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Research Article

Importance Analysis of Structural Seismic Demand Based on Support Vector Machine

Xiuzhen Wang,[1,2] Zhaoxia Xu ,[1] Lianjie Jiang,[1,2] Chuanzhi Sun,[1,2] Jun Yan,[1,2] and Li Gao[1,2]

[1]*School of Civil Engineering and Architecture, Suqian University, Suqian 223800, China*
[2]*Jiangsu Prefabricated Building and Intelligent Construction Engineering Research Center, Suqian University, Suqian 223800, China*

Correspondence should be addressed to Zhaoxia Xu; liuyunmantian@126.com

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Seismic demand analysis of structures plays an important role in the structural seismic calculation; however, studies on the importance analysis of seismic demand are limited. A new method based on a support vector machine (SVM) is proposed to analyze the importance of structural seismic demand and study the influence of random variables on structural seismic demand in this study, where the linear kernel function, Gauss kernel function, and polynomial kernel function are used in SVM. The time history analysis of the steel-reinforced concrete (SRC) frame structures has been carried out by the finite element software OpenSees under the action of different seismic records. Four kinds of seismic demand of the SRC frame structure are analyzed in this study, which are top displacement, maximum floor acceleration, base shear, and maximum interstory drift angle, respectively. Importance indexes of the four kinds of structural seismic demand are in good agreement with those of the Monte Carlo (MC) numerical simulation method and Tornado graphic method, which verify the accuracy of the proposed method. Moreover, the sample size of the proposed method is greatly smaller than that of the MC method. Therefore, the computation efficiency has been improved significantly by the proposed method.

1. Introduction

Seismic demand analysis of structures is an important research direction of structural seismic analysis. There are several parameters that affect the seismic demand of structures, such as the randomness of seismic intensity [1] and the random variables of structures [2, 3]. However, there are few studies on the effects of the uncertainty of the random variables on the structural seismic demand. Therefore, it is very important to study and deal with the random variables in structures to analyze the seismic demand of structures for structural safety [4].

The analysis of the influence of random variables on the seismic demand of structures belongs to the uncertainty analysis [3]. There are many research methods for the uncertainty analysis [5, 6], in which the sensitivity analysis of random variables is the prevailing method for the uncertainty analysis [7, 8]. It is well known that the sensitivity analysis includes two common methods, which are the local sensitivity analysis (LSA) and the global sensitivity analysis (GSA, also known as importance analysis), respectively [9]. The LSA method can only study the influence of random variables on the output response under certain conditions, which means the influence of random variables on the output response is only informative at a nominal point [10, 11], while the GSA method can study the influence of random variables on output response when their possible range of values changes and can study the influences of the random variables simultaneously [12]. Hence, GSA has been widely used in the field of reliability engineering. For example, Hariri-Ardebili et al. [13] proposed an efficient sensitivity analysis framework based on polynomial chaos expansion metamodel to find the most critical elements of infrastructures and capture the spatial uncertainty using random field theory; the results show the impact of uncertainty quantification in system identification of infrastructures. Amini et al. [14] introduced an efficient reliability and sensitivity methodology considering nonlinear dependency among random variables via copula theory and compared the effects of vine copula (i.e., the nonlinear correlation between random variables) and Gaussian copula (linear correlation) on the sensitivity analysis results. Zhou et al. [15] developed a GSA approach based on the theory of active subspaces and Kriging surrogate metamodeling to find the most significant inputs of a radome structure in fiber-reinforced composites.

Therefore, the GSA is adopted to study the effects of the uncertainty of the random variables on the structural seismic demand in this paper. It is worth noting that the importance analysis of random variables should satisfy three conditions: quantifiability, globality, and universality [16]. Borgonovo [17] considered that the important measure index can fully reflect the average influence of the distribution of random variables on the distribution characteristics of the output response. It is a quantitative index with clear physical meaning. Importance measure analysis can link the uncertainty of random variables with the uncertainty of output response [4]. The importance measure index can determine the magnitude of the impact of the uncertainty of each random variable on the output response and then determine their priority in research or experiment. Therefore, the importance ordering of random variables or even the unknown parameters can be determined. Then, the uncertainty range of output response can be reduced ultimately. Finally, the output response with a small uncertainty range can be obtained [12, 18]. This importance measure analysis has provided a new and effective method to improve the structural model. Therefore, the importance measure analysis of random variables has become an important research direction in the field of reliability engineering in recent years.

There are three importance measure analysis methods for random variables to date, which are variance-based importance analysis [19], information entropy-based importance analysis [20], and the moment-independent importance analysis [21, 22], respectively. The importance analysis method based on variance is used more widely than the other two. According to work by Sobol [12], the importance analysis method based on the variance has the following advantages: (1) the interaction between random variables can be reflected by the total measure index; (2) the influence of random variables on the variance of output response can be obtained when the random variables change in their whole range; (3) the random variables can be classified and discussed; (4) the general applicability of this method for any input-output model. Therefore, the importance analysis based on the variance is applied for the seismic demand analysis of structures in this article.

Monte Carlo (MC) numerical simulation method is a common solution method in the importance analysis based on variance [23]. However, it needs a large number of samples. Even if the efficient sampling method is applied to MC [24], the sample size is still large, which will increase the calculation difficulty for the complicated structures. In view of this, this article proposes a new method based on the support vector machine (SVM) algorithm [25, 26] to perform the importance analysis and investigate the influence of random variables on the seismic demand of structures, where the sample size required by the proposed method is far less than that of MC. The corresponding importance index obtained by SVM is called the importance measure index of SVM. The importance of the structural seismic demand of two SRC frame structures is analyzed. The accuracy and efficiency of the proposed method are verified by comparing it with the MC method because the MC method is usually considered the precise solution. The results are also compared with the Tornado graphic method, which is a LSA method [27].

2. Importance Analysis Method Based on Support Vector Machine

2.1. Basic Principles of Support Vector Machine Algorithms. Support vector machine was first proposed by Vladimir N. Vapnik and developed by Corinna and Vapnik [28], which was originally used for pattern recognition. It can also be used for regression problems. These two approaches are similar. Suppose the training sample sets are $\{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$, $x_i, y_i \in R$, and $x = (x_1, x_2, \ldots, x_n)'$ is the dataset. Assuming that all vectors represent column vectors, then $x_1 \sim x_n$ represent the transposed row vectors. Let $I = (1, 1, \ldots, 1)^T$; the length of I is n. Then, the linear regression function is defined as follows:

$$f(x) = wx + b, \tag{1}$$

where w and b both are the undetermined coefficients.

The objective function of SVM is to make all sample points approach the optimal hyperplane and minimize the total deviation of sample points. When the sum of absolute deviations between real and predicted results of all samples is not greater than a sufficiently small positive number ε, it can be considered that the obtained hyperplane is determined by w and b, as follows:

$$\sum_{i=1}^{n} \left| f(x_i) - y_i \right| \leq \varepsilon. \tag{2}$$

The sum of absolute residuals is affected by w and b. The distance from point (x_i, y_i) to hyperplane is used to correct the above conditions:

$$\sum_{i=1}^{n} \frac{\left| x_i w + bI - y_i \right|}{\sqrt{1 + ||w||^2}} \leq \sum_{i=1}^{n} \left| f(x_i) - y_i \right| \leq \varepsilon \longrightarrow \sum_{i=1}^{n} \left| f(x_i) - y_i \right| \in \left[0, \varepsilon \cdot \sqrt{1 + ||w||^2} \right]. \tag{3}$$

It can be seen that the smaller $||w||^2$ is, the closer the corresponding hyperplane is for the optimal hyperplane. Therefore, SVM should solve the following optimization problems:

$$\begin{gathered} \min \frac{1}{2} ||w||^2, \\ \text{s.t.} |xw + bI - y| \leq \varepsilon. \end{gathered} \tag{4}$$

Generally, the existence of fitting errors is allowed, and the relaxation factors ξ^* and ξ are introduced, then the above problem is transformed into the following:

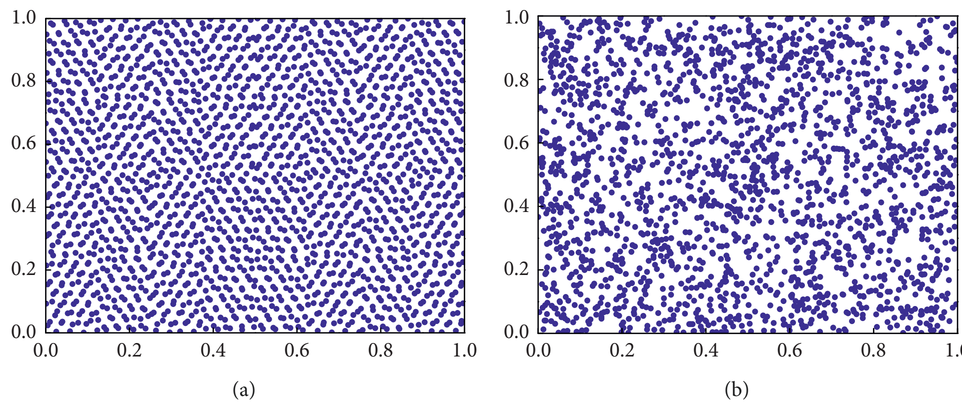


FIGURE 1: Sample comparison: (a) Sobol sequence and (b) ordinary random sampling.

$$\min \frac{1}{2}\|w\|^2 + C(\xi^* + \xi)'I,$$
$$\text{s.t.}\begin{cases} xw + bI - y \le \varepsilon + \xi^*, \\ y - xw - bI \le \varepsilon + \xi^*, \\ \xi, \xi^* \ge 0. \end{cases} \tag{5}$$

The constant $C > 0$ is used to balance the number of deviations greater than the number of sample points and the flatness of the regression function f. When the sample size is small, the dual optimization problem can be obtained according to the duality theory:

$$\max_{\alpha,\alpha^*}\left\{-\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}(\alpha_i-\alpha_i^*)(\alpha_j-\alpha_j^*)x_i^{'}x_j - \varepsilon\sum_{i=1}^{n}(\alpha_i+\alpha_i^*) + \sum_{i=1}^{n}y_i(\alpha_i-\alpha_i^*)\right\}. \tag{6}$$

After the parameters α and α^* are obtained by dual theory, the regression function is obtained by $w = x'(\alpha - \alpha^*)$, as follows:

$$f(x_i) = \sum_{j=1}^{n}(\alpha_j - \alpha_j^*)x_i x_j^{'} + b, \tag{7}$$

where b is obtained by the following:

$$b = y_i - \sum_{j=1}^{n}(\alpha_j - \alpha_j^*)x_i x_j^{'} - \varepsilon. \tag{8}$$

The basic idea of nonlinear SVM is to map data x into Hilbert high-dimensional feature space through nonlinear mapping Φ and then carry out linear regression; that is, the nonlinear regression in low-dimensional space corresponds to the linear regression in high-dimensional space. This process is realized by the kernel function $k(x_i, x_j) = \Phi(x_i)\Phi(x_j)$. There are many kernel functions, such as linear kernel function, polynomial kernel function, Gauss radial basis kernel function, exponential kernel function, and Laplacian kernel function. The linear kernel function is the simplest and easy to calculate, especially in the case of huge sample data. The polynomial kernel function is a nonstandard kernel function, which is very suitable for the orthogonal normalized data, but it has many parameters. The Gaussian kernel function is very representative and widely used, which is not limited by dimensions. Therefore, the abovementioned three kernel functions are selected in this study, listed as follows:

(1) Linear kernel function:

$$k(x_i, x_j) = (x_i, x_j^*). \tag{9}$$

(2) Gauss radial basis kernel function:

$$k(x_i, x_j) = e^{-\frac{\|x_i - x_j\|^2}{2\sigma^2}}. \tag{10}$$

(3) Polynomial kernel function:

$$k(x_i, x_j) = (x_i x_j^* + c)^p, \quad p \in N,\ c \ge 0. \tag{11}$$

After introducing the kernel function, the optimization problem becomes

$$\max_{\alpha,\alpha^*}\left\{-\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}(\alpha_i-\alpha_i^*)(\alpha_j-\alpha_j^*)k(x_i,x_j) - \varepsilon\sum_{i=1}^{n}(\alpha_i+\alpha_i^*) + \sum_{i=1}^{n}y_i(\alpha_i-\alpha_i^*)\right\}. \tag{12}$$

Then, w is updated as follows:

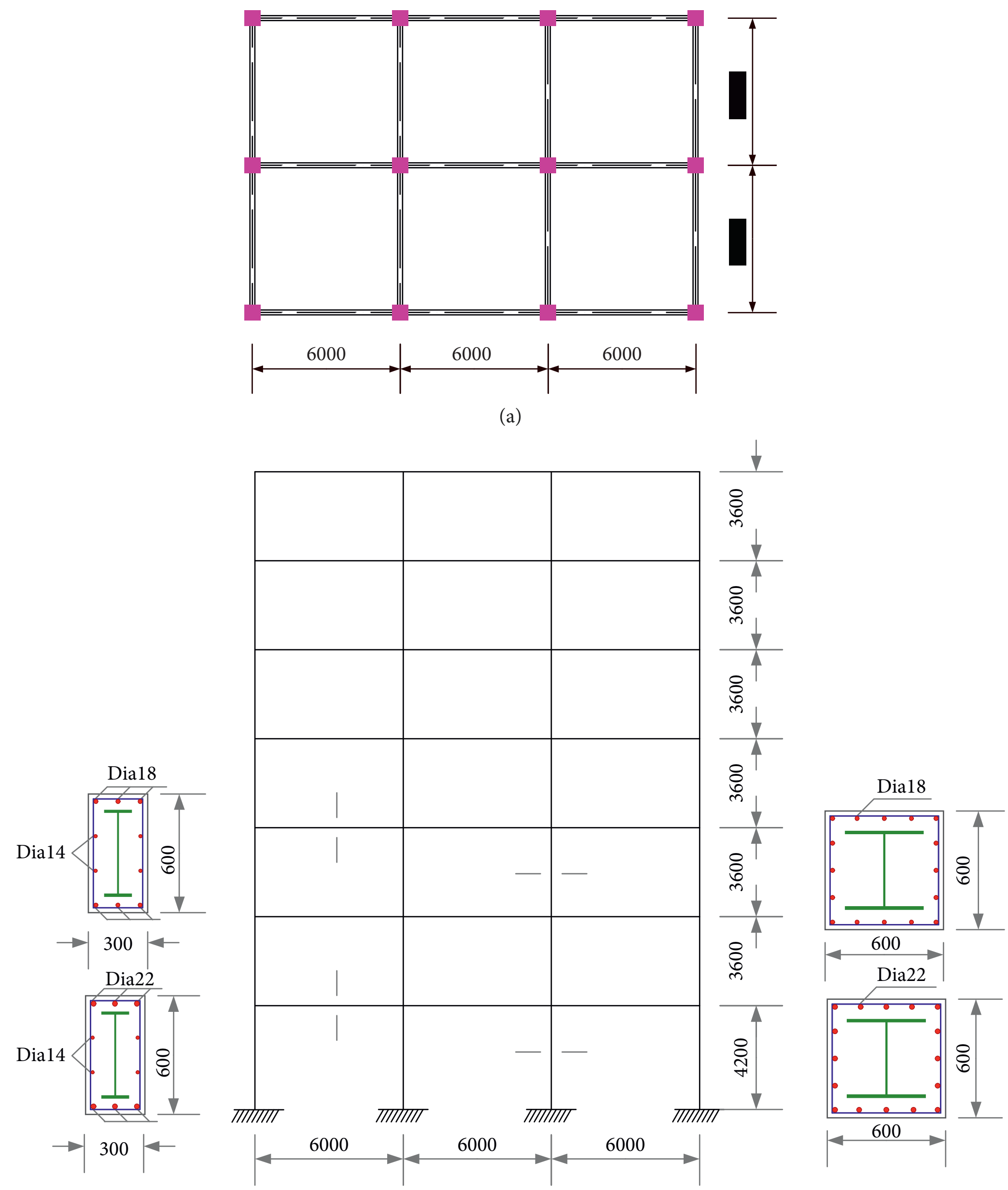
$$w = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)\Phi(x_i). \tag{13}$$

Further, $f(x)$ can be expressed as follows:

$$\begin{aligned} f(x) &= \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)(\Phi(x_i)\Phi(x)) + b, \\ &= \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)k(x_i, x') + b, \end{aligned} \tag{14}$$

where $b = y_i - \sum_{j=1}^{n}(\alpha_j - \alpha_j^*)k(x_i, x_j') - \varepsilon$.

Therefore, the optimal parameters α and α^* can be obtained based on the dual theory, and the corresponding



(a)

(b)

Figure 2: Structure diagram: (a) plan; (b) elevation.

Table 1: Section information.

Story	Beam section/(mm × mm)	Area of reinforcement/mm^2	Column section/(mm × mm)	Area of reinforcement/mm^2
1	300 × 600	2280	600 × 600	6082
2~7		1526	500 × 500	4072

mathematical model of the SVM algorithm can be obtained. On this basis, the predicted value $\hat{y}_i$ of y_i $(i = 1, 2, \ldots, n)$ can be obtained.

2.2. Computation Flow. The existing sampling methods need a lot of samples to guarantee the accuracy of the results, so it costs a lot of time to simulate the structure by the finite element method. For the importance measure analysis of structural seismic demand, the larger the sample size of the random variables, the longer the operation time. In order to perform the importance measure analysis of structural seismic demand efficiently, the low-deviation Sobol sequence is adopted in this study. According to Fox [29] and Zhu [30], the Sobol sequence can be briefly described as follows: each dimension of the Sobol sequence consists of a

Table 2: Statistical parameters of random variables.

Random variables	Symbol	Variation coefficients	Units	Distributions	Means
Concrete strength	f_c	0.140	Mpa	Normal [32]	34.82
Steel strength	f_y	0.078	Mpa	Lognormal [33]	384
Section steel strength	f_{ys}	0.078	Mpa	Normal [34]	396
Concrete modulus	E_c	0.080	Mpa	Normal [35]	33904
Steel modulus	E_s	0.033	Mpa	Normal [36]	228559
Section steel modulus	E_{ss}	0.033	Mpa	Normal [36]	228559
Representative value of gravity load	M_s	0.100	kN/m^2	Normal [37]	6
Structural damping ratio	D_A	0.200	—	Normal [27]	0.05

Note: the structural quality in the table is taken as the representative value of gravity load.

Table 3: Ground motion record.

Earthquake	Magnitude	Occurrence time	Serial number
Cape Mendocino	7.0	1992	RSN 3747
Northridge-01	6.7	1994	RSN 1083
Northridge-01	6.7	1994	RSN 947
Big Bear-01	6.5	1992	RSN 902
TaiwanSMART1(45)	7.3	1986	RSN 578
Friuli_Italy-02	5.9	1976	RSN130
Imperial Valley-02	7.0	1940	RSN 6

base-2 radical inversion, but the radical inversion of each dimension has its own different matrix. Its generation can directly use bit operations to achieve radical inversion, which is very efficient. The results show that it is a relatively efficient sampling method because a better result can be obtained as the sample size is only several hundreds.

Figure 1 shows the two-dimensional uniform distribution of 2048 samples on [0, 1] obtained by the low-deviation Sobol sequence and the common sampling method. It can be seen that the samples of the Sobol sequence are more evenly filled in the two-dimensional space than those obtained by the common sampling method. The blank area in Figure 1(b) means the absence of parameter information. To make the information more complete, more data points are needed to fill these blank areas, which means more sample size. Hence, in order to make the distribution of sample points more uniform, the common method needs to generate more sample points, so as to ensure the accuracy of the results. In summary, the Sobol sequence is more efficient because it can obtain more accurate results with fewer samples.

The specific sampling process is expressed as follows:

(1) Simulate the sample of random variables based on the low-deviation Sobol sequences and the probability distribution of random variables. The $N \times n$ dimension sample matrix A is expressed as follows, where n is the number of random variables and N is the sample size:

$$A = \begin{bmatrix} x_{11} & \cdots & x_{n1} \\ \vdots & \ddots & \vdots \\ x_{1N} & \cdots & x_{nN} \end{bmatrix}. \tag{15}$$

(2) Input the matrix A into the model established by OpenSEES software [31] and calculate the seismic demand of structures to obtain the sample value of N structural seismic demand Y (i.e., the output response):

$$Y = \begin{bmatrix} y_1 \\ \vdots \\ y_N \end{bmatrix} = \begin{bmatrix} g(x_{11}, \ldots, x_{i1}, \ldots, x_{n1}) \\ \vdots \\ g(x_{1N}, \ldots, x_{iN}, \ldots, x_{nN}) \end{bmatrix}. \tag{16}$$

The total variance of structural seismic demand Y is calculated by the following:

$$\mathrm{Var}(Y) = \frac{1}{N-1}\sum_{k=1}^{N}\left(y_k - \overline{y}\right)^2, \tag{17}$$

where $\overline{y}$ is the mean value of all sample values for structural seismic demand in (16).

(3) The variance $\mathrm{Var}(\widehat{Y})$ of $\widehat{Y}$ is expressed as follows:

$$\mathrm{Var}(\widehat{Y}) = \frac{1}{N-1}\sum_{k=1}^{N}\left(\widehat{y}_k - \overline{\widehat{y}}\right)^2, \tag{18}$$

where $\overline{\widehat{y}}$ is the mean value of all predictive values for structural seismic demand and $\widehat{Y}$ is the predictive value of the structural seismic demand Y, which is calculated by the SVM model.

(4) Calculate the importance measure index S_i of SVM using the following equation:

$$S_i = \frac{\mathrm{Var}(\widehat{Y})}{\mathrm{Var}(Y)}. \tag{19}$$

When the random variable is n-dimensional, n random variables are substituted into the support vector machine model to get the predictive value of SVM, and then the importance measure index $S_i\,(i = 1, 2, \ldots, n)$ of each random variable can be obtained.

3. Case Study

3.1. Engineering Example 1. As shown in Figure 2, a seven-story three-span steel-reinforced concrete (SRC) frame structure is taken as an engineering example, in which the standard floor's story height is 3,600 mm and the bottom floor's story height is 4,200 mm. Other information is as follows: the slab thickness is 120 mm, the column spacing is 6000 mm, the intensity grade of reinforcing bars is HRB335

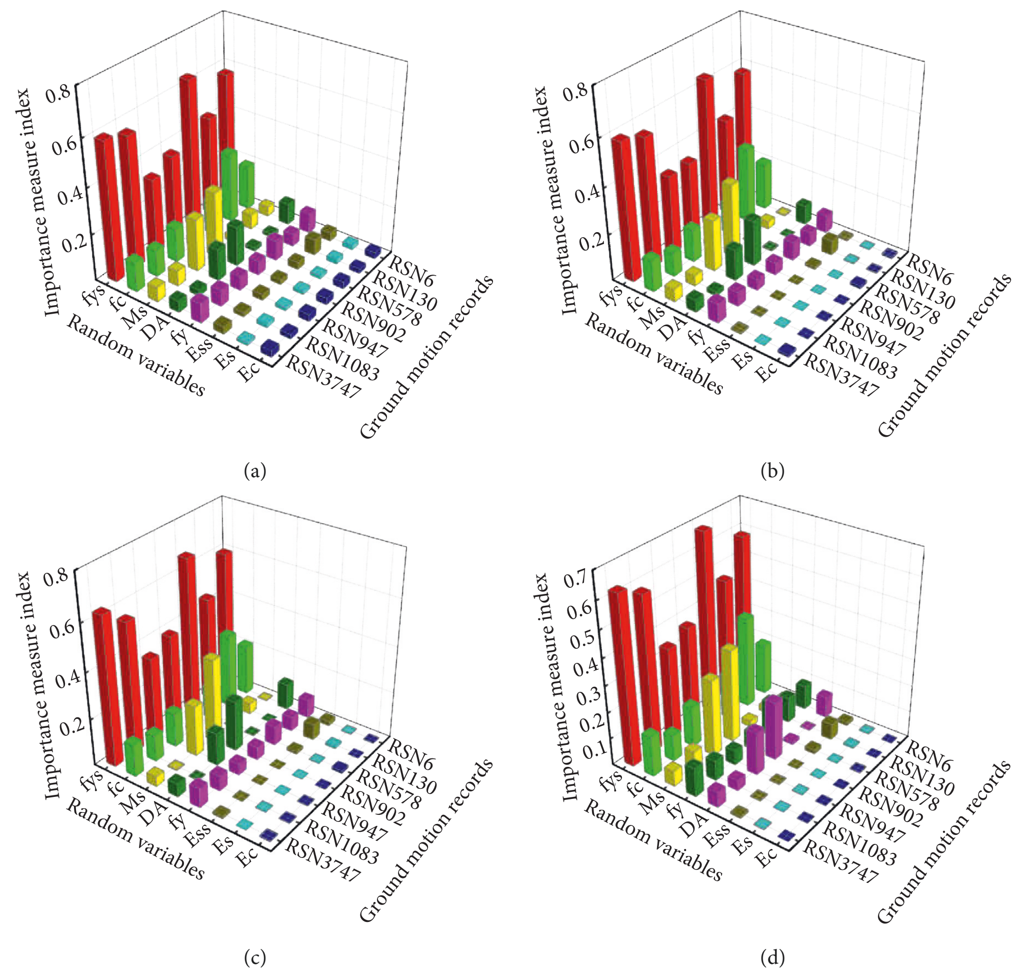


Figure 3: Importance measure indexes obtained by different methods for base shear demand: (a) the results obtained by SVM based on RBF kernel function, (b) the results obtained by SVM based on ploy kernel function, (c) the results obtained by SVM based on linear kernel function, and (d) the results obtained by MC.

(reinforcing bar with the standard yield strength of 335 N/mm^2), and the diameter of reinforcing bars is shown in Figure 2. The section steels are welded H-section steel whose strength grade is Q345 (section steel with a standard yield strength of 345 N/mm^2), and the steel dimensions of all columns on the bottom floor and those on floors 2 to 7 are $H400 \times 400 \times 11 \times 18$ and $H300 \times 300 \times 10 \times 15$, respectively. The steel dimensions of the beams are $H140 \times 440 \times 10 \times 16$. The concrete strength grade is C40 (concrete with standard cubic compressive strength of 40 N/mm^2), and the thickness of concrete cover is 25 mm. In addition, the reinforcement situations of beam and column sections are shown in Table 1 and the details of input random variables are listed in Table 2, in which the sample size $N = 1000$.

In this study, the finite element software OpenSees is used to analyze the dynamic nonlinear time history in which the El Centro seismic wave is selected. The macro nonlinear fiber beam-column element is used to simulate the columns and beams. The material model of steel bar and concrete are simulated by Steel02 element and Concrete02 element, respectively. Moreover, the maximum interstory drift angle and base shear are selected as the seismic demand parameters. Then the importance of each input random variable is investigated.

In OpenSees software, the constitutive relation of Giuffr6-Me does not affect the entire consistent negoa0-Pinto model [38] is adopted for the Steel02 element (for the parameter information, please refer to [39, 40]), and the constitutive relation of Kent–Scott–Park model [41] is adopted for the compressive section of Concrete02 element (for the parameter information, please refer to [42, 43]). With the increase of the maximum tensile strain, the degradation of cyclic loading stiffness and tensile hardening are considered after the concrete is cracked in the drawing section. The modified Karsan–Jirsa constitutive model [44] is used for unloading. The selected ground motion records are shown in Table 3, and in order to study the seismic demand of structure under the condition of large ground motion records, the PGA is 0.6 g instead of the actual value, which acts on the longitudinal direction of the frame structure.

3.1.1. The Results of Importance Analysis. The importance measure indexes obtained by the three kernel functions and

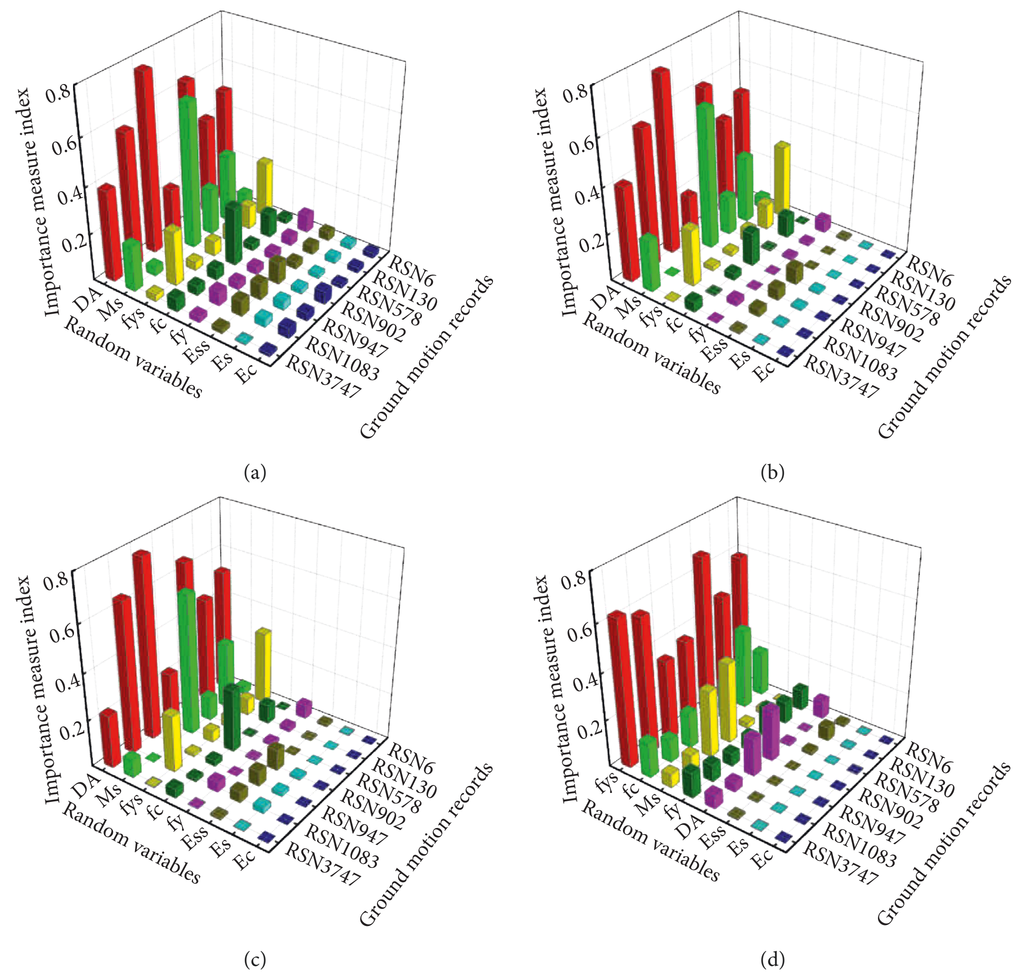


Figure 4: Importance measure indexes obtained by different methods for maximum interstory drift angle demand: (a) the results obtained by SVM based on RBF kernel function, (b) the results obtained by SVM based on ploy kernel function, (c) the results obtained by SVM based on linear kernel function, and (d) the results obtained by MC.

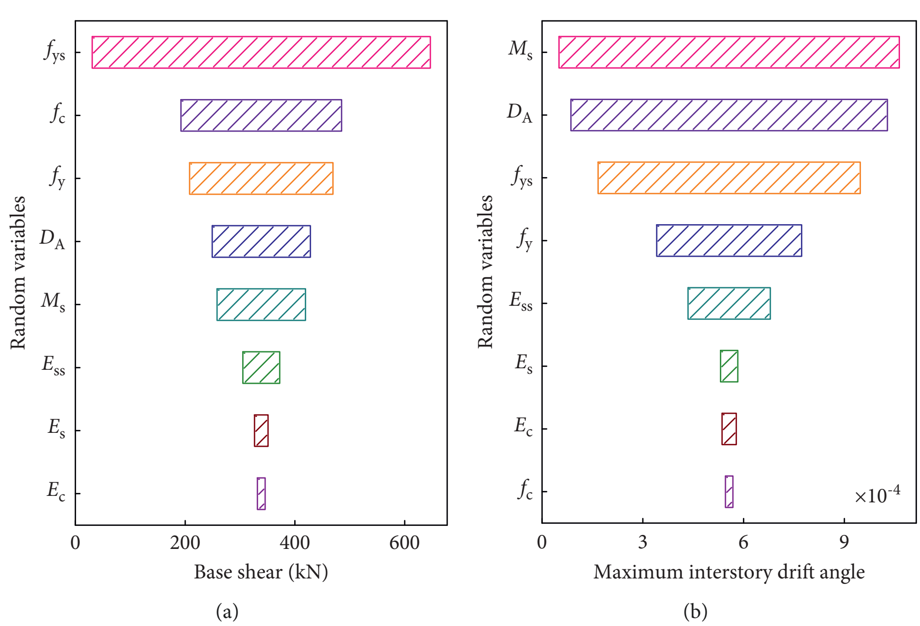


Figure 5: Importance ordering of random variables: (a) base shear demand and (b) maximum interstory drift angle demand.

Table 4: Section information.

Floor	Beam section/(mm × mm)	Area of reinforcement/mm^2	Column section/(mm × mm)	Area of reinforcement/mm^2
1	300 × 600	3220	600 × 600	6081
2~4		2537		4114
5~7		1821	500 × 500	3216

Table 5: Statistical parameters of random variables.

Parameters	Symbol	Mean value	Distribution	Variation coefficient
Damping ratio	D_A	0.055	Normal	0.2 [18]
Damping coefficient of viscous damper/kN·s·mm^{-1}	c	3	Normal	0.1
Stiffness of viscous damper/kN·mm^{-1}	k	100	Normal	0.1

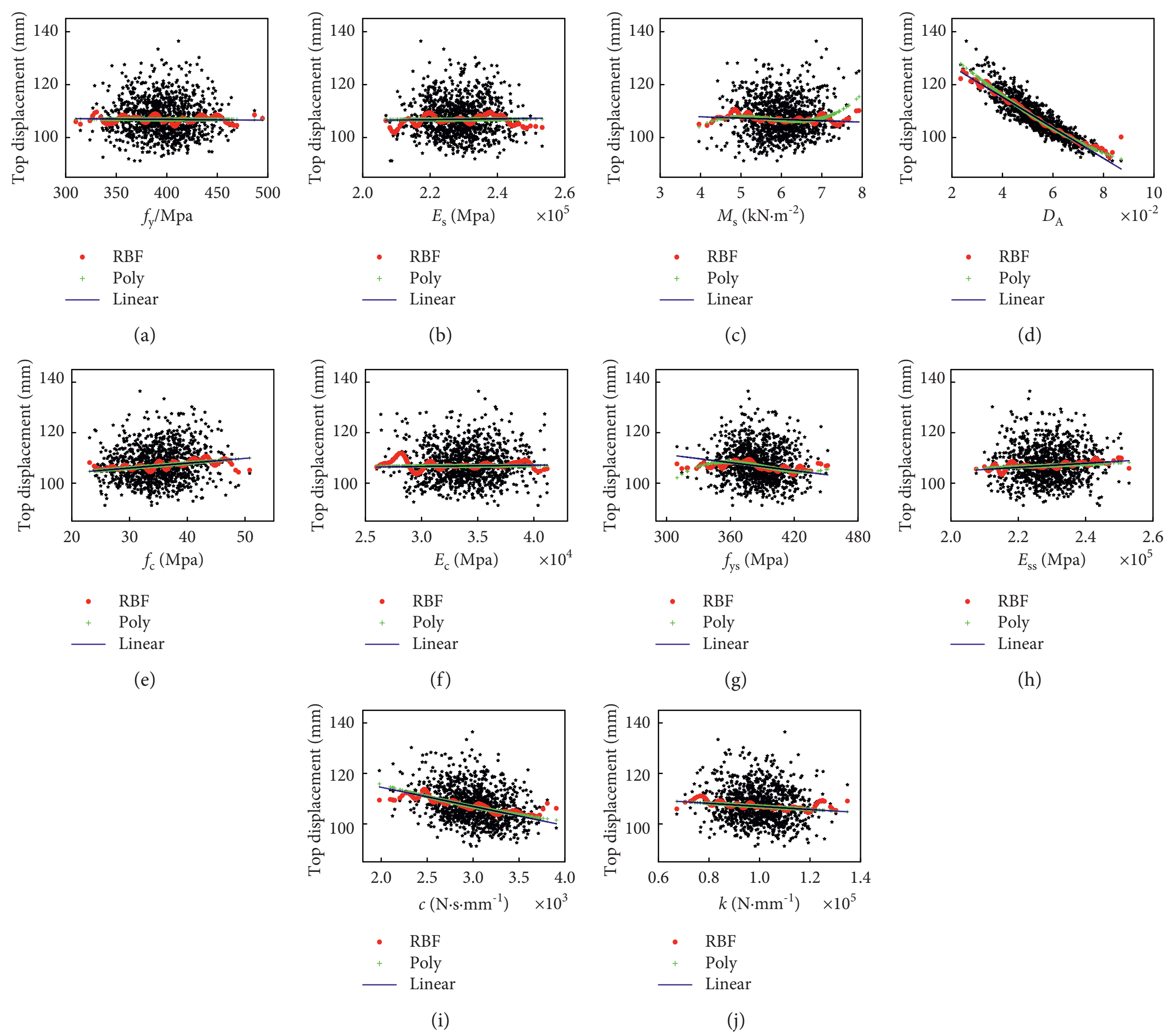


Figure 6: The prediction values of the top displacement demand under different kernel functions: (a) f_y, (b) E_s, (c) M_s, (d) D_A, (e) f_c, (f) E_c, (g) f_{ys}, (h) E_{ss}, (i) c, and (j) k.

MC method for the random variables under two kinds of seismic demand are shown in Figures 3 and 4, respectively.

Figure 3 shows the results of the importance measure indexes obtained by different methods under the base shear demand. It is obvious that the importance measure index of f_{ys} is the largest one for the most ground motion records, while the importance measure indexes of E_s and E_c are the smallest. All of the four methods have the same results for the abovementioned random variables. There is a little difference between the importance measure indexes of the

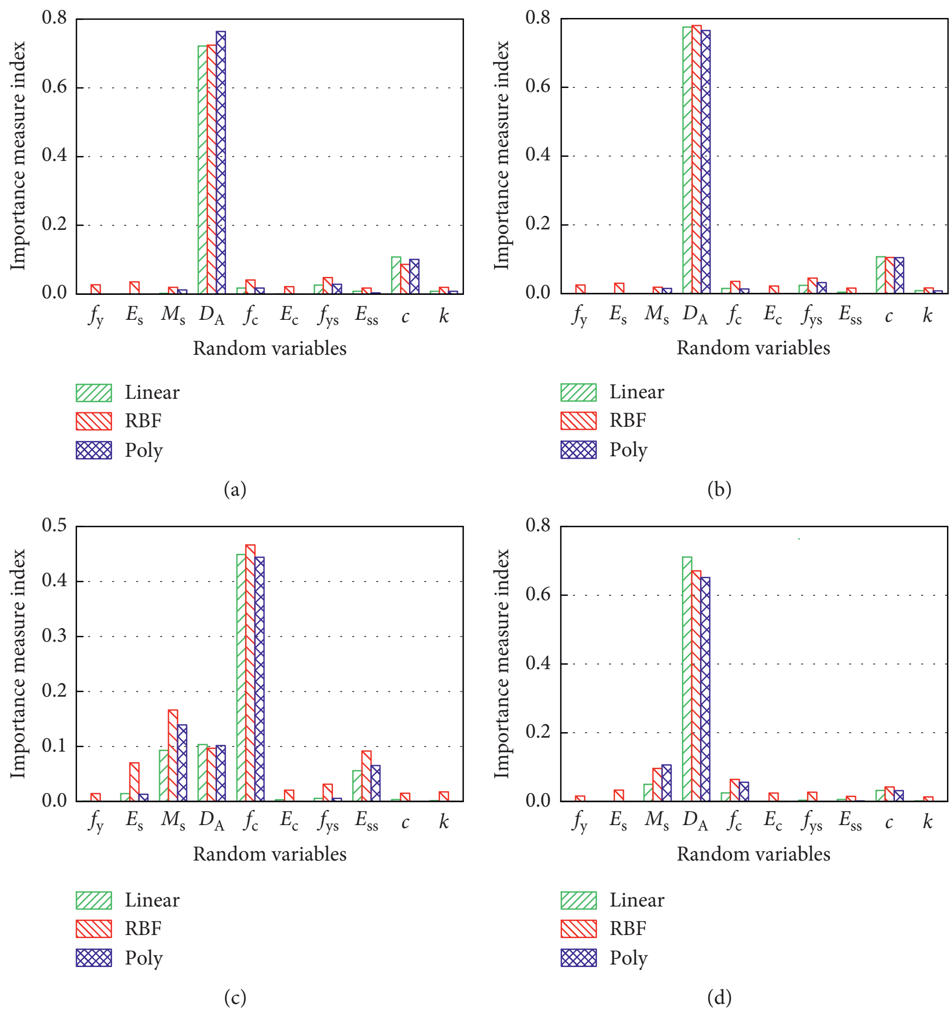


Figure 7: SVM importance measure indexes: (a) top displacement demand, (b) maximum interstory drift angle demand, (c) base shear demand, and (d) maximum floor acceleration demand.

rest random variables obtained by the four methods. However, the characteristics of importance measure indexes obtained by SVM based on RBF kernel function and MC method are the same.

For most ground motion records, Figure 4 shows that D_A and M_S have the largest importance indexes for maximum interstory drift angle demand, while E_s and E_c have the smaller importance indexes. The importance measure indexes obtained by SVM is somewhat similar to that obtained by MC method. The importance indexes of D_A and M_S for maximum interstory drift angle demand are the largest, while the corresponding importance indexes of E_s and E_c are the smallest.

In a word, from the above mentioned, a conclusion can be drawn that the importance measure indexes obtained by SVM and MC method have the same variation characteristic, which is that the random variables with large importance measure index obtained by SVM are consistent with those obtained by MC method and the same as the random variables with small importance measure indexes.

3.1.2. The Results of Sensitive Analysis Obtained by Tornado Graphic Method. The sensitivity analysis results of the Tornado graphic method under the action of RSN3747 seismic records are shown in Figure 5, where f_{ys} has the greatest influence on the base shear demand and M_s, D_A, and f_{ys} have a great influence on maximum interstory drift angle demand, while E_s, E_c, and E_{ss} have less influence. The influence of random variables on the base shear demand and maximum interstory drift angle demand is different.

3.2. Engineering Example 2. The SRC frame structure is the same as engineering example 1, but the parameters information is different. The reinforcement area is listed in Table 4. The statistical information of other random variables is listed in Table 5. The structural sketch is no longer given due to the limitation of space in this study. The El Centro seismic record (RSN6) is adopted for dynamic nonlinear time history analysis, and the Maxwell element is used to simulate the viscous damper. Moreover, the damping exponent is 1. The structure is loaded along the two directions simultaneously.

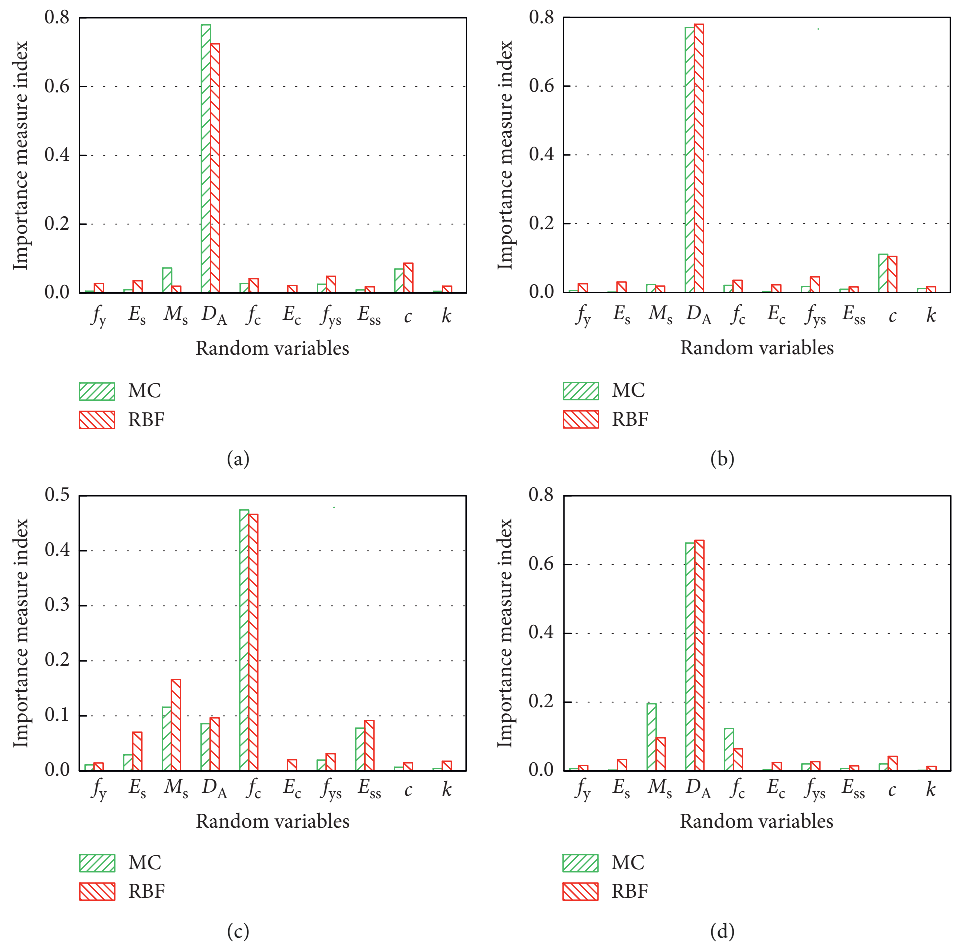


FIGURE 8: Comparison of importance measure indexes between SVM and MC: (a) top displacement demand, (b) maximum interstory drift angle demand, (c) base shear demand, and (d) maximum floor acceleration demand.

3.2.1. The Importance Measure Indexes Obtained by SVM. Figure 6 shows the predictive values of structural top displacement based on the model of SVM with three different kernel functions, where the red points are the predictive values of structural top displacement based on the model of SVM with Gauss radial basis kernel function (RBF), the green points are those obtained by the model of SVM with polynomial kernel function (Poly), and the blue line is that obtained by the model of SVM with linear kernel function (linear). In addition, the black points in Figure 6 are the output responses (i.e., the top displacements) corresponding to the realization values of the random variable. For example, the black points in Figure 6(a) are the scatter plot drawn with the realized values of the random variable f_y as the abscissa and the corresponding output responses as the ordinate. It is obvious that the top displacement of the structure varies with 10 random variables, and the variation characteristics of the top displacement obtained by the three different kernel functions are all significant and approximately consistent. For example, the top displacement of the structure decreases significantly with the increase of D_A and decreases slowly with the increase of f_{ys}, c, and k while increasing with the increase of E_{ss} and f_c. However, the top displacement of the structure varies little with the increase of f_y, E_s, E_c, and M_s. Limited by the article length, the prediction values of the other three structure seismic demand are no longer listed.

As shown in Figure 7, the values of SVM importance measure indexes obtained by the three kernel functions are consistent. It is obvious that the influence of D_A is largest on the four seismic demand of the steel-reinforced concrete frame structure, while the influence of the rest of the random variables is relatively smaller compared to D_A.

3.2.2. Comparison with the Importance Measure Indexes of MC Method. MC importance analysis method has been used widely and is usually considered the precise solution. Therefore, the comparison of the importance measure indexes obtained by MC is performed to verify the accuracy and efficiency of the proposed method. The importance measure indexes obtained by SVM based on RBF kernel function and MC are shown in Figure 8. It is apparent that the importance measure indexes of the random variables have little difference between RBF and MC except for M_s, where there is a slightly big difference

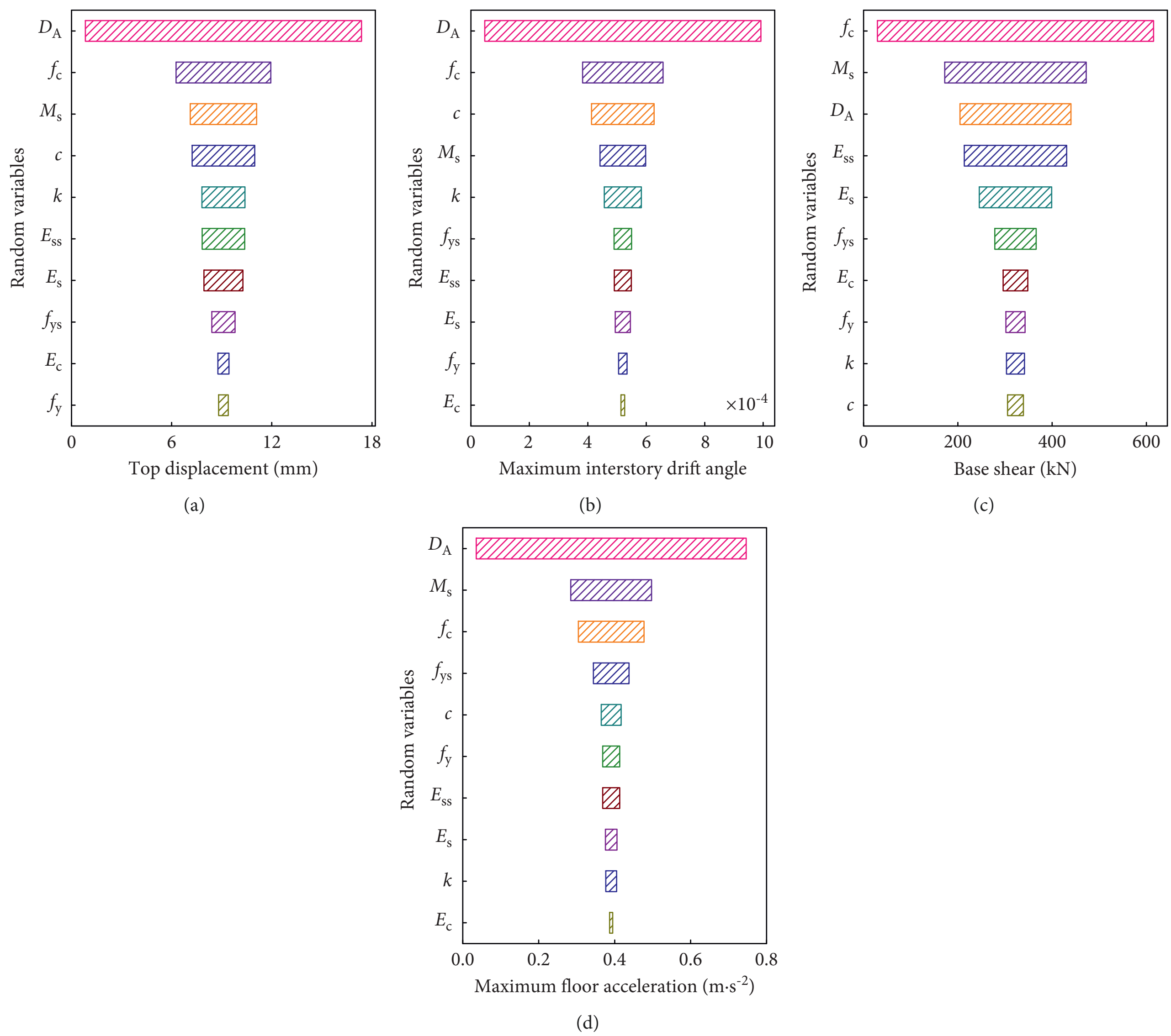


Figure 9: Importance ordering of random variables: (a) top displacement demand, (b) maximum interstory drift angle demand, (c) base shear demand, and (d) maximum floor acceleration demand.

in the importance measure indexes of M_s obtained by these two methods. However, the difference of M_s between RBF and MC does not affect the overall consistency of the results for random variables. In addition, it is worth noting that the sample size of the SVM importance analysis method proposed in this article is only $1/(n+1)$ of the MC method, where n is the number of random variables and $n = 10$. Therefore, the computational efficiency has been improved significantly.

3.2.3. The Results of Sensitive Analysis Obtained by Tornado Graphic Method. As shown in Figure 9, the results of the Tornado graphical sensitivity analysis method are variable. The influence level of each random variable on four different seismic demands is not consistent. For example, the damping coefficients of viscous dampers have a greater influence on maximum interstory drift angle demand and the top displacement demand, a moderate influence on the maximum floor acceleration demand, and a smaller influence on the base shear demand.

4. Discussion

Three importance analysis methods are adopted for structural seismic demand analysis in this study, and the importance orderings of the importance measure indexes obtained by these three methods are listed in Table 6. It indicates that there are some differences in the orderings of the importance measure indexes. For example, the importance orders of random variables obtained by these three methods for the top displacement seismic requirement are $D_A > M_s > c > f_c > f_{ys} > E_s > E_{ss} > f_y > k > E_c$, $D_A > M_s > c > f_c > f_{ys} > E_s > E_{ss} > f_y > k > E_c$, and $D_A > f_c > M_s > c > k > E_{ss} > E_s > f_{ys} > E_c > f_y$, respectively, which are not exactly the same. The first two importance orderings are obtained by SVM based

Table 6: Importance ordering of random variables.

Parameters	Top displacement demand	Maximum interstory drift angle demand	Base shear demand	Maximum floor acceleration demand
f_y	8-8-10	6-9-9	9-7-8	8-7-6
E_s	6-6-7	5-10-8	5-5-5	5-9-8
M_s	2-2-3	8-3-4	2-2-2	2-2-2
D_A	1-1-1	1-1-1	3-3-3	1-1-1
f_c	4-4-2	4-4-2	1-1-1	3-3-3
E_c	10-10-9	7-9-10	7-10-7	7-8-10
f_{ys}	5-5-8	3-5-6	6-6-6	6-5-4
E_{ss}	7-7-6	10-7-7	4-4-4	9-6-7
c	3-3-4	2-2-3	10-8-10	4-4-5
k	9-9-5	9-6-5	8-9-9	10-10-9

Note: the first number is the importance ordering of the importance measure indexes obtained by SVM based on the RBF kernel function, the second number is the importance ordering of the importance measure indexes obtained by MC, and the third number is the importance ordering of the importance measure indexes obtained by Tornado graphic method.

on RBF kernel function and MC, respectively, and the third importance ordering is obtained by Tornado graphic method, where SVM importance analysis method and MC importance analysis method are both GSA methods, while the Tornado graphic method is a single factor LSA method. Therefore, the results indicate that the importance measure of structural parameters cannot be only analyzed by the traditional Tornado graphic method. However, the random variables with greater influence are basically the same, i.e., D_A, M_s, c, and f_c, and the random variables with smaller influence are also consistent, i.e., E_s, E_{ss}, f_y, and E_c.

It is well known that there are many uncertainties in the design of engineering structures, such as material randomness, manufacturing anomalies, and external loading, which play an important role in reliability-based design optimization (RBDO) [45]. In addition, the particle swarm optimization algorithm (PSO) is a very classic intelligent optimization algorithm, which has good results in parameter optimization and is widely used in various fields [46]. Since the current research in this study focuses on the actual ground motion records, the follow-up research will be carried out from the following aspects: first, study the influence of artificially synthesized ground motion records and fully consider the uncertainty of parameters and the randomness of ground motions. Secondly, PSO will be used to intelligently optimize the parameters of the SVM. Finally, the influence of the uncertainty of each parameter on the structural reliability index is analyzed to realize the probabilistic earthquake safety assessment.

5. Conclusions

In this article, the dynamic nonlinear time history analysis of SRC frame structures is performed based on three methods, and four kinds of structural seismic demands have been analyzed. The importance measure indexes of several random variables have been obtained by SVM based on the RBF kernel function. For comparison, the Tornado graphics method and MC method are also adopted to calculate the importance measure indexes of those random variables. The conclusions are as follows:

(1) Compared with the results of the MC method, the values of the importance measure indexes obtained by the SVM method are basically consistent with those obtained by MC, which indicates that the proposed method is accurate and efficient. Moreover, the sample size of random variables based on the proposed method is only $1/(n+1)$ of that of the MC method, so the computational efficiency has been improved significantly.

(2) The importance measure indexes of D_A and f_c are higher than those of E_c, f_y , and k for the four structural seismic demands analysis, and this characteristic of importance measure indexes obtained by SVM based on three kernel functions is approximately the same.

(3) The importance measure indexes of the same random variable are different for the four kinds of structural seismic demands analysis. That means the influence of random variables on different seismic demands is different.

(4) The importance orderings of random variables obtained by SVM based on the RBF kernel function method and MC method are not exactly the same as those obtained by the Tornado graph method. However, the random variables with greater influence are basically the same.

In conclusion, the importance analysis method of SVM based on RBF kernel function for the four structural seismic demands has been proved to be effective and accurate. For the importance measurement analysis of complex structures, the results are very consistent with those obtained by other methods, even under the case of a small sample size. The computational efficiency of the proposed method is obviously higher than that of the MC method. In addition, the random variables with a larger importance index can be adjusted to improve structural safety and engineering optimization in the actual engineering application. In the next work, we will consider the uncertainty of parameters and the randomness of ground motions, improve SVM using PSO to investigate the influence of the uncertainty of each parameter on the structural reliability index, and finally realize the probabilistic earthquake safety assessment.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

Authors' Contributions

Xiuzhen Wang was responsible for importance analysis and OpenSees programming; Zhaoxia Xu was responsible for the development of the support vector machine (SVM) algorithm and article writing; Lianlian Jiang and Jun Yan completed the data collation of the top displacement, maximum floor acceleration, base shear, and maximum interstory drift angle in this article; Chuanzhi Sun and Li Gao drew the diagrams in this article.

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