

**Research Article***Copyright © All rights are reserved by Omar M Nofal*

Stochastic Modeling of Uncertainties in the Wind Load Pressure on Residential Buildings Using Different Stochastic Techniques

Omar M Nofal*

Colorado State University, USA

***Corresponding author:** Omar M Nofal, Department of Civil and Environmental Engineering, Colorado State University, USA.**Received Date:** August 21, 2020**Published Date:** September 10, 2020**Abstract**

There are different methods to quantify the amount of uncertainties in the analysis of structures and their design procedures. The efficiency and the suitability of each method depend on the type of analysis and the load scenario that will be used for this analysis. In this paper, different uncertainty propagation methods are used to quantify the amount of uncertainties in the wind load analysis procedures to quantify the load impact on the gable roofs of residential buildings. Therefore, Direct Monte Carlo Simulation, Importance Sampling, First Order Reliability Method, and Taylor Approximation are used to further investigate the impact of each method on the uncertainty quantification. The selected example structure to perform the analysis is one of the different archetypes that has been used for the tornado analysis in the literature. The different wind load demand parameters and components statistics are used to conduct the different stochastic analyses. The analysis results showed that MCS is the most efficient method with the least coefficient of variation in the simulated wind pressure and the calculated failure probabilities associated with each stochastic model.

Keywords: Wind load analysis; Direct monte carlo simulation (MCS); Markov chain monte carlo (MCMC); First order reliability method (FORM); Subset analysis; Importance sampling

Introduction

Wind hazard losses are catastrophic and devastating specifically for wind-driven by hurricane and tornados. The current literature is populated with many studies that investigate the impact of wind loads on buildings and infrastructure [1–4]. However, these studies, while they are novel, there is still a huge amount of uncertainties within the input parameters for the wind load calculation and the resistance of the impacted structures [5]. The current research trend in the vulnerability analysis of buildings and infrastructure to natural hazards is moving from deterministic to probabilistic approaches. This includes buildings vulnerability to earthquake hazard [6,7], wind hazards [8–10], and flood hazards [11,12]. However, the focus of this article is spotted on wind hazards and the quantification of

the uncertainties associated with its parameters. Several probabilistic analyses of the wind load impacts on building and infrastructure were investigated in the literature including wind hazard induced by tornados [13–15] and hurricanes [16–19]. Additionally, multiple numerical and experimental studies in the literature focus on propagating uncertainties in wind damage models using fragility functions to describe the probabilistic performance of buildings and infrastructure [9,13,20–23]. Most all of these functions are using Monte Carlo simulation (MCS) to propagate uncertainties in the wind demand and capacity parameters based on a specific number of simulations. However, there are multiple approaches that could be used to propagate uncertainties ranging from simple to compu-

tationally expensive approaches. Additionally, the number of used simulations highly impacts the accuracy of the analysis results. Therefore, different stochastic simulation methods are needed to investigate the uncertainty quantification within wind load parameters including resistance and demand parameters. There are wide different stochastic simulation techniques that could be used to propagate these uncertainties. However, the suitability and the efficiency of each technique should be tested and compared to the other available methods. Therefore, in this paper, the uncertainties in the wind pressure model parameter will be propagated along with the uncertainties within the wind resistance parameters us-

ing different stochastic simulation techniques such as Direct Monte Carlo Simulation (MCS), Importance Sampling (IS), First Order Reliability Method (FORM), and Taylor Approximation (TA). This was done using an illustrative example building archetype to illustrate the proposed approach. Therefore, a one-story single-family wood-frame residential building archetype is analyzed using a number of stochastic modeling techniques. The expected value of the resulted wind pressure on this archetype was investigated using different stochastic simulation techniques along with the failure probability of the building components (Figure 1).

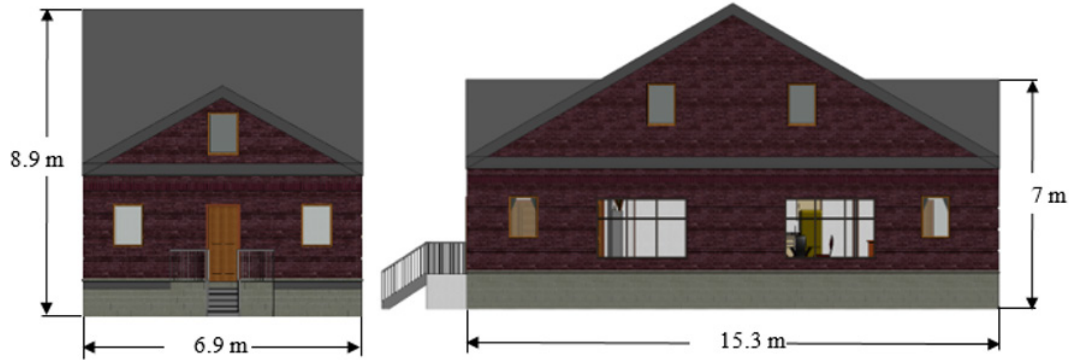


Figure 1: One-Story wood-frame residential building archetype used in this study.

Problem Characterization

There are wide different stochastic simulation techniques that could be used to quantify the amount of uncertainties within engineering systems. However, the main challenge is choosing the most suitable and efficient technique that fit each specific system and the characteristics of its parameters with the lowest number of simulations. Therefore, different stochastic models should be tested, and their analysis results should be compared to determine the most accurate and suitable techniques. In terms of wind load, when buildings are designed for wind, the wind pressure is the main characteristic load that buildings' components get designed for. The most challenging aspect of the wind pressure quantification is the diversity of parameters included within the pressure equation that accounts for different types of buildings and wind load characteristics. Based on the ASCE7-16 [24], the extreme wind loads are calculated using Eqs. (1) and (2). The wind load analysis conducted herein does not include the tornado factors that have been included in multiple researches related wind hazards induced by tornados [13,25] as shown in Eq. (3). Therefore, the tornado factors are assumed to be 1.0 to make the analysis more general and simple.

$$q_h = 0.613K_hK_{zt}K_dV^2 \left(N / m^2 \right) \quad (1)$$

$$P = q_h \left[(GC_p) - (GC_{pi}) \right] \left(N / m^2 \right) \quad (2)$$

$$P_T = q_h \left[T_e (GC_p) - T_i (GC_{pi}) \right] \left(N / m^2 \right) \quad (3)$$

where q_h = the wind velocity pressure calculated at mean roof height h ; K_h = velocity pressure exposure coefficient at mean roof height; K_{zt} = topographic factor which is assumed to be deterministic and equal to 1.0 in this study; K_d = directionality factor which is also assumed to be deterministic and equal to 0.85; V = 3-s gust wind speed; G = gust-effect factor; GC_p = external pressure coefficient; GC_{pi} = internal pressure coefficient. In the model presented herein, the uncertainty within K_h , GC_p , and GC_{pi} were propagated using the statistical models provided in these references [8, 10, 24] as shown in (Table 1).

Wind loads mainly impact the building envelop including walls sheathing and framing, roof sheathing and framing, doors, and windows. The behavior of these components controls the damage state (DS) of buildings subjected to wind loads as described herein [9, 13, 22, 23]. However, the most vulnerable building component is the exterior components. Therefore, the focus of this study is spotted on the roof sheathing, plywood covering, doors, and windows. A wood-frame residential building archetype developed by Amini and van de Lindt [8] is used herein as an example to illustrate the analysis approach. Table 2 lists the statistical models for some of these components which are provided by Unnikrishnan and Barba to [26] and Lee and Rosowsky [20]. Afterwards, different stochastic methods were used to account for the different uncertainties within the wind load parameters such as MCS, IS, FORM, and TA.

Table 1: Wind load statistics.

Parameter	Description	Nominal	Mean	COV	Reference
K_z	0-4.75m (0-15ft)	0.85	0.82	0.14	[8]
	6.1m (20ft)	0.9	0.84	0.14	
	7.62m (25ft)	0.94	0.88	0.14	
	9.14m (30ft)	0.98	0.94	0.14	
	12.19m (40ft)	1.04	1	0.14	
GC_{pi}	enclosed building	0.18	0.15	0.33	[8]
	Partially enclosed building	0.55	0.46	0.33	
GC_p	Roof Cover Zone 1'	-0.9	-0.86	0.12	[10]
	Roof Cover Zone 1	-1.7	-1.62	0.12	
	Roof Cover Zone 2	-2.3	-2.19	0.12	
	Roof Cover Zone 3	-3.2	-3.04	0.12	

Table 2: Components resistance statistics.

Components	Mean	COV	Reference
Doors	4.79	0.2	[26]
Windows	3.33	0.2	[26]
Garage doors	2.5	0.2	[26]
Roof sheathing	6.67	0.21	[20]
Roof plywood	10.9	0.07	[20]

Structure Definition and Numerical Models

The archetype selected herein is this study is one of the most common one-story residential building adopted in the US buildings industry. It is a one-story single-family wood residential building with a small rectangular plan of (15.3m × 6.9m) with a total area of 105 m² (1130 ft²). The readers are referred to these articles [8, 22] for more details about the statistical parameters for the resistance of this archetype. Fig. 1 shows detailed dimensions of the chosen archetype. Additionally, the wind load parameters statistics are presented in Table 1 and the building components resistance statistics are presented in (Table 2).

Methodology

First, the wind load pressure parameters statistics and the component's resistance statistics were collected from the literature as discussed above. The mean value and the coefficient of variation of the wind pressure were calculated using MCS, IS, FORM, and TA with the goal of investigating the impact of the different stochastic modeling techniques on the resulted variation in the value of the wind pressure. The mean value was calculated by evaluating the general stochastic integral in Eq. 4 Then, the failure probability of the roof sheathing was calculated and compared the results from adopted methods.

$$E_f [g(\xi)] = \int g(\xi) f(\xi) d\xi \quad (4)$$

where $f(\xi)$ = the probability density function of the estimated parameter, $g(\xi)$ = the scalar function of the random variable, and $E_f[g(\xi)]$ of the random variable.

Direct Mont Carlo Simulation analysis

The Direct Monte Carlo simulation (MCS) technique depends on the Central Limit Theorem which includes developing a number of simulations for each random variable to quantify the estimator for Eq. (3). MCS is used to calculate the average value of the integral (H_k) by dividing the total number of the simulated values of the scalar function of the random variable (ξ) by the total number of simulations using Eq. (5). The MCS process conducted herein included generating 1000 samples in a standard Gaussian space to evaluate the wind pressure at each sample point. Then, the mean value and the coefficient of variation for the wind pressure was calculated. The coefficient of variation is calculated using Eq.(6).

$$H_k = \frac{1}{k} \sum_{i=1}^k g(\xi) \quad (5)$$

$$COV(H_k) \approx \frac{1}{\sqrt{k}} \frac{\sqrt{\text{variance}(g(\xi))}}{\text{Mean}(g(\xi))} \quad (6)$$

Importance Sampling Analysis

The Importance Sampling (IS) technique is used to generate samples that are within the important region which will help to reduce the variance induced by MCS. Therefore, usually, the COV associated with IS estimator is lower than the one calculated using MCS. Using IS will help to find an optimal distribution that matches the original one by assuming a distribution close enough to the peak of the integrand. The optimal sampling density is assumed to

have a positive relationship with the integrand in Eq.(4) which is calculated using Eq.(7).

$$q^*(\xi) = \frac{|g(\xi)| f(\xi)}{\int |g(\xi)| f(\xi) d\xi} \alpha |g(\xi)| f(\xi) \quad (7)$$

Taylor Approximation

Taylor Approximation estimates the stochastic integral in Eq. (4) using Taylor series. The main goal of using Taylor series is to make the stochastic integral easier and suitable for the differentiation process by including exponential in the integrand as shown in Eq.(8). Then, the estimator for Eq. (4) was evaluated in Eq. (9) by using the second-order Taylor Polynomial and optimizing the integrand to calculate the Hessian $H_{\ln k(\xi)}$

$$H = \int g(\xi) f(\xi) d\xi = \int k(\xi) d\xi = \int e^{\ln(k(\xi))} d\xi \quad (8)$$

$$H \approx \frac{(2\pi)^{n/2} k(\xi^*)}{\sqrt{|\det H_{\ln k(\xi^*)}|}} \quad (9)$$

where $k(\xi^*)$ is the value of the integrand function at ξ^* , and $H_{\ln k(\xi^*)}$ is the Hessian of the logarithmic value of the integrand evaluated at ξ^* .

First Order Reliability Method

The First Order Reliability Method (FORM) depends on the simplification of the integrand using the idea that the probability density function gets decreased as we move away from the center of the distribution. In this method, a failure region F is assumed to be bounded by a certain threshold and there are some points ξ located within this threshold and other points ξ^* with highest probability density function value. Hence, the points around ξ^* will exhibit more contribution to the failure probability. The failure probability is the approximation of the F calculated from Eq.(10) which is a function of the reliability index β calculated from Eq.(11).

$$F = \left\{ \xi \in R^n : g_n = -\beta^2 + (\xi, \xi^*) > 0 \right\} \quad (10)$$

$$\beta = \|\xi^*\| = \sqrt{\xi^{*T} \cdot \xi^*} \quad (11)$$

Failure Probability Calculation

In the last part, different stochastic modeling methods were investigated to calculate the mean value of the wind pressure at the roof of the impacted residential buildings. The roof failure analysis is conducted by assuming the wind velocity to be 70.0 m/s which represents a category 4 hurricane on the Saffir-Simpson hurricane wind scale or category 3 tornado on the enhanced Fujita scale. Then, the calculated wind pressure will be compared with the resistance of the roof sheathing to calculate the failure probability of this component. The failure probability was calculated using failure indicator function $F(\xi)$. The indicator function is equal to 1.0 in case of failure at wind pressure exceeding the resistance pressure value and is equal to 0.0 in case of no failure at wind pressure less than resistance pressure value. The failure probability will be calculated using Eq. (12).

$$P_F = E_F [I_F(\xi)] = \int I_F(\xi) f(\xi) d\xi \quad (12)$$

The methods used to evaluate the mean value of the wind pressure were used to calculate the failure probability by replacing $g(\xi)$ with $I_{F(\xi)}$. In addition to these methods, the first-order reliability method was also used to calculate the failure probability.

Results

An algorithm that formulates these stochastic models was created using the static models of both wind demand parameters and the roof sheathing statistics. The number of simulations used to conduct the analyses related to each stochastic model is 1000 simulation. The mean value and COV of the wind pressure were calculated using MCS, IS, and Taylor Approximation. (Table 3) Summarizes the wind pressure results calculated from the different stochastic methods. The analysis results show that all the used methods gave very close results. However, MCS gave less coefficient of variation.

Table 3: The resulted mean wind pressure value and C.O.V using MCS, IS, and Taylor Approximation for the roof sheathing.

	MCS	IS	TA
P-mean (N/m ²)	6772.1	6769.4	6681.2
P-COV	0.0058	0.0083	--

Figure 2 shows how the increase in the number of samples will result in stabilizing the value of the mean wind pressure. Increasing the number of samples is also increasing the efficiency of both MCS and IS method in reducing the coefficient of variation with the adopted number of samples. To that end, MCS is considered the most efficient with less COV. The failure probability for the different components of the selected residential building archetype was then

tested using the same methods that have been used before in addition to the FORM method (Table 4). Presents the summary of the results from the different stochastic methods for the select building components. The results showed that the MCS is as efficient as the IS approach which gives almost the same variation resulted from the IS.

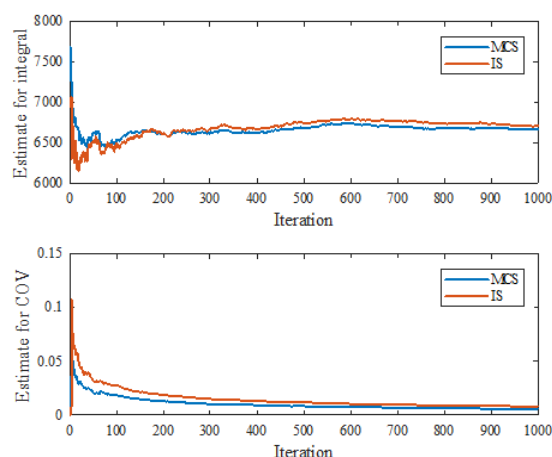


Figure 2: MCS vs IS in terms of the mean value of the wind pressure and COV.

Table 4: The failure probability of the different building components along with the C.O.V using MCS, IS, and FORM.

Building Component	Statistical Parameter	MCS	IS	FORM
Doors	Mean	0.952	0.9488	0.974
	COV	0.005	0.005	-
Windows	Mean	0.999	0.9981	0.9976
	COV	0.0007	0.0018	-
Garage doors	Mean	1	0.996	0.9958
	COV	0	0.0017	-
Roof Sheathing	Mean	0.477	0.4839	0.4972
	COV	0.0234	0.0135	-
Roof Plywood	Mean	0.001	0.0008	0.0011
	COV	0.07	0.07	-

Summary and conclusion

The overarching goal of this study is to propagate uncertainties within the wind load pressure parameters using different stochastic simulation techniques to capture the impact of using different techniques on the wind pressure mean value and its variation. Therefore, Direct Monte Carlo Simulation, Importance Sampling, and Taylor Approximation were used to pick the efficient technique that will induce less coefficient of variation. Additionally, the failure probability of the building components was further investigated using Direct Monte Carlo Simulation, Importance Sampling, and First Order Reliability Method. The results showed that both Direct Monte Carlo Simulation and Importance Sampling method result in almost the same results in terms of the coefficient of variance of the wind load pressure. However, the MCS method gives less variation with less effort based on the low COV. In terms of failure probability of the different building components, the MCS method showed better efficiency than the other methods based on the resulted low coefficient of variance. So, Monte Carlo simulation did an outstanding performance in the wind pressure calculation with respect to the other methods. That is why all the wind load-based fragility analysis literature is based on the MCS analysis.

Acknowledgement

None.

Conflicts of Interest

No conflict of interest.

References

- Pita G, Pinelli JP, Cocke S, Gurley K, Mitrani-Reiser J, et al. (2012) Assessment of hurricane-induced internal damage to low-rise buildings in the Florida Public Hurricane Loss Model. *Journal of wind engineering and industrial aerodynamics* 104: 76–87.
- Aghababaei M, Koliou M, Paal SG (2018) Performance assessment of building infrastructure impacted by the 2017 Hurricane Harvey in the Port Aransas region. *Journal of Performance of Constructed Facilities* 32(5): 4018069.
- Reinoso E, Niño M, Berny E, Inzunza I (2020) Wind Risk Assessment of Electric Power Lines due to Hurricane Hazard. *Natural Hazards Review* 21(2): 4020010.
- Huang Z, Fan X, Cai L, Shi SQ (2016) Tornado hazard for structural engineering. *Natural Hazards* 83(3): 1821–1842.
- Li Y, Ellingwood BR (2006) Hurricane damage to residential construction in the US: Importance of uncertainty modeling in risk assessment. *Engineering structures* 28(7): 1009–1018.
- Aghababaei M, Mahsuli M (2018) Detailed seismic risk analysis of

- buildings using structural reliability methods. *Probabilistic Engineering Mechanics* 53: 23–38.
7. Aghababaei M, Mahsuli M (2019) Component damage models for detailed seismic risk analysis using structural reliability methods. *Structural Safety* 76: 108–122.
 8. Amini MO, van de Lindt JW (2013) Quantitative insight into rational tornado design wind speeds for residential wood-frame structures using fragility approach. *Journal of Structural Engineering* 140(7): 4014033.
 9. Memari M, Attary N, Masoomi H, Mahmoud H, van de Lindt JW, et al. (2018) Minimal building fragility portfolio for damage assessment of communities subjected to tornadoes. *Journal of Structural Engineering* 144(7): 4018072.
 10. Ellingwood BR, Tekie PB (1999) Wind load statistics for probability-based structural design. *Journal of Structural Engineering* 125(4): 453–463.
 11. Nofal OM, van de Lindt JW, Do TQ (2020) Multi-variate and Single-variable Flood Fragility and Loss Approaches for Wood Frame Buildings. *Reliability Engineering & System Safety* 106971.
 12. Nofal OM, van de Lindt JW (2020) Minimal Building Flood Fragility and Loss Function Portfolio for Resilience Analysis at the Community-Level. *Water* 12(8): 2277.
 13. Masoomi H, van de Lindt JW (2016) Tornado fragility and risk assessment of an archetype masonry school building. *Engineering Structures* 128: 26–43.
 14. Unnikrishnan VU, van de Lindt JW (2016) Probabilistic framework for performance assessment of electrical power networks to tornadoes. *Sustainable and Resilient Infrastructure* 1(3–4): 137–152.
 15. Standohar-Alfano CD, van de Lindt JW (2016) Tornado risk analysis for residential wood-frame roof damage across the United States. *Journal of Structural Engineering* 142(1): 4015099.
 16. Kakareko G, Jung S, Mishra S, Vanli OA (2020) Bayesian capacity model for hurricane vulnerability estimation. *Structure and Infrastructure Engineering* 1–11.
 17. Mishra S, Vanli OA, Alduse BP, Jung S (2017) Hurricane loss estimation in wood-frame buildings using Bayesian model updating: Assessing uncertainty in fragility and reliability analyses. *Engineering Structures* 135: 81–94.
 18. Khajwal AB, Noshadravan A (2020) Probabilistic Hurricane Wind-Induced Loss Model for Risk Assessment on a Regional Scale. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering* 6(2): 4020020.
 19. Ouyang M, Duenas-Osorio L (2014) Multi-dimensional hurricane resilience assessment of electric power systems. *Structural Safety* 48: 15–24.
 20. Lee KH, Rosowsky DV (2005) Fragility assessment for roof sheathing failure in high wind regions. *Engineering Structures* 27(6): 857–868.
 21. Van de Lindt J, Amini MO, Standohar-Alfano C, Dao T (2012) Systematic study of the failure of a light-frame wood roof in a tornado. *Buildings* 2(4): 519–533.
 22. Masoomi H, Ameri MR, van de Lindt JW (2018) Wind performance enhancement strategies for residential wood-frame buildings. *Journal of Performance of Constructed Facilities* 32(3): 4018024.
 23. Koliou M, Masoomi H, van de Lindt JW (2017) Performance assessment of tilt-up big-box buildings subjected to extreme hazards: Tornadoes and earthquakes. *Journal of Performance of Constructed Facilities* 31(5): 4017060.
 24. ASCE (2016) Minimum Design Loads and Associated Criteria for Buildings and other Structures (7-16).
 25. van de Lindt JW, Pei S, Dao T, Graettinger A, Prevatt DO, et al. (2013) Dual-objective-based tornado design philosophy. *Journal of Structural Engineering* 139(2): 251–263.
 26. Unnikrishnan VU, Barbato M (2016) Performance-based comparison of different storm mitigation techniques for residential buildings. *Journal of Structural Engineering* 142(6): 4016011.