Estimation of peak wind response of building using regression analysis

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Abstract. The maximum along-wind displacement of a considerable amount of building under simulated wind loads is computed with the aim to produce a simple prediction model using multiple regression analysis with variables transformation. The Shinozuka and Newmark methods are used to simulate the turbulent wind and to calculate the dynamic response, respectively. In order to evaluate the prediction performance of the regression model with longer degree of determination, two complex structural models were analyzed dynamically. In addition, the prediction model proposed is used to estimate and compare the maximum response of two test buildings studied with wind loads by other authors. Finally, it was proved that the prediction model is reliable to estimate the maximum displacements of structures subjected to the wind loads.

Keywords: wind simulation; dynamic analysis; maximum displacement; multiple regression; spectral density

1. Introduction

In building design, the maximum displacement of a structure is one of the main parameters to compute the structural performance which can be estimated with good accuracy using the dynamic analysis; however, for many structural engineers the dynamic analysis could be impractical; in addition, the dynamic analysis requires real wind speed records, which are not available in most of the cases. For this reason, most of wind design codes suggest the use of the static analysis by means of equivalent wind loads, which consider the dynamic effects through a factor named as dynamic amplification factor (Davenport 1967). Some changes and developments in the method to compute the equivalent static wind loads, originally presented by Davenport and King (1984), have been suggested by different authors (Zhou et al. 2000, Repetto and Solari 2004, Chen and Kareem 2006). These methods use some variables such as power spectral density, background response, resonant response and others, which a priori require an independent calculation process; therefore, the task to know the maximum response of a building under wind loads can be complicated. Due to the problems mentioned above, other authors have proposed simplified methods to predict the response of structures (Materazzi et al. 2007, Guo et al. 2013, Huang et al. 2013); however, an approach to the specific prediction of some important design parameter could offer better simplicity and could be a useful tool in engineering practice. Therefore, the aim of this work is to generate and evaluate a simple mathematical

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model in order to predict in a practical way the maximum along-wind displacement of prismatic buildings under dynamic loads.

For this work, the peak wind response of a considerable amount of shear-buildings discretized as Multi-Degree of Freedom (MDOF) structures is estimated and stored to a database in terms of regional wind speeds, terrain categories and structural characteristics such as height, slenderness ratio, fundamental period, distributed mass and stiffness ratio. Due to the lack of real wind records, several studies propose that the use of spectral density models are adequate to represent the velocity field of the turbulent wind (Choi and Noh 1999, Ding et al. 2006, Bojórquez et al. 2017, Payán-Serrano et al. 2017); therefore, the dynamic wind loads needed to excite the MDOF structures are generated from synthetic records obtained by spectral representation with the well-known Shinozuka method (Shinozuka and Jan 1972), which is a simulation technique that uses a spectral density function to represent the amplitude of the waves that constitute spectrally a series of time. Finally, the mathematical model is obtained from the application of regression analysis in the database using variable transformation. The theory used to perform all these tasks is described below.

2. Theoretical framework

The theoretical framework is organized in the following way: Section 2.1 describe the vector components of the turbulent wind. Section 2.2 exposes the equation to calculate the load from wind speeds, which are obtained by simulation of the part turbulent of the longitudinal component. Section 2.3 shows the differential equation of

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motion that governs the behavior of the MDOF structures and the assumptions adopted by Newmark to solve it. Finally, the mathematical technique to obtain the prediction models by regression analysis using transformation of variables is presented in Section 2.4.

2.1 Turbulent wind

According to Davenport (1963), Solari (1982) and Xu (2013) the turbulent wind at a point in the space m(0,0,z) can be decomposed as a mean wind speed $\overline{U}(z)$ with a predominant direction x and three perpendicular turbulent components (longitudinal u(t), lateral v(t) and vertical w(t)); with the longitudinal turbulent component aligned to the x-axis, forming a horizontal plane with lateral component aligned to the y-axis and the vertical component perpendicular to the plane and aligned to the z-axis (Fig. 1).

Due to the irregularities of the surface of the earth, the wind acquires a turbulent behavior. The variation of wind speed with height is called wind speed profile. The wind speed profile corresponding to the mean speed can be calculate with an expression known as power law as follows

$$\overline{\mathbf{U}}(z) = \mathbf{f}_{s} \overline{b} \overline{\mathbf{U}}_{10,\mathrm{II}} \left(\frac{z}{10}\right)^{\alpha} \tag{1}$$

where f_s is a time scale factor according to Mackey (1970) $f_s = 0.702$ in order to scale 3-second to 10-minute of mean wind speeds, \bar{b} is the roughness factor which is defined in Table 1, $\overline{U}_{10,II}$ is the basic wind speed and it is a mean wind speed taking at reference height 10 m and terrain category II and α is an exponent that according to Counihanm (1975) depends of the characteristics of roughness and it can be approximated by exposed equations in Eurocode (2005) for different classifications of terrain categories. Therefore, the longitudinal component as a function of the height is expressed as

$$U(z,t) = \overline{U}(z) + u(z,t)$$
(2)

where the turbulent part u(z, t) can be represented as a stationary stochastic processes with mean zero. The estimation of u(z, t) is the key aspect for having simulated wind records.

2.2 Simulated wind loads

The dynamic loads are generated from synthetic records, where the turbulent parts of the longitudinal components are obtained by spectral representation.



Fig. 1 Wind vector decomposition

The mathematical relationship between the loads and the wind speeds is determined by the kinetic energy equation, which can be expressed in terms of pressure or force acting on a contact area as follows (Holmes 2015)

$$F_{j}(t) = \frac{1}{2} C_{d} \rho A_{j} (U_{j}(t) - \dot{x}_{j}(t))^{2}$$
(3)

where $F_j(t)$ is the wind force at j-th floor, C_d is the drag coefficient, ρ is the density of the air for this study $\rho = 1.25 \text{ kg/m}^3$, A_j is the contact area at j-th floor, $U_j(t)$ is the longitudinal component of the wind defined as the sum of the mean velocity and its corresponding turbulent part $U_j(t) = \overline{U}_j + u_j(t)$ and $\dot{x}_j(t)$ is the velocity of the mass lumped at j-th floor. For rectangular prismatic in smooth flow, i.e. the turbulence level is low, the drag coefficient is a function of the ratio b/d, where b is the along-wind, and b is the cross-wind dimension. In turbulent boundary-layer flow, the drag coefficients are much lower ($C_d \approx 1$) than smooth uniform because of the high turbulence (Holmes 2015).

The spectral representation methods appear to be most commonly used because they are conceptually straightforward. These methods try to define a signal or series of time from their spectral characteristics like amplitude and phase. The Shinozuka method (Shinozuka and Jan 1972) is a spectral representation method based on the compact form of Fourier series with a spectral density function as the variable responsible for the amplitude of the sinusoidal waves that correspond to each frequency. The turbulent part $u_i(t)$ of the longitudinal component can be generated from spectral representation method proposed by Shinozuka and Jan. Considering the case of Np stationary stochastic processes $u_i(t)$, $j = 1, 2, 3, ..., N_p$; and discrete time $t = i\Delta t$, $i = 0, 1, 2, ..., N_s$, the mathematical expression for the generation of synthetic records is as follows

$$u_j(t) = \sum_{k=1}^{j} \sum_{n=1}^{N_f} |\overline{H}_{jk}(\omega_n)| \sqrt{2\Delta\omega} \cos[\omega_n t + \theta_{kn}]$$
(4)

where $u_j(t)$ is the turbulent part of the longitudinal component at jth point in the space, $H_{jk}(\omega_n)$ is an element of the lower triangular matrix $\mathbf{H}(\omega_n)$ of size $N_p x N_p$ which is defined by the Cholesky factorization process from the cross spectral density matrix, θ_{kn} is an element of the random phase angle matrix $\mathbf{\Theta}$ of size $N_p x N_f$ with uniform distribution between $[0, 2\pi]$, ω_n is the discrete angular frequency (rad/s), $\Delta \omega$ is the increment of angular frequency and N_f is the amount of values contained in the discrete spectral density function.

The cross-spectral describes the effect of the turbulence components at two points at a given frequency. This influence is due to the spatial dimension of the vortices in the wind field. According to the Cholesky factorization process, if the cross spectral density matrix $S^{0}(\omega)$ is symmetric positive definite, then $S^{0}(\omega)$ can be decomposed as (Veers 1987)

$$\mathbf{S}^{0}(\omega) = \overline{\mathbf{H}}(\omega)\overline{\mathbf{H}}^{\mathrm{T}}(\omega) \tag{5}$$

where $S^{0}(\omega)$ is the cross spectral density matrix for angular frequency ω and $\overline{\mathbf{H}}(\omega)$ is a lower triangular matrix. The process of Cholesky factorization is as follows H $(\omega) = S^{0}(\omega)^{1/2}$

$$H_{11}(\omega) = S_{11}(\omega) + H_{21}(\omega) = S_{21}^{0}(\omega)/H_{11}(\omega)$$

$$H_{22}(\omega) = (S_{22}^{0}(\omega) - H_{21}(\omega)^{2})^{1/2}$$

$$H_{31}(\omega) = S_{31}^{0}(\omega)/H_{11}(\omega)$$

$$\vdots$$

$$H_{jk}(\omega) = \left(S_{jk}^{0}(\omega) - \sum_{l=1}^{k-1} H_{jl}(\omega)H_{kl}(\omega)\right)/H_{kk}(\omega)$$

$$H_{kk}(\omega) = \left(S_{kk}^{0}(\omega) - \sum_{l=1}^{k-1} H_{kl}(\omega)^{2}\right)^{1/2}$$
(6)

For two points with vertical separation r_y , the $S_{ij}^0(\omega)$ corresponding elements are obtained by the cross-spectral density function $S_{uu}(z_i, z_j, n)$

$$S_{uu}(z_i, z_j, n) = \sqrt{S_u(z_i, n)S_u(z_j, n)} \sqrt{\operatorname{coh}(r_y, n)}$$
(7)

where $S_{uu}(z_i, z_j, n)$ is the cross spectral density function for two longitudinal turbulent components at space points z_1 and z_2 , $S_u(z_i, n)$ is the single power density spectrum at z_i , $\sqrt{\operatorname{coh}(r_y, n)}$ is the root-coherence function and n is the the frequency in Hz.

A modification of the wind spectral density function of von Karman was presented by Harris (von Karman 1948, Harris 1990). This spectral density function has revealed an excellent accuracy in high frequency with application to wind codes (Lungu and van Gelder 1997). In fact, Xu (2013) consider that this is the most mathematically correct wind spectrum. The mathematical form of von Karman-Harris expression is

$$S_u(z,n) = \frac{4(\sigma_u^2)L_u(z)/\overline{U}(z)}{\left[1 + 70.8\left(\frac{nL_u(z)}{\overline{U}(z)}\right)^2\right]^{5/6}}$$
(8)

where σ_u is standard deviations for the turbulence components and $L_u(z)$ is the integral length scale, which can be approximated by exposed equations in Eurocode (2005).

The root-coherence function defines the statistic dependence between two turbulent components at two different points. This function tends to zero when the separation r_y increases, in other words, the influence of the turbulent winds between two components decreases when their separation increases. Davenport (1961) suggested an exponential expression as root-coherence function

$$\sqrt{\operatorname{coh}(r_y, n)} = e^{\left(-c_y r_y \frac{n}{U}\right)}$$
(9)

where \overline{U} is the average speed between two points calculated as $1/2 \left[\overline{U}(z_i) + \overline{U}(z_j) \right]$ and C_y is a non-dimensional decay constant, with typical value equals 10.

2.3 Dynamic analysis

The Newmark method is used to solve the differential equation of motion (Newmark 1959). This method is based on two assumptions with the aim to solve the equation of motion. The assumptions are that the acceleration between two times instants could be linear or a mean constant. The idealization of a prismatic building as shear-building can be represented as a MDOF system (Chopra 2007). The governing equation of motion for MDOF structures under external loads can be written in matrix form as follows

$$\mathbf{M}\ddot{\mathbf{x}} + \mathbf{C}\dot{\mathbf{x}} + \mathbf{K}\mathbf{x} = \mathbf{F} \tag{10}$$

where **M**, **C** and **K** are the mass, damping and stiffness matrices, respectively; \mathbf{x} , $\dot{\mathbf{x}}$ and $\ddot{\mathbf{x}}$ are the displacement, velocity and acceleration vectors, respectively; and **F** is a matrix with the force vectors.

The form of the damping matrix C depends of the damping characteristic of the structure, which can be classical or nonclassical damping. According to Chopra (2007), the classical damping is an appropriate idealization if similar damping mechanisms are distributed throughout the structure; e.g., a multistory building with a similar structural system and structural materials over its height. In this work the Rayleigh Damping method is used in order to build a classical matrix C.

For a MDOF system, the equation of motion can be rewritten in terms of its possible modes of vibration Φ

$$\overline{\mathbf{M}}\overline{\mathbf{q}} + \overline{\mathbf{C}}\overline{\mathbf{q}} + \overline{\mathbf{K}}\mathbf{q} = \overline{\mathbf{F}} \tag{11}$$

where **q** is the modal coordinate, $\overline{\mathbf{M}} = \boldsymbol{\Phi}^{\mathrm{T}} \mathbf{M} \boldsymbol{\Phi}$, $\overline{\mathbf{C}} = \boldsymbol{\Phi}^{\mathrm{T}} \mathbf{C} \boldsymbol{\Phi}$, $\overline{\mathbf{K}} = \boldsymbol{\Phi}^{\mathrm{T}} \mathbf{K} \boldsymbol{\Phi}$ and $\overline{\mathbf{F}} = \boldsymbol{\Phi}^{\mathrm{T}} \mathbf{F}$ are modal transformation matrices corresponding to the mass, damping, stiffness, and forces matrices, respectively.

2.4 Multiple regression

The regression is a process that try to determine the degree of dependence or relationship between two or more variables. In the case of an independent variable (predictor) and a dependent variable (response), the process is named simple regression. When the response depends on the influence of two or more predictor variables, the process is known as multiple regression.

The linear model for a classical regression of N_d samples of data with N_v independent variables x_k , takes the next mathematical form

$$\mathbf{Y} = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 \boldsymbol{x}_1 + \boldsymbol{\beta}_2 \boldsymbol{x}_2 + \dots + \boldsymbol{\beta}_{N_v} \boldsymbol{x}_{N_v} + \boldsymbol{\epsilon}$$
(12)

where Y is a vector of dependent variable (response) with size N_dx1, x_k is a vector of independent variable *k*-th with size N_dx1, β_k is the coefficient corresponding to the variable predictor *k*-th and ϵ is the error.

The matrix form of a multiple regression model is as follows (Bauer *et al.* 2005)

$$\mathbf{Y} = \mathbf{X}\mathbf{B} + \boldsymbol{\epsilon} \tag{13}$$

Model Name	Transformation of the variable Y	Transformation of the variable X	Linear model	Conversion
Exponential	$\mathbf{Z} = \log_b(\mathbf{Y})$	$\mathbf{X} = \mathbf{X}$	$\mathbf{Z} = \mathbf{X}\mathbf{B} + \boldsymbol{\epsilon}$	$Y = b^Z$
Logarithmic	$\mathbf{Y} = \mathbf{Y}$	$\mathbf{W} = \log_b(\mathbf{X})$	$\mathbf{Y} = \mathbf{W}\mathbf{B} + \boldsymbol{\epsilon}$	Y = Y
Log-log	$\mathbf{Z} = \log_b(\mathbf{Y})$	$\mathbf{W} = \log_b(\mathbf{X})$	$\mathbf{Z} = \mathbf{W}\mathbf{B} + \boldsymbol{\epsilon}$	$Y = b^Z$

Table 1 Transformation of variables

where **X** is a matrix of size $N_d x(N_v + 1)$ and B is a vector of size $(N_v + 1)x1$. The reason of adding a column in **X** and a row in B is due to the consideration of the coefficient β_0 which can be represented as $\beta_0 x_0$, where $x_0=1$. There are several processes for the determination of the coefficients; one of the most widely used is known as least squares. The expression for estimating the coefficients by least squares is as follows

$$\mathbf{B} = (\mathbf{X}^{\mathsf{T}}\mathbf{X})^{-1}\mathbf{X}^{\mathsf{T}}\mathbf{Y} \tag{14}$$

The deviation of the values predicted with relate to the target values can be measured with the root-mean-square error

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N_{d}} (\dot{y}_{i} - y_{i})^{2}}{N_{d} - N_{v} - 1}}$$
(15)

where \dot{y}_i is the predicted value *i*-th and y_i is the target value *i*-th.

The statistical parameter to measure the degree of prediction for a model with simple regression is known as coefficient of determination, denoted R^2

$$R^{2} = 1 - \frac{\sum_{i=1}^{N_{d}} (\dot{y}_{i} - y_{i})^{2}}{\sum_{i=1}^{N_{d}} (y_{i} - \bar{y})^{2}}$$
(16)

where \overline{y} is the mean of the target values.

When the number of predictor variables increases, the coefficient of determination R^2 is not adequate to establish which of the models is the best to explain the dependent variable. Due to the increase of the number of predictor variables, the error decreases and, therefore, it will be necessary to work with a measure that takes into account the number of predictor variables of the model, this coefficient is known as the adjusted coefficient of determination R^2_{adj} and is calculated as follows

$$R_{adj}^{2} = 1 - \left(\frac{N_{d} - 1}{N_{d} - N_{v} - 1}\right) \frac{\sum_{i=1}^{N_{d}} (\dot{y}_{i} - y_{i})^{2}}{\sum_{i=1}^{N_{d}} (y_{i} - \bar{y})^{2}}$$
(17)

One way to increase the level of determination of a model is transforming the variables in order to increase the linear correlation between them. Some of the most common transformation models are shown in Table 1 (Cohen *et al.* 2013).

Box and Cox (1964) proposed a method of power transform with the intention of correcting the nonlinearity of the relation respect to Y. The model of Box and Cox is represented as follows

$$\mathbf{Y}' = \mathbf{X}\mathbf{B} + \boldsymbol{\epsilon} \tag{18}$$

where Y' must satisfy the following conditions

$$Y' = \begin{cases} \frac{Y^{\lambda} - 1}{\lambda}, & \lambda \neq 0\\ \ln(Y), & \lambda = 0 \end{cases}$$
(19)

For the process to select the best λ value is necessary to choose a discretized range of possible values, commonly [-2, 2], and evaluating the error of the regression for each possible value of λ . The process ends when the smallest error is obtained. Note that the conversion of the response variable is given by the transposition of the variable using the selected condition.

3. Definition of the database

In order to build the prediction model through regression analysis, a large response database has been constructed by combining some wind and structural variables with an acceptable range of possible values allows to define a considerable amount of study cases. The Fig. 2 shows the combination of the selected values for wind and structural variables that permits to cover a great amount of sensitive buildings to the dynamic effects of the wind. The slenderness relation is defined as $R_e = H/b$, where H is the total height of the structure and b is the plane dimension parallel to the direction of the wind. The stiffness ratio describes the difference of story stiffness between the last and the first level, i.e., $R_k = k_{last}/k_{first}$. The distributed mass represents the mass concentration per unit area for each floor. According to Eq. (10), the equation of motion for MDOF structures is defined indirectly from of these structural variables, where the stiffness matrix can be estimated by an iterative process where the problem of eigenvalues that relates the stiffness, mass and period of a structure is solved (Chopra 2007).

The Newmark method is used to solve the differential equation of motion (Newmark 1959). This method is based on two assumptions with the aim to solve the equation of motion. The assumptions are that the acceleration between two times instants could be linear or a mean constant. The idealization of a prismatic building as shear-building can be represented as a MDOF system with one degree of freedom per floor (Chopra 2007).

With the loads calculated and the structures defined, the Newmark method is employed to obtain the dynamic response of 1600 structures where each one is exposed to 16 turbulent wind conditions. The maximum displacements of each study case are registered in a database with fields associated to the wind and structural variables (see Fig. 3).



Fig. 2 Variables to define the structures and dynamic wind loads

Terrain Categories	Regional Speed [km/h]	Height [m]	Sienderness Ratio	Fundamental Period [s]	Distributed Mass [kg/m²]	Stiffness Ratio	Maximum displacement [mm]
1	100	50	3	1	500	1	16.13
1	100	50	3	1	500	0.9	17.05
1	100	50	3	1	500	0.8	18.56
	599		+++	2.000	0777.0		
	***	***	+++			***	
4	250	200	6	5	800	0.7	616.58

Fig. 3 Representation of the database with the records of the maximum displacements of each study case

4. Prediction models

The maximum displacements obtained in the dynamic analyses are the dataset employed for the generation of prediction models by multiple regression methods. The height, slenderness ratio, fundamental period of the MDOF system, distributed mass, stiffness ratio, terrain categories and basic wind speed represent the independent variable or predictors and the maximum displacement is the dependent variable or response. Table 2 shows the mathematical models obtained from the regression analysis with transformation of variables of the dataset; in addition, the prediction efficiency of each mathematical model is presented in terms of the adjusted coefficient of determination and the root-mean-square error. It was observed that the variable transformations help to produce a better linear relationship between the predictor and response variables. The regression model with log-log transformation has the best degree of prediction. Graphically, this is confirmed in Fig. 4 where the log-log model presents the lowest dispersion to the ideal line Y=Target, i.e., values emitted by the mathematical model (predictions of the model) are closest to the maximum displacement values stored in the database (target values).

4.1 Evaluation and validation of the log-log prediction model

In order to evaluate the performance of the log-log model, which was generated from results of several dynamic analyses using simplify structure systems, two complex structures are subjected under wind effects, The selected buildings to the evaluation were designed by Federal Emergency Management Agency of USA (FEMA 2000) for 9- and 20-story structures in Boston city with consideration of controlled wind loads. The buildings are modeled with elastic beam-column elements connected by zero-length elements, which work as rotational springs to represent a nonlinear behavior. The springs follow a bilinear hysteretic response, which is an idealization of elastic and plastic deformations by two lines based on the Modified Ibarra Krawinkler Deterioration Model (Lignos and Krawinkler 2011). The panel zones are explicitly modeled with eight elastic beam-column elements and one zero-length element, which serves as rotational spring to represent shear distortions in the panel zone. A leaning column with gravity loads is linked to the frame by truss elements in order to consider the effect of contribution of these loads in the lateral displacements also known as P-Delta effects. OpenSees (McKenna 2011) is the used

Regression	Models (Mathematical expressions)	R^2_{adj}	RMSE
Classical	$Y = -349.54 - 2.9336H + 72.717R_e - 0.53583M_d - 25.273R_k + 186.82T_0 - 46.251C_t + 3.66U_{10,II}$	0.597	319
Exponential	$logY = 0.75819 - 0.0035034H + 0.10048R_{e} - 0.00067961M_{d} - 0.032531R_{k} + 0.34136T_{0} - 0.059699C_{t} + 0.0054277U_{10,II}$	0.884	171
Logarithmic	$Y = 357.87 - 768.6H + 719.11R_{e} - 792.43M_{d} - 48.677R_{k} + 994.85T_{0} - 215.89C_{t} + 1334.6U_{10,II}$	0.561	333
Log-log	$\begin{split} \log \mathrm{Y} &= 0.79758 - 0.88589 \mathrm{logH} + 1.0029 \mathrm{logR}_{\mathrm{e}} - 1.0003 \mathrm{logM}_{\mathrm{d}} - 0.062754 \mathrm{logR}_{k} \\ &+ 2.0108 \mathrm{logT}_{\mathrm{0}} - 0.27755 \mathrm{logC}_{\mathrm{t}} + 2.0561 \mathrm{logU}_{\mathrm{10, II}} \end{split}$	0.985	59
Box-Cox	$Y^{(\lambda=0.0821)} = 1.5112 - 0.012313H + 0.34762R_{e} - 0.0023676M_{d} - 0.11362R_{k} + 1.1648T_{0} - 0.20783C_{t} + 0.018778U_{10 \text{ II}}$	0.962	130

Table 2 Models of general regression to direct calculate the maximum displacement

Table 3 Maximum dynamic displacements and predictions estimated by the log-log model

Building	Structural characteristic and wind	Max	Prediction	Error
	condition	displacement		
9-story structure	H=37 m, R_e =0.8, M_d =488 kg/m ² , R_k =0.7; T_0 =2.5 s, C_t =4, and $U_{10,II}$ =180 km/h.	73.91 mm	80.64 mm	6.73 mm (9.10 %)
20-story structure	H=81 m, R_e =2.6, M_d =488 kg/m ² , R_k =0.7; T_0 =2.9 s, C_t =4, and $U_{10,II}$ =180 km/h.	173.02 mm	178.89 mm	5.87 mm (3.39 %)



Fig. 4 Relationship between targets and prediction values

software to model and analyze the structure response of the selected buildings because OpenSees has a fully programmable scripting language for defining models, solution procedures and post-processing. A schematic representation of the models is presented in Figs. 5(a)-5(c).

The dynamic wind loads are generated from simulated records with attention of the wind conditions described by the American Society of Civil Engineers for Boston city in Standards (ASCE 2006). The wind loads are applied to the OpenSees models in order to produce the dynamic response and to determinate the maximum displacement. Figs. 6-7 show the time series corresponding to the structural response of 9- and 20-story buildings. In Table 3, the maximum dynamic response are compared with the prediction values calculated with the log-log model. It is observed that the prediction values are close to the maximum displacements reported by the dynamic analysis, also a better prediction for the building with 20-story is exposed, this is due to the fact that some structural characteristics of the building with 9 floors are not within the range of values considered in the database.

Another evaluation of the prediction of the log-log model is shown in Table 4, which presents the maximum along-wind displacement of structures reported by other studies and the respective value predicted by the log-log regression model. It is observed that the log-log regression

Paper	Structural characteristic and wind	Max	Prediction	Error
	condition	displacement		
Huang and	H=200 m, $R_e=5$, $M_d=1000$ kg/m ² , $R_k=1$; $T_0=4.71$ s, $C_t=2$, and	180 mm	100 mm	5 55 %
Chen (2007)	$U_{10,II} = 165 \text{ km/h}.$	100 1111	190 11111	5.55 70
Venanzi et	H=180 m, R_e =6, M_d =509 kg/m ² , R_k =1; T_0 =4.87 s, C_t =4, and	176 mm	162 mm	2 20 %
al.(2014)	$U_{10,II} = 168.12 \text{ km/h}.$	470 11111	402 11111	2.29 %

Table 4 Maximum along-wind displacements reported by other studies and predictions estimated by the log-log model.



Fig. 5 Schematic representation of the building modeling on OpenSees



Fig. 6 Dynamic response at roof level of the 9-story structure



Fig. 7 Dynamic response at roof level of the 20-story structure

model is able to predict with an acceptable accuracy the peak demand; therefore, the regression data generated from the application of the Shinozuka and Newmark methods are adequate.

5. Conclusions

The Shinozuka and Newmark methods were employed to simulate synthetic wind records and to obtain the dynamic response of 1600 shear-buildings discretized as MDOF structures, respectively. With the results, a database with fields related to the maximum response, basic structural characteristics and regional wind conditions was built. With the aim to generate prediction models, the database was analyzed with classical regression and regression with transformation of variables. The regression model with log-log transformation had the best degree of prediction with an adjusted coefficient of determination of 98.5%. In order to validate the log-log model generated from analysis results with simplified structural systems, two buildings, 9- and 20-story structures were analyzed. In this validation, it was observed that the prediction model provides similar maximum dynamic values compared with the complex structures; however, it was notable a better performance of the prediction model for the building with 20-story due to the fact that some structural characteristics of the building with 9-story are not within the range of values considered in the variables of the database. In addition, a comparison between the prediction of the loglog model and the maximum displacement of some buildings reported in other papers was presented. Here, it was observed that the log-log regression model is able to predict with an acceptable accuracy the peak demand, therefore, the regression data generated from the application of the Shinozuka and Newmark methods are adequate. The evaluation and validation of the log-log model allows to determine that its prediction values are reliable when the eolic and structural characteristics are within the range of values considered in the database.

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