IMs, it can be seen that the vector IM with the best prediction effect is $[PGV, S_a(T)]$, and the R^2 of both the training and testing sets reaches above 0.95 , with the β value below 0.3 . This IM can be used as the optimal IM for quantitative evaluation of structural response in this paper.

3. when using $[PGV, S_a(T)]$ to predict structural response, the standard deviation is reduced by more than 20% compared with that of using scalar IMs. The dispersion is greatly reduced.

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Conflicts of interest

The authors declare no conflict of interest.

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