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Research Article

The Moment-Independent Importance Analysis of Structural Seismic Requirements Based on Orthogonal Polynomial Estimation

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The structural damping ratio, structural quality, yield strength, and elastic modulus of section steel, compressive strength, elastic modulus of concrete, yield strength, and elastic modulus of steel bars play important roles in the stability of the steel-reinforced concrete (SRC) frame structure, which are usually uncertain. However, their importance influence on the different seismic demands of SRC is rarely investigated simultaneously. In order to investigate the effects of the above parameters on four seismic demands (i.e., the top displacement, the maximum floor acceleration, the base shear force, and the maximum interstory displacement angle) of SRC frame structures, the orthogonal polynomial estimation method is first applied to the importance analysis of structural seismic demand based on the moment-independent method. Two engineering examples are performed to verify the accuracy and efficiency of the proposed method. The results have the characteristics of fast convergence and are in good agreement with those obtained by the moment-independent method based on kernel density estimation. The variance importance index based on Monte Carlo (MC) method is also calculated for comparison. The influence of each random variable on the four structural seismic demands is basically the same. Therefore, the accuracy and efficiency of the proposed method are proved sufficiently.

1. Introduction

It is well known that the structural seismic requirement analysis plays an important role in seismic vulnerability analysis. There are many research studies of structural seismic requirement analysis in recent years. For example, Ge et al. [1] studied the seismic requirements of steel columns partially filled with concrete at the bottom. Fajfar et al. [2] proposed the simple formulas for seismic requirements of single-degree-of-freedom systems and long-period ranges.

Seismic requirement is affected by many factors. Generally speaking, they can be divided into two parts: the randomness of earthquake ground motion and the randomness of structural parameters. Existing studies have found that the randomness of earthquake ground motion has a great influence on the seismic requirement of structures. At the same time, the random variables of structures also have important influence on the seismic capacity and seismic requirement of structures. Therefore, the influence of the structural random variables should be taken into account in the safety assessment of structures [3]. However, there are few researches which study the influence of the uncertainty of random variables on the structure seismic requirement. As aforementioned, there are many parameters which impact the seismic requirement of the structure, while the degree of the influence is different. Therefore, it is necessary to focus on the stochastic variable with priority ranking ahead and ignore the random variable with priority ranking backward in the seismic requirement analysis of structures [4, 5], and then the computational process is simplified, and the efficiency of calculation has been

improved. Considering the importance of the random variables, the influence of the random variables on the structure seismic requirement has been analyzed in this study.

Sensitivity is generally applied to investigate the influence of the uncertainty of the input random variables on the output response. Recently, it has received more and more attention in structural engineering. For example, Ratto et al. [6] developed a state dependent parameter (SDP) model to analyze the sensitivity of random variables based on the variance method, in which the sample size has been reduced greatly, and then the calculation efficiency has been improved for the structural system model. Gu [7] studied the sensitivity influence of earthquake quality, ground motion record, and intensity on the probabilistic seismic behavior of wooden buildings based on two engineering cases, which are two-story building and four-story building, respectively. Chikh et al. [8] proposed a new definition of inelastic deformation ratio C-eta and studied the sensitivity of the average inelastic deformation ratio for the yield strength coefficient based on the selected 140 seismic records. In order to analyze the influence of random variables on seismic requirement in bridges, Song et al. [9] proposed a global sensitivity analysis method to rank the importance of random variables.

There are two methods in the sensitivity analysis of random variables for structures, which are local sensitivity analysis and global sensitivity analysis, respectively. The local sensitivity analysis can only investigate the influence of nominal values of random variables on the output response, while the influence of the whole values of random variables on the output response cannot be studied [10]. The global sensitivity analysis, also known as importance analysis, can investigate the effect of random variables on the output response when they change within their whole range of values [11]. Compared with global sensitivity analysis, the local sensitivity analysis neglects the influence of some values of input random variables on the output response. Therefore, the global sensitivity analysis has more advantages and can rank the importance of each random variable [12]. According to the uncertainty of the structure random variables, the global sensitivity analysis is adopted in this study for the structure seismic requirement analysis.

The methods of the global sensitivity analysis include variance importance analysis [13], information entropy importance analysis [14], and moment-independent importance analysis [15], where the variance importance index will inevitably lose some information of the random variables by assumed that the first moment of variance can fully describe the distribution characteristics of the output response [16]. The moment-independent importance index avoids the aforementioned disadvantages and has been used widely in recent years. Therefore, the moment-independent method is adopted to analyze the seismic requirement of structures, in which the orthogonal polynomial estimation method is first applied to the moment-independent importance analysis of structure seismic requirement in this study. The influence of the random variables on the seismic requirement of the SRC frame structure is investigated, and the moment-independent importance index of each random variable for the seismic requirement is obtained. The random variables which have significant or little influence on the seismic requirement of frame structures are screened out. The results provide a certain reference value for the seismic analysis of practical engineering. At the same time, the above results are compared with the results of moment-independent importance analysis based on kernel density estimation and variance importance analysis based on Monte Carlo (MC) method to verify the accuracy and effectiveness of this method.

It is worth noting that the Sobol sequence is applied to simulate the samples of random variables in this study, which is different from the ordinary MC method. The results show that good convergence can be obtained even when the sample size is small. Therefore, the proposed method in this study provides a new sampling method for the importance analysis and seismic analysis of the large-scale structures.

This study is organized as follows: the moment-independent importance analysis method and the variance importance analysis method are briefly described in Sections 2 and 3, respectively; two engineering case studies are listed in Section 4; and the research conclusions are summarized in Section 5.

2. Moment-Independent Importance Analysis Method

2.1. Moment-Independent Importance Analysis Index. Set X_i are the random variables in a structure, and Y are various seismic demands (i.e., the output response), which can be obtained by $Y = g(X_1, X_2, \ldots, X_n)$. According to Borgonovo [17], when the values of random variables X_i take their implementation values, the cumulative impact of X_i on the density of the output response is defined as the absolute value of the difference between the unconditional density function of Y and the conditional density function of Y. The cumulative impact on the density of the output response Y can be expressed as follows:

$$s(X_i) = \int_{-\infty}^{+\infty} \left| f_Y(y) - f_{Y|X_i}(y) \right| \mathrm{d}y, \tag{1}$$

where $f_Y(y)$ and $f_{Y|X_i}(y)$ are the unconditional probability density function and the conditional probability density function of Y, respectively, and the value of $f_{Y|X_i}(y)$ can be obtained by the implementation values x_i^* of the random variables X_i, where x_i^* can be obtained by the probability density function of X_i.

When the random variables X_i take all the implementation values, the average value of the cumulative impact of X_i on the distribution function of the output responses can be represented as the mathematical expectation of $s(X_i)$:

$$E_{X_i}[s(X_i)] = \int_{-\infty}^{+\infty} f_{X_i}(x_i) s(X_i) \mathrm{d}x_i. \tag{2}$$

Generally, the importance measure index of the influence of the general random variables on the distribution function of the structural output response Y is between 0 and 1, so it can be expressed as follows:

$$\delta_{\mathrm{i}} = \frac{1}{2}E_{X_i}[s(X_i)]. \tag{3}$$

Similarly, the importance measure indexes for a set of random variables $X_{i1}, X_{i2}, \ldots, X_{ir}$ can be defined as follows:

$$\begin{aligned}\delta_{X_{i1},X_{i2},\ldots,X_{ir}} &= \int f_{X_{i1},X_{i2},\ldots,X_{ir}}(X_{i1}, X_{i2}, \ldots, X_{ir}) \\ &\quad \times s(X_{i1}, X_{i2}, \ldots, X_{ir})\mathrm{d}x_{i1}, x_{i2}, \ldots, x_{ir} \\ &= \frac{1}{2}E_{X_{i1},X_{i2},\ldots,X_{ir}}[s(X_{i1}, X_{i2}, \ldots, X_{ir})],\end{aligned} \tag{4}$$

where r is the number of the random variables, $f_{X_{i1},X_{i2},\ldots,X_{ir}}(X_{i1}, X_{i2}, \ldots, X_{ir})$ denotes the joint probability distribution function for this group of random variables $(X_{i1}, X_{i2}, \ldots, X_{ir})$, and $s(X_{i1}, X_{i2}, \ldots, X_{ir}) = \int_{-\infty}^{+\infty}|f_Y(y) - f_{Y|X_{i1},X_{i2},\ldots,X_{ir}}(y)|\mathrm{d}y$, where $f_{Y|X_{i1},X_{i2},\ldots,X_{ir}}(y)$ is the probability density function of Y when the values of random variables $X_{i1}, X_{i2}, \ldots, X_{ir}$ take their implementation values.

2.2. Solution Methods. Since there is usually no explicit expression of $f_Y(y)$ and $f_{Y|X_i}(y)$ in practical engineering, many researchers developed a lot of estimation methods to obtain $f_Y(y)$ and $f_{Y|X_i}(y)$, such as the point approximation method [18], the histogram estimation method [19], the orthogonal polynomial estimation method (OPE) [20], the kernel density estimation method (KDE) [21], the maximum entropy principle method [22], and the linear mixed frequency polygon estimation method [23]. The orthogonal polynomial estimation method is introduced to estimate $f_Y(y)$ and $f_{Y|X_i}(y)$ in this study because of its high calculation efficiency and convergence for the multivariable structure.

2.2.1. The Orthogonal Polynomial Estimation Method. According to the works by Samuels [24], the relationship between the moment and the probability distribution can be described as follows: if the moments $\mu_1, \mu_2, \ldots \mu_r\ (r \geq 3)$ exist, the characteristic function of the probability distribution $|\Phi|^v$ is integrable when $v \geq 1$. Then, the finite term f_n can be obtained by Fourier inverse transformation, which is expanded by the eigenfunction Φ through Taylor series. When $n \geq v$ and $n \longrightarrow \infty$, all values of the random variable x should satisfy the following equation [24]:

$$f_n(x) - \varphi(x)\left(1 + \sum_{k=3}^{r} n^{-(k/2)+1}P_k(x)\right) = 0\left(n^{-(r/2)+1}\right), \tag{5}$$

where $P_k(x)$ is a real polynomial that depends only on the moments $\mu_1, \mu_2, \ldots \mu_r$, which means it is independent of n and r, $f(x)$ is the probability density function of x, and $\varphi(x)$ is the Gaussian function.

It is generally believed that $f(x)$ can be obtained by the expansion approximation of the high-order moment, in which the expansion is the normal distribution multiplied by the correction coefficient, so $f(x)$ can be expanded to a polynomial with weighted function. The Hermite orthogonal polynomial is used to expansion approximation in this study, which is expressed as follows:

$$H_n(x) = (-1)^n e^{x^2}\frac{\mathrm{d}^n\left(e^{-x^2}\right)}{\mathrm{d}x^n}, \quad n = 0, 1, \ldots. \tag{6}$$

Suppose the performance function is $Z = g(x) = g(x_1, x_2, \ldots x_n)$, then the origin moment of each order of Z can be described as

$$M_k(g) = \int_{-\infty}^{+\infty}(g(x))^k f(x)\mathrm{d}x, \quad k = 1, 2, \ldots, N. \tag{7}$$

A new performance function Y_z is adopted to solve the moment of Z in this study, which can make the original moment of each order as the same as the center distance. The original moment of each order is expressed as follows:

$$\mu_k(Y_z) = \int_{-\infty}^{+\infty} Y_z^k f(x)\mathrm{d}x, \quad k = 1, 2, \ldots, N, \tag{8}$$

where $Y_z = (z - \mu_z/\sigma_z) = (g(x) - M_1(g)/\sqrt{M_2(g) - M_1(g)^2})$; μ_z and σ_z are the mean value and sigma of Z, respectively.

When the distribution type of $f(x)$ is determined, it can be considered as a weight function. For a weight function, the calculation accuracy and efficiency could be improved greatly by the Gauss integral point. The weight function is different for different probability distribution types. For example, the weight functions of exponential distribution, normal distribution, and uniform distribution are e^{-x}, e^{-x^2}, and 1, respectively. Then, the Gaussian integration points are selected according to different weight functions.

In order to determine $f(x)$, the orthogonal polynomial estimation method is applied to approximate $f(x)$ in this study, which is expressed as follows:

$$\omega_k(x) = \sum_{m=0}^{k} A_{km}x^m, \quad k = 0, 1, 2, \ldots, \tag{9}$$

where A_{km} is an ascertainable constant.

According to the properties of the orthogonal polynomials, the following equation is set up:

$$\int_a^b \rho(x)\omega_i(x)\omega_j(x)\mathrm{d}x = \begin{cases} h_i, & i = j, \\ 0, & i \neq j, \end{cases} \tag{10}$$

where a and b are both real numbers and h_i is a specific function of integer i or a constant.

Generally, the distribution type of $f(x)$ is considered as normal distribution, so the normalized performance function is used to approximate to $f(x)$. Then, $f(x)$ can be defined as follows:

$$f(x) \approx \rho(x)\sum_{k=0}^{N} a_k\omega_k(x), \tag{11}$$

where a_k is the undetermined coefficient, and $a_k = \sum_{m=0}^{k} A_{km}\mu_m(x)/h_k$, and $\rho(x)$ is the weight function, which is generally taken as $(1/\sqrt{2\pi}\,\sigma)\exp[-(x - \mu^2)/2\sigma^2]$.

Considering the output response and conditional output response as random variables, substitute them into equations (6)–(11), respectively; then, $\widehat{f}_Y(y)$ and $\widehat{f}_{Y|x_i}(y)$ can be obtained.

2.2.2. Kernel Density Estimation. For comparison, the kernel density estimation is also adopted to estimate the probability distribution of the random variables. For the output response $y_1, y_2, \ldots, y_n$, the probability function of the kernel density estimation can be expressed as follows [21]:

$$\widehat{f}_Y(y) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{y - y_i}{h}\right), \tag{12}$$

where y is the output response, $\widehat{f}_Y(y)$ the kernel density estimation of $f_Y(y)$, whose value is a weighted mean, and $K(y)$ is the kernel function which is also a weight function.

When the value of $f_Y(y)$ at point y is estimated, the number of points and the degree of utilization of the data are controlled by the range and shape of the kernel function, and the accuracy of kernel density estimation is determined by the selection of the kernel function $K(y)$ and the bandwidth h. In order to ensure the reasonableness of the estimation, the kernel function needs to satisfy the following requirements:

$$\int_{-\infty}^{+\infty} K(y)\mathrm{d}y = 1, \quad K(y) \geq 0. \tag{13}$$

The Gauss kernel function and the optimal window width are used for the kernel density estimation in this study.

In summary, the calculation process is described as follows:

(1) Simulate N samples of random variables $x_k (k = 1, 2, \ldots, N)$ by the low deviation Sobol sequence. When the number of samples is above 500, the error of the average and standard deviation are not more than 5/1000 based on this sampling method.

(2) Substitute the simulated samples into the finite element model for calculation, and obtain various seismic demands Y ($Y = y_k (k = 1, 2, \ldots, N)$).

(3) Calculate $\widehat{f}_Y(y)$ and $\widehat{f}_{Y|x_i}(y)$ by the method of the orthogonal polynomial estimation and the kernel density estimation method, respectively (i.e., equations (11) and (12), respectively), where $\widehat{f}_Y(y)$ and $\widehat{f}_{Y|x_i}(y)$ are the estimated values of the unconditional probability density function $f_Y(y)$ and the conditional probability density function $f_{Y|x_i}(y)$, respectively.

(4) Substitute $\widehat{f}_Y(y)$ and $\widehat{f}_{Y|x_i}(y)$ into equation (1) to calculate $s(X_i)$, and then the importance measure index δ_i based on moment independence is obtained by equation (3).

3. Variance Importance Analysis Method

3.1. Variance Importance Analysis Index. To verify the accuracy and efficiency of the proposed method, the variance-based (VAR) importance measure method is also used to calculate the importance index in this study. According to the works by Saltelli and Sobol [11, 25], the variance importance measure index is expressed as follows:

$$\delta_i^v = \frac{\mathrm{Var}\left(E\left(Y \mid X_i\right)\right)}{\mathrm{Var}(Y)} = \frac{\mathrm{Var}(Y) - E\left(\mathrm{Var}\left(Y \mid X_i\right)\right)}{\mathrm{Var}(Y)}, \tag{14}$$

where $\mathrm{Var}(Y)$ is the variance of the output response Y and $E(\mathrm{Var}(Y \mid X_i))$ is the mathematical expectation of the conditional variance of Y.

Since the value of $\mathrm{Var}(Y)$ does not affect the importance order of X_i, so equation (14) can be rewritten as follows:

$$\delta_i^v = \mathrm{Var}(Y) - E\left(\mathrm{Var}\left(Y \mid X_i\right)\right). \tag{15}$$

3.2. Solution Method. The Monte Carlo (MC) simulation method is generally used to solve equation (15) because the sample mean converges to the global mean, and the frequency converges to the probability of occurrence, i.e., the law of large numbers. Therefore, the variance-based importance measure index based on MC is considered as an exact solution in structural engineering. When the random variable takes its realization value, the conditional variance and conditional mean are the variance and mean value of the random variable, respectively. According to the law of large numbers, $\mathrm{Var}(Y)$ is expressed as follows [9]:

$$\mathrm{Var}(Y) = \frac{\sum_{i=1}^{N_1}\left(Y_i - \overline{Y}\right)^2}{N_1 - 1}, \tag{16}$$

where Y_i is the output response, $\overline{Y}$ is the unconditional average value of the output response Y, and N is the sample size of the random variables.

Similarly, the conditional variance $\mathrm{Var}(Y \mid X_i)$ of the output response Y can be obtained by

$$\mathrm{Var}\left(Y \mid X_i\right) = \frac{\sum_{j=1}^{N_2}\left(Y_j \mid X_i - \overline{Y}_j \mid X_i\right)^2}{\left(N_2 - 1\right)}, \tag{17}$$

where $Y_j|X_i$ and $\overline{Y}_j|X_i$ are the unconditional value and the unconditional mean value of the output response Y, respectively.

After calculating the expectation according to equation (17) and substituting it with equation (16) into equation (15), the variance importance measure index can be obtained. It is worth to note that the accuracy of the calculation increases as the sample size N increases.

4. Case Study

4.1. Importance Analysis of a 7-Storey 3-Span SRC Frame Structure. As shown in Figure 1, a 7-storey 3-span SRC frame structure is used as a case study, in which the underlying floor height is 4,200 mm, the standard storey height is 3,600 mm, the column spacing is 6,000 mm, the floor thickness is 120 mm, and the concrete protective layer

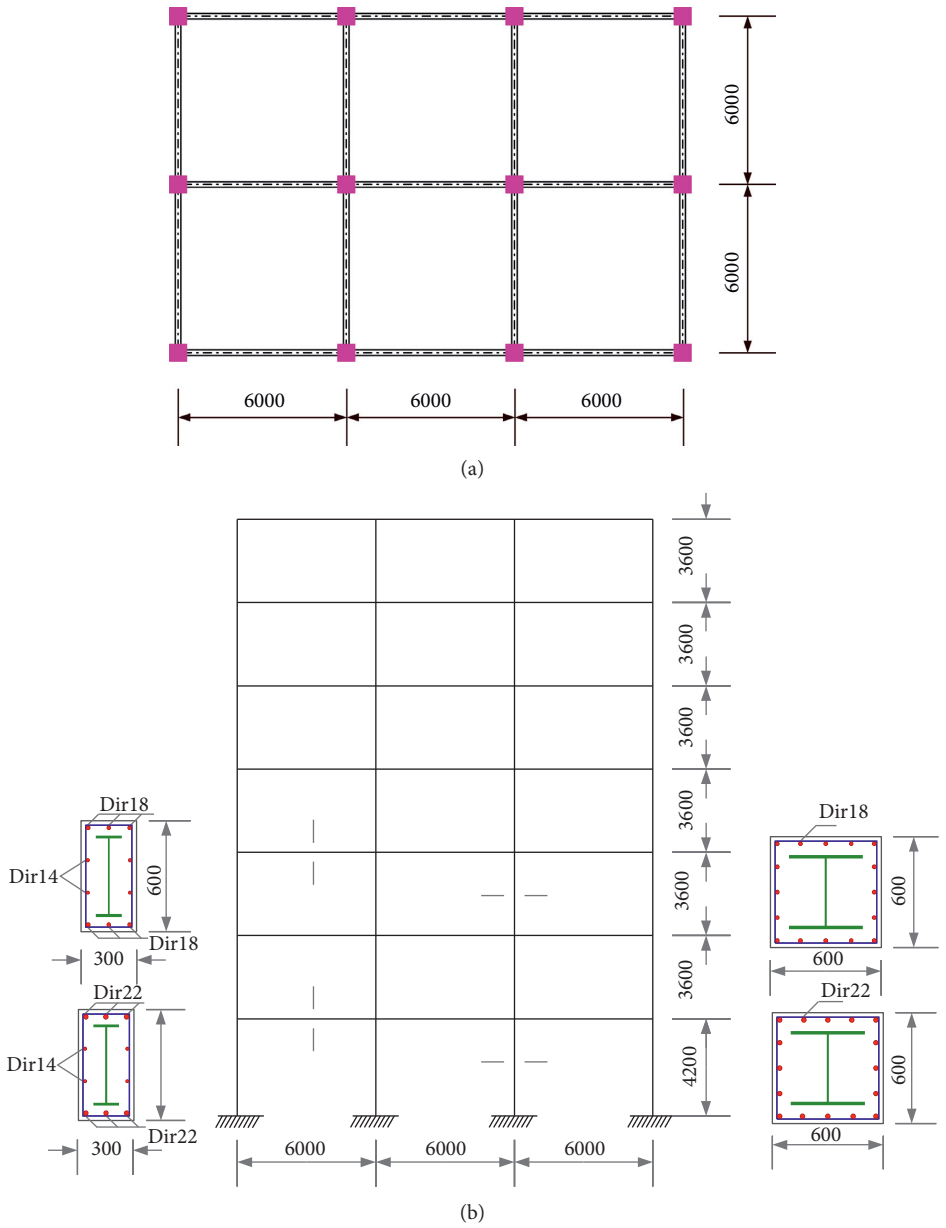

Figure 1: Structure diagram. (a) Structural plan. (b) Structural elevation.

Table 1: Statistical parameters of random variables.

Random variables	Units	Distributions	Symbol	Means	Variation coefficients
Steel modulus	MPa	Normal [26]	E_s	228559	0.033
Steel strength	MPa	Lognormal [27]	f_y	384	0.078
Concrete modulus	MPa	Normal [28]	E_c	33904	0.08
Concrete strength	MPa	Normal [29]	f_c	34.82	0.14
Structural damping ratio	—	Normal [30]	D_A	0.05	0.2
Representative value of gravity load	kN/m^2	Normal [31]	M_s	6	0.1
Section steel strength	MPa	Normal [32]	f_{ys}	396	0.078
Section steel modulus	MPa	Normal [26]	E_{ss}	228559	0.033

thickness is 25 mm. The random variables are listed in Table 1, in which the loading conditions have been considered as the structural mass (i.e., M_s). It is suggested that the structural mass is usually thought to be the ratio of its nominal dead weight to the acceleration of gravity and follows a normal distribution with the variation coefficient which is 0.1 [33, 34]. The representative value of gravity load is taken as the mean value of M_s, and its variation coefficient

is 0.10 in this paper. Briefly, the cross sections of the beam and the column are designed based on the load code for the design of building structures (GB50009—2012) [35], code for seismic design of buildings (GB50011—2010) [36], and code for design of composite structures (JGJ138—2016) [37] under the conditions of that the antiseismic grade is 1~3, and the number of layers is more than 2 in this paper. The designed sizes of the cross sections have passed all the requirements of structural seismic checking, so they are reasonable and usable, and the information is listed in Table 2.

The nonlinear time history analysis is carried out by OpenSEES software to obtain the output response. For making the simulating results more realistic, the El Centro (RSN6) original record which comes from the NGA-West2 database of PEER is adopted for the ground motion records. The two directions of the structure were loaded at the same time, and the peak ground acceleration (PGA) of the longitudinal and transverse structure is 0.28 g and 0.21 g, respectively. The columns and beams were all nonlinear fiber beam column units. The concrete was Concrete02 unit, and the steel bar adopts the Steel02 element material model.

4.1.1. Results of Moment-Independent Importance Analysis. In this study, the importance measure indexes of 4 kinds of seismic demands are investigated, which are the top displacement, the maximum floor acceleration, the base shear, and the maximum story drift angle, respectively. The corresponding relationship between the structural output response (i.e., the top displacement demand) and the random variables is shown in Figure 2. It is found that the top displacement demand varies with random variables. For example, the top displacement demand decreases with the increase of D_A and M_s, while it increases with the increase of the concrete strength f_c. The variation characteristics of the top displacement demand are not very obvious for the other random variables compared with these three random variables. In addition, there is a linear cap line in the top right side of Figure 2(d). The possible reason of this characteristic may be that D_A can significantly reduce the seismic response of the structure, and the larger the value, the faster the vibration attenuation of the structure so that the top displacement demand of the structure is significantly reduced.

The moment-independent importance measure indexes δ_i of each random variable under different N conditions are obtained by orthogonal polynomial estimation, which are shown in Figure 3. It is obvious from Figure 3(a) that the moment-independent importance measure index of D_A for the structural top displacement demand is the largest one, while the moment-independent importance measure indexes of E_{ss}, E_s, and E_c are smaller. As shown in Figure 3(b), the moment-independent importance index of f_c is the largest one and then followed by M_s, and the moment-independent importance indexes of other random variables are smaller. Figure 3(c) shows that the moment-independent importance index of M_s and D_A for the maximum floor acceleration demand is larger than other random variables. Figure 3(d) shows that the moment-independent importance measure index of D_A for the maximum displacement angle between stories is the largest one, while the moment-independent importance measure indexes of other random variables are smaller.

In a word, the moment-independent importance measure indexes of the 8 random variables under the four seismic demands corresponding to each random variable vary greatly when $N < 384$, while the moment-independent importance measures of each random variable tend to be stable when $N \geq 384$. Except for the importance measure indexes corresponding to very few random variables with less influence have some changes, the values of the importance measures corresponding to other random variables are basically unchanged, and the importance ranking of each random variable does not change too. In addition, the moment-independent importance measure index of each random variable tends to be stable when $N \geq 384$ except for M_s in the seismic requirement of the maximum floor acceleration, as shown in Figure 3(c). However, the variation magnitude of the moment-independent importance measure index of M_s is small when N increases from 384 to 1024. Therefore, the aforementioned results indicate that the sample size N used in this study is proved to be effective. Moreover, when load conditions (i.e., M_s) change over their entire normal distribution range, the importance indexes of the 8 random variables under the four seismic demands also nearly unchanged when N increases from 384 to 1024.

4.1.2. The Results of the Three Methods. Figure 4 shows the importance analysis results of the moment-independence method based on orthogonal polynomial estimation (OPE), kernel density estimation (KDE), and variance-based MC numerical simulation method (VAR), in which the sample size is $N = 1024$. As shown in Figure 4, the same random variables have different importance impacts to different seismic demands, and the importance index of D_A, M_s, and f_c is relatively larger; the moment-independent importance indexes obtained by the two methods are basically the same. There are some differences between the moment-independent importance index and the variance-based importance index, and the same random variables have different effects on different seismic demands. For example, D_A has the greatest influence on the structural top displacement demand and the maximum interstory displacement angle demand, while f_c has the greatest influence on the base shear demand.

In this study, a variety of methods are applied to importance analysis of the structure, in which the moment-independent importance analysis and variance-based importance analysis are studied based on the global sensitivity analysis methods. In order to facilitate the comparative analysis, the results of importance analysis of the random variables are listed in Table 3.

Table 3 shows that the importance order of random variables obtained by the three methods is approximately the same for the same seismic requirement. For example, the importance orders of the eight random variables obtained by these three methods for the top displacement seismic

Table 2: Section information.

Floor	Cross section of beam (mm × mm)	Reinforcement of beam (mm^2)	Cross section of column (mm × mm)	Reinforcement of column (mm^2)
1	300 × 600	2280	600 × 600	6082
2~7		1526		4072

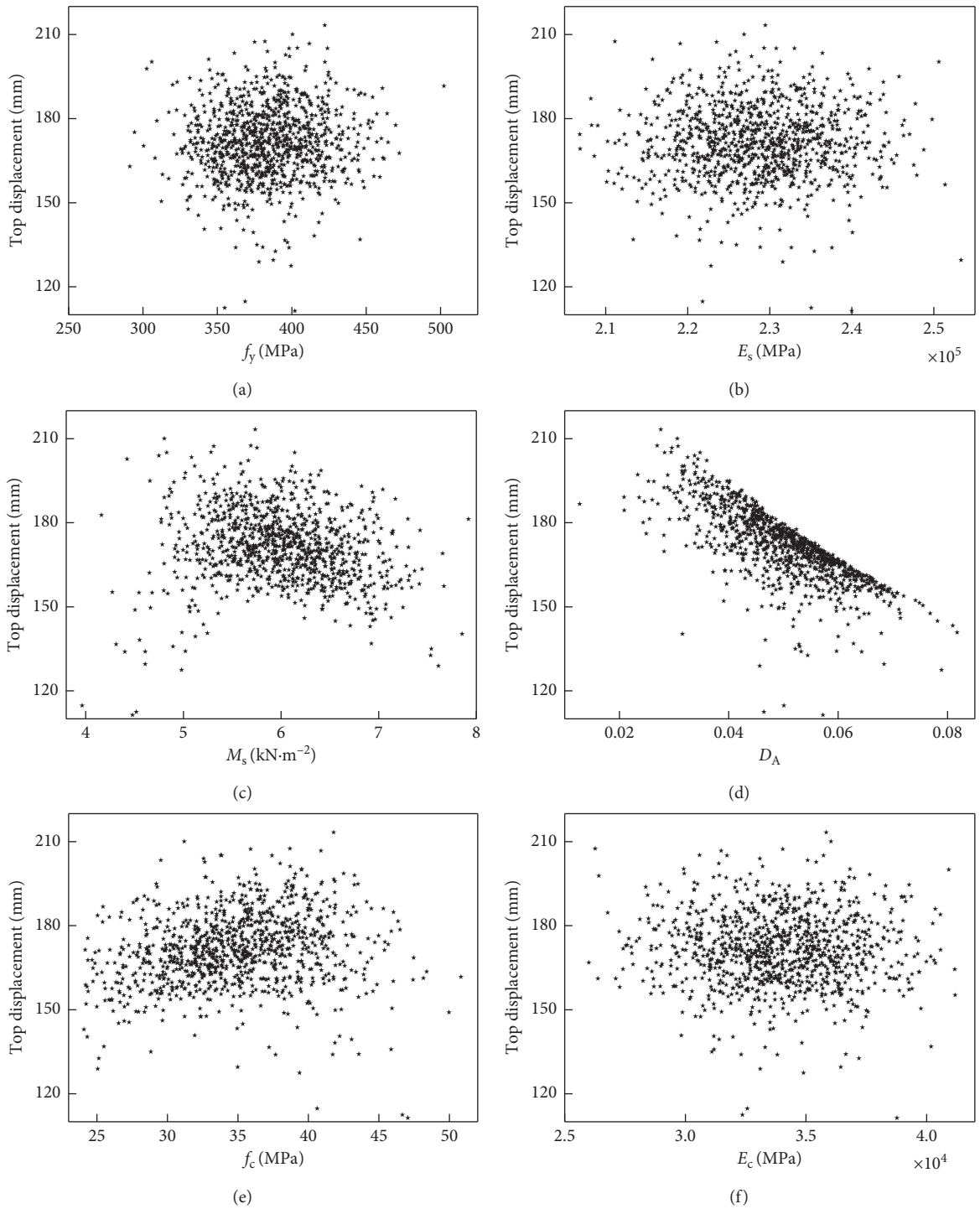

Figure 2: Continued.

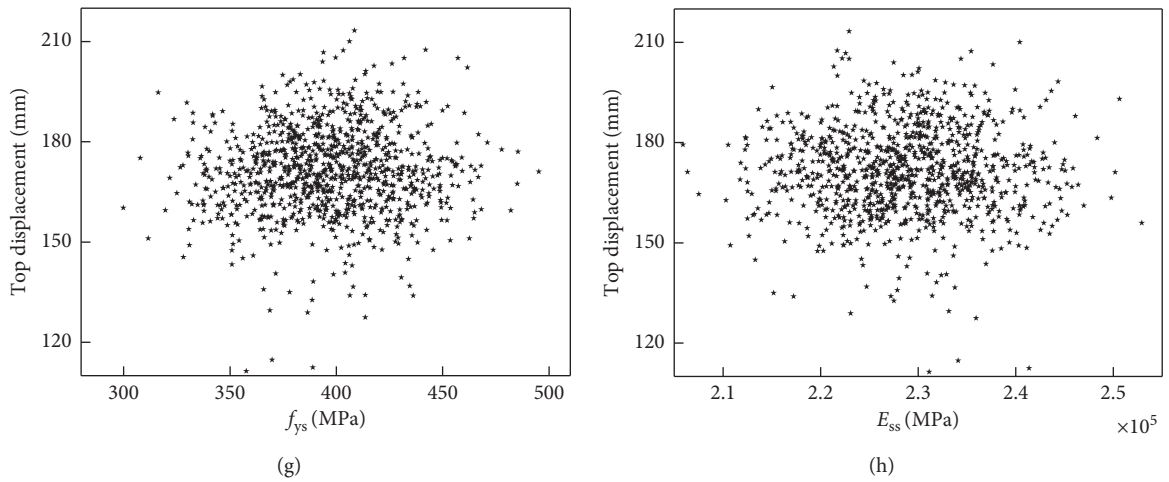

FIGURE 2: The relationship of top displacement demand and random variables: (a) f_y; (b) E_s; (c) M_s; (d) D_A; (e) f_c; (f) E_c; (g) f_{ys}; (h) E_{ss}.

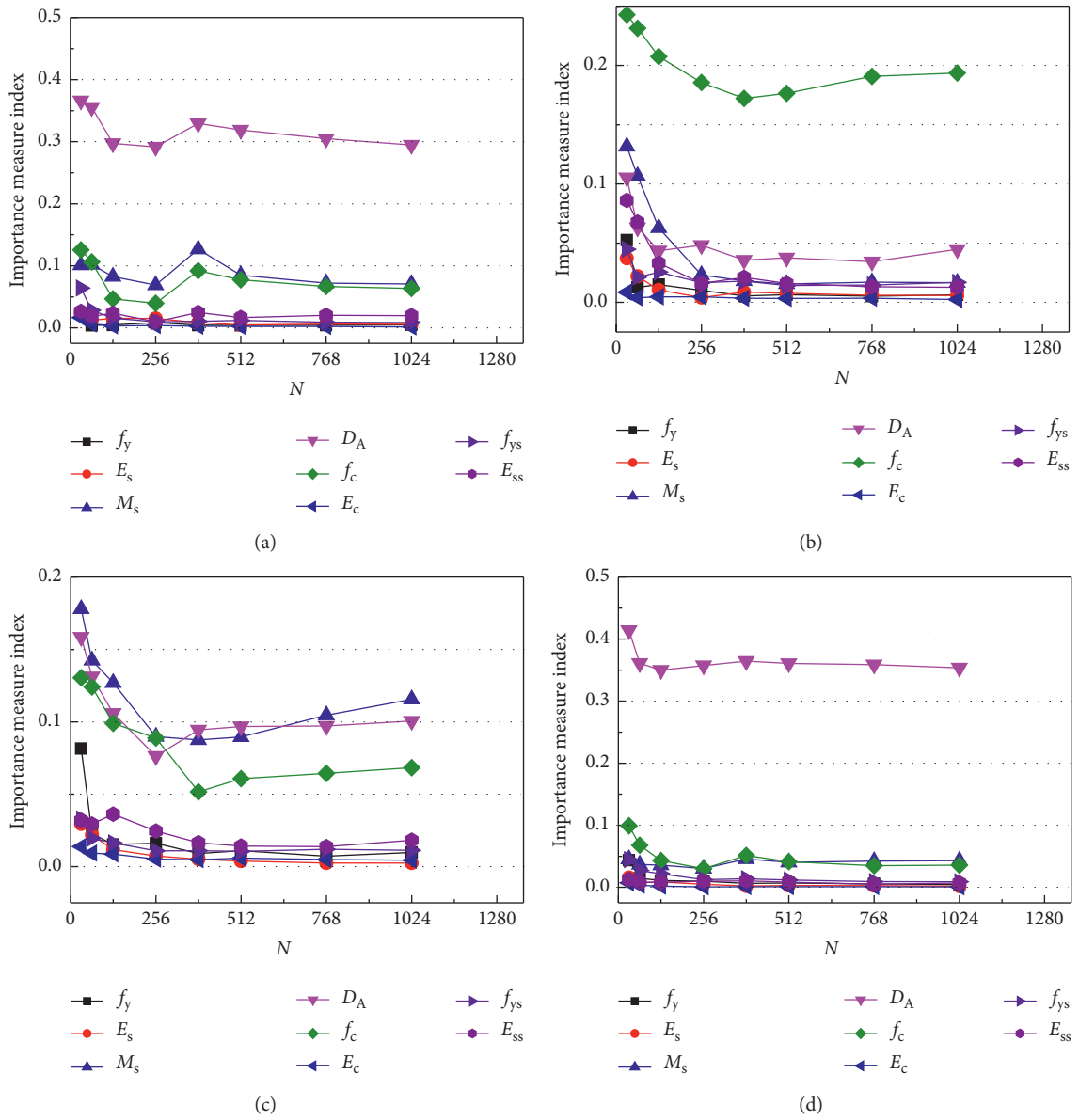

FIGURE 3: Importance measure index under different quantiles. (a) Top displacement. (b) Base shear. (c) Maximum floor acceleration. (d) Maximum story drift angle.

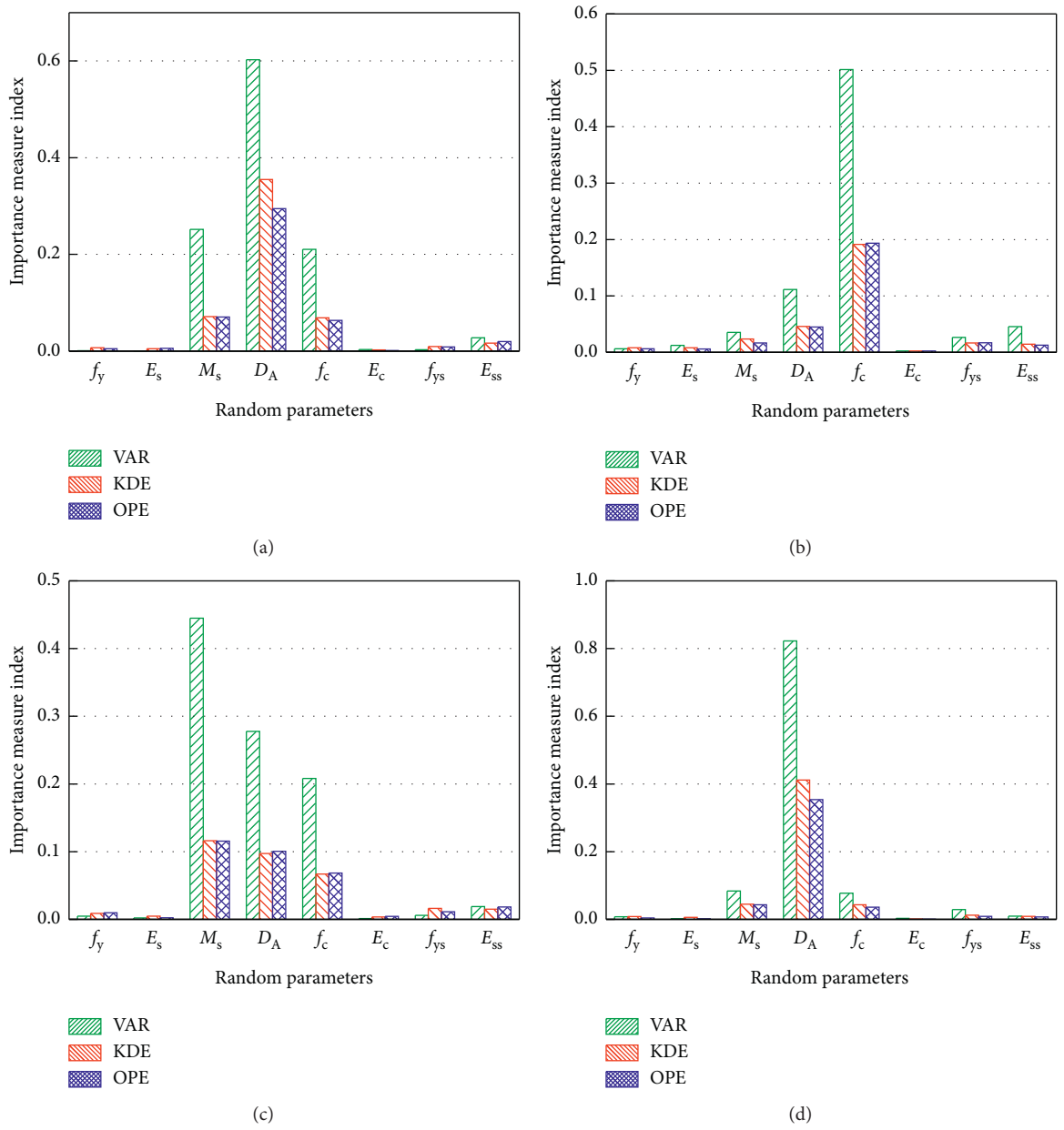

Figure 4: Importance measure index under different methods. (a) Top displacement. (b) Base shear. (c) Maximum floor acceleration. (d) Maximum story drift angle.

Table 3: Sensitivity ordering of random variables.

Seismic requirement	Top displacement	Base shear	Maximum floor acceleration	Maximum interstory drift angle
f_y	7-6-7*	6-7-7	6-6-6	6-6-6
E_s	6-7-8	7-6-6	8-7-7	7-7-8
M_s	2-2-2	4-3-4	1-1-1	2-2-2
D_A	1-1-1	2-2-2	2-2-2	1-1-1
f_c	3-3-3	1-1-1	3-3-3	3-3-3
E_c	8-8-5	8-8-8	7-8-8	8-8-7
f_{ys}	5-5-6	3-4-5	5-4-5	4-4-4
E_{ss}	4-4-4	5-5-3	4-5-4	5-5-5

*7-6-7: the first number is the order of moment-independent importance based on orthogonal polynomial estimation, the second is the order of moment-independent importance based on kernel density estimation, and the third is the order of importance based on Monte Carlo numerical simulation, and so on.

requirement are $D_A > M_s > f_c > E_{ss} > f_{ys} > E_s > f_y > E_c$, $D_A > M_s > f_c > E_{ss} > f_{ys} > f_y > E_s > E_c$, and $D_A > M_s > f_c > E_{ss} > E_c > f_{ys} > f_y > E_s$, respectively, which are nearly the same. The importance influence of the individual random variable is different for different seismic requirements. For example, the importance indexes of D_A obtained by these three methods are all the largest for the top displacement seismic requirement, while the importance indexes of f_c obtained by these three methods are all the largest for the base shear seismic requirement. Taking the results obtained by the orthogonal polynomial estimation as an example, the importance orders of the random variables for the top displacement, the base shear, the maximum floor acceleration, and the maximum interstory drift angle seismic demands are, respectively, $D_A > M_s > f_c > E_{ss} > f_{ys} > E_s > f_y > E_c$, $f_c > D_A > f_{ys} > M_s > E_{ss} > f_y > E_s > E_c$, $M_s > D_A > f_c > E_{ss} > f_{ys} > f_y > E_c > E_s$, and $D_A > M_s > f_c > f_{ys} > E_{ss} > f_y > E_s > E_c$. All three methods show that E_c and E_s have a relatively small impact on the four structure seismic demands.

According to the results of the importance orders, the random variables with larger values of the importance index can be appropriately adjusted to improve structural safety and engineering optimization in the actual engineering application. For example, it is obvious that the random variables D_A, M_s, f_c, and E_{ss} have greater influence on the top displacement seismic requirement. Therefore, adjusting the values of D_A, M_s, f_c, and E_{ss} can improve the safety of the structure more than adjusting the values of other variables. Comprehensive consideration of four seismic requirements, the random variables D_A, M_s, f_c, and E_{ss} or f_{ys} have greater influence on these four seismic requirements based on the results in Table 3, so the aforementioned random variables should be major consideration random variables.

4.2. Importance Analysis of the SRC Frame Structure with Different Ground Motion Records. A certain steel concrete frame structure is similar to the structure in engineering example 1, but different ground motion records are selected, and the modes of action are also different. The selected ground motion records are listed in Table 4, which act on the longitudinal direction of the frame structure. The output response of the structure is obtained by the nonlinear time history analysis using OpenSEES software. It is worth noting that, in the process of the calculation, PGAs of all ground motion records are uniformly increased to 0.6 g.

Figure 5 shows the characteristic of the importance index of the two kinds of seismic demands (i.e., the base shear force and the maximum interstory displacement angle), which are obtained by the orthogonal polynomial estimation (OPE), kernel density estimation (KDE), and variance-based method (VAR), respectively. It is found from Figure 5 that the importance indexes of each random variable of 7 selected ground motion records are different to some extent. For example, for the base shear demand of most ground motion records, according to Figures 5(a), 5(c), and 5(e), the importance measure orders of the eight random variables obtained by these aforementioned three methods are slightly different, which are $f_{ys} > M_s > f_c > D_A > f_y > E_{ss} > E_s > E_c$, $f_{ys} > M_s > f_c > D_A > f_y > E_{ss} > E_s > E_c$, and $f_{ys} > f_c > M_s > f_y > D_A > E_{ss} > E_s > E_c$, respectively. However, the importance index of f_{ys} is the largest, while that of E_s and E_c is the smallest among the results obtained by the three methods. For the maximum interstory displacement angle of most ground motion records, according to Figures 5(b), 5(d), and 5(f), the importance orders of the eight random variables obtained by these three methods are consistent, which are $D_A > M_s > f_{ys} > f_c > E_{ss} > f_y > E_s > E_c$. Obviously, the important indexes of D_A, M_s, f_{ys}, and f_c are generally higher than those of E_{ss}, f_y, E_s, and E_c. In addition, it is found from Figures 5(a) and 5(b) that the importance orders of the eight random variables obtained by OPE for the two kinds of seismic demands are different, and the results obtained by the other two methods have the same characteristics. Therefore, the importance influence of the individual random variable on different seismic demands is different.

5. Discussion

It is well known that the soil-structure interaction (SSI) plays an important and essential role in engineering design. Actually, the influence of SSI on the seismic response of structures has attracted the attention of a large number of engineers, and many research methods have been developed [38–41]. Research studies show that the rocking-induced nonlinearities are inevitable in soil and soil-foundation interface, which will cause permanent deformations and thus damage the building, particularly for the buildings adopting the shallow foundations, as it pointed out that the deep foundations (e.g., plie foundations) are the most common solution for the problems caused by the rocking-induced nonlinearities. For example, Hokmabadi et al. [42] studied the effects of soil-pile-structure interaction (SPSI) based on finite element analysis and concluded that the impact of SPSI should not be neglected in structural design. Fatahi et al. [43] investigated that the influence of the separation gap on the seismic response of midrise buildings supported on piles with the seismic soil-pile-structure interaction (SSPSI) is considered based on the three-dimensional numerical modeling method. However, the construction cost of plie foundations is also much higher than the shallow foundations. In view of this, Xu and Fatahi [44] proposed a geosynthetic reinforced composite soil (GRCS) foundation system to address the issues of residual structural drift or permanent foundation settlement under MCE level of shaking for seismic protection of midrise buildings supported by a shallow foundation, where the effects of geosynthetics on the seismic response of the buildings considering SSI have also been investigated. The accuracy and efficiency have been verified by the three famous engineering cases, and this method provides a reference for engineers in improving the structural safety of buildings using shallow foundations and saving construction costs.

The aforementioned references have shown that the influence of soil-pile-structure interaction (SPSI) should be considered in the structural design because it will amplify the overall seismic response of the building, especially the lateral and interstory displacements [43]. The proposed method could also be used for the cases where seismic soil-structure interaction is important. That will be the future work.

Table 4: Ground motion records.

Ground motion records	Serial number	Time of occurrence	Magnitude	PGA
Friuli_Italy-02	RSN130	1976	5.9	0.110 g
Big Bear-01	RSN902	1992	6.5	0.225 g
Northridge-01	RSN1083	1994	6.7	0.157 g
Northridge-01	RSN947	1994	6.7	0.094 g
Imperial Valley-02	RSN6	1940	7.0	0.281 g
Cape Mendocino	RSN3747	1992	7.0	0.176 g
TaiwanSMART1(45)	RSN578	1986	7.3	0.242 g

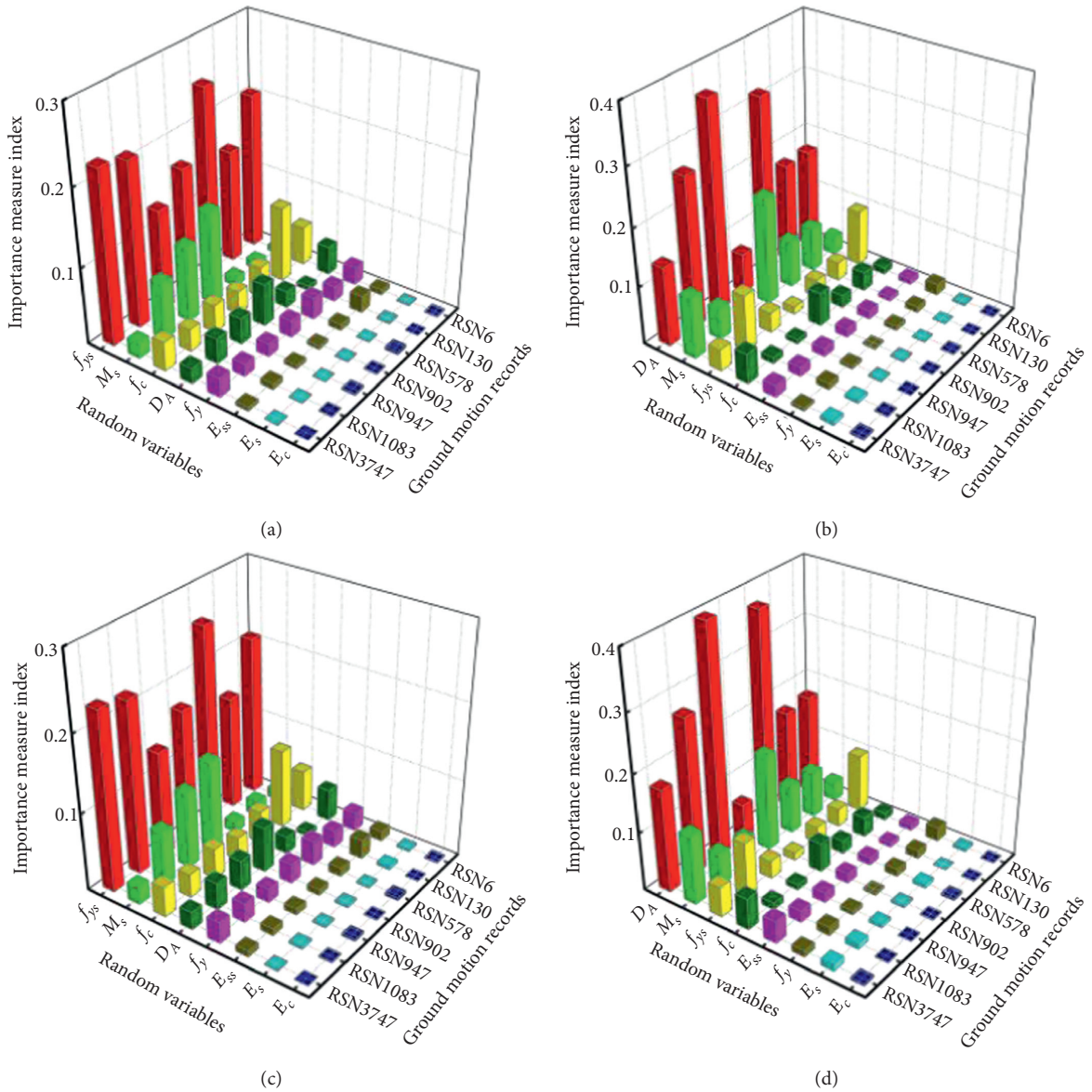

Figure 5: Continued.

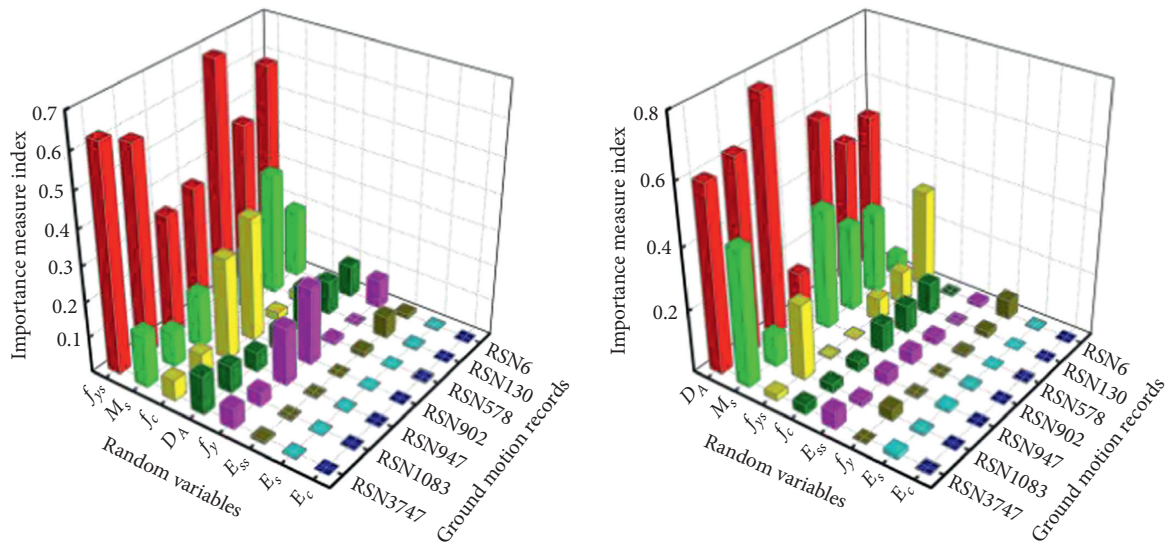

Figure 5: Importance measure index under different methods. (a) Base shear (OPE). (b) Maximum interstory drift angle (OPE). (c) Base shear (KDE). (d) Maximum interstory drift angle (KDE). (e) Base shear (VAR). (f) Maximum interstory drift angle (VAR).

6. Conclusion

The moment-independent importance analysis of seismic requirement for SRC frame structures is first carried out by orthogonal polynomial estimation in this study. The results had been compared with the moment-independent importance analysis based on the kernel density estimation method and the analysis of variance-based MC numerical simulation method, respectively. The following conclusions are obtained:

(1) The importance index of each random variable obtained by the moment-independent importance analysis method based on orthogonal polynomial estimation for structural seismic requirement tends to be stable when $N \geq 384$

(2) The importance indexes obtained by moment-independent importance analysis based on the orthogonal polynomial estimation method are close to those obtained by the kernel density estimation method, which proved the accuracy and efficiency of the proposed method

(3) The importance order obtained by the moment-independent importance analysis method is basically consistent with that obtained by the variance-based MC numerical simulation method, which also proved the accuracy and efficiency of the proposed method

(4) For the structure seismic requirement selected in this study, the importance influence of the random variable on different seismic demands is different

(5) The sampling method adopted in this study can get ideal results when the number of samples is small, which has practical significance for the importance analysis of complex structures

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 conflicts of interest.

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