Determination of the Drag Force Disturbance Index for Analysis of Neighborhood Effect in Tall Buildings Subject to Wind

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Abstract. The presence of obstacles around a building can interfere with the wind flow, altering the pressures on the façades and, consequently, the resulting forces and moments. These interferences can generate protective effects or increase the pressure coefficients. Reliability analyses are commonly used to examine the behavior of structures subjected to such phenomena, and one of these analyses considers the reliability index beta, which has various representations. In this case, the determination of beta is proposed, not considering it as a failure criterion, but rather as a change in the state of the drag force. In this context, this work presents the determination, through reliability analysis, of the drag force perturbation index, and, how much the drag force is being modified due to the presence of a neighboring building, in order to evaluate the behavior of wind effects on a tall building model (CAARC), using experimental data generated in a wind tunnel. Probabilistic concepts and result graphs are presented and discussed in relation to the directions adopted by the CAARC model for beta variation indices. From the results obtained, it was observed that the existence of a neighboring building affects the mean values of the drag force, as well as the disturbance index, both for increases and reductions compared to the isolated building, depending on the situation. Therefore, this study presents interpretations that can help predict the behavior of tall buildings subjected to wind loads in the presence of neighboring buildings.

Keywords: Neighborhood effect; Wind tunnel; Reliability index.

1 Introduction

Natural systems can be described deterministically, but only in a limited way. In many everyday situations, classical descriptions work well; however, as systems become more complex or when greater accuracy in predictions is required, these approaches prove inadequate. The complexity and chaotic behavior of many phenomena, as well as the stochastic nature of others, make probabilistic and statistical tools more appropriate. Thus, the main challenge in structural reliability lies in determining these probabilities (KROETZ [1]).

One way to evaluate reliability in structural design is to determine the reliability index beta and the corresponding probability of failure associated with beta (PANTOJA [2]).

According to Blessmann [3], the existence of obstacles can interfere with the wind flow around a building, causing changes in the pressures on the façades, and consequently, in the resulting forces and moments, due to the interaction between the building and other surrounding structures, that is, in the neighboring regions. These interferences can occur in various ways, such as generating protective effects, reducing, or increasing the pressure coefficients.

The objective of this work is to analyze the behavior of wind flow around buildings in the presence of neighboring structures using experimental data generated in a wind tunnel conducted by Lavôr [4], based on structural reliability criteria for a tall building subjected to wind action, both in isolation and with different neighboring structures.

Reliability analysis will be used to evaluate the resulting forces of wind flow on a given structure through the beta index and statistical parameters. The determination of beta is proposed, not as a failure criterion, but as a change in the state of the drag force. In this context, the present work presents the determination, through reliability analysis, of the drag force perturbation index, that is, how much the drag force is being modified due to the presence of a neighboring building, to evaluate the behavior of wind effects on the model of a standard tall building (CAARC).

2 Numerical Experimental Study – CAARC (Standard Tall Building)

The CAARC Standard Tall Building is a tall building model conceptualized in 1969 by the Commonwealth Advisory Aeronautical Research Council (CAARC). It was designed as a simple building model and is used as a standard for comparison between techniques and experimental tests in boundary layer wind tunnels. This standard resulted in greater reliability in the data obtained through these tests, being required for various types of tests, such as dynamic and pressure measurements on façades. The CAARC is a prismatic building with a rectangular cross-section, with real-scale dimensions of 30.48 m x 45.72 m x 182.88 m.

To evaluate neighborhood factors from pressure coefficients, Lavôr [4] generated experimental data of instantaneous pressures in the Joaquim Blessmann atmospheric boundary layer wind tunnel, located at the Construction Aerodynamics Laboratory of the Federal University of Rio Grande do Sul.

Part of the pressure data was kindly provided by Lavôr [4] and used in the present work, with this data set being reanalyzed by directly applying the evaluation of the global drag force.

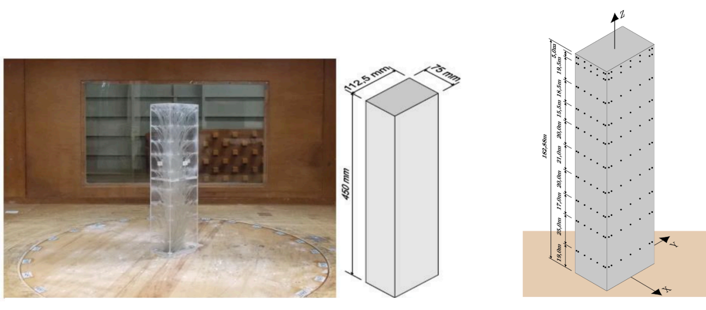
Due to the complexity of on-site analysis or because the studied situation is an idealization that does not exist at full scale, conducting tests on a reduced scale becomes an interesting alternative, used when it is not feasible to analyze the structure at its actual scale.

To ensure an accurate reproduction of wind flow simulation and the application of the scaled model, it is essential to consider the conditions of similarity theory. These conditions link geometric, kinematic, and dynamic properties, establishing a reduced-scale relationship between the flow and the model, compared to their real-scale counterparts (REIS [5]).

Figure 1 shows the scaled-down CAARC model with all the pressure taps installed and already positioned in the wind tunnel for testing.

Considering the length scale of 1:406.4, the dimensions of the experimental model used are 112.50 mm by 75.00 mm at the base and a height of 450 mm. Thus, the top of the model was positioned at half the height of the tunnel.

Thus, in the model studied by Lavôr [4], 280 pressure taps were distributed across the four façades of the model, arranged in 10 horizontal lines with 28 taps each (Figure 1(c)). Each test was conducted over a time interval of 16 seconds. During this period, the electronic transducer recorded 8192 pressure data points per tap, with an acquisition rate of 512 Hz, approximately one recording per tap every 0.001953 seconds. According to similarity theory, the mentioned period corresponded to an interval of 600 seconds in the actual structure.



(a) (b) (c)

Figure 1. (a) CAARC instrumented with pressure taps; (b) model dimensions; and (c) Full-scale CAARC standard tall building and positions of the pressure taps. Source: Lavôr [4]

3 Theoretical basis

In this section, essential concepts will be presented to enable the application of structural reliability, based on the data obtained from the wind tunnel. First, a detailed statistical analysis of these data is necessary to determine which probability distributions best fit them, using uncertainty modeling and goodness-of-fit tests, for the subsequent application of structural reliability.

3.4.1. Uncertainty Modeling

The mean or expected value of X is a measure of central tendency in the data, also known as the first central moment and denoted as E(X). It can be calculated as (HALDAR; MAHADEVAN [6]):

$$Mean = E(X) = \mu_x = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{1}$$

The variance of X, a measure of dispersion in the data around the mean, also known as the second central moment and denoted as Var(X), can be estimated as (HALDAR; MAHADEVAN [6]):

$$Variance = Var(X) = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \mu_x)^2 \tag{2}$$

The standard deviation determines an interval, centered on the arithmetic mean, within which most of the data are concentrated and can be obtained by taking the square root of the variance (HALDAR; MAHADEVAN [6]):

$$\sigma_x = \sqrt{Var(X)} \tag{3}$$

3.4.2. Goodness-of-Fit Test

The goodness-of-fit test is a non-parametric test used to determine if a random variable follows a specific distribution. The term "goodness-of-fit" means there is a good correlation between the dataset and the candidate distribution.

Various goodness-of-fit tests have different statistics and decision criteria, but they share two common hypotheses: the hypothesis that the random variable fits the candidate distribution, and the alternative hypothesis that the random variable does not fit the candidate distribution (TORMAN, COSTER, and RIBOLDI [7]).

3.3.1. Hypothesis testing

In hypothesis testing, two contradictory hypotheses are considered. The objective is to decide, based on sample data, which hypothesis is correct. The problem is formulated so that one hypothesis is initially favored. This hypothesis will not be rejected in favor of the other unless the sample evidence contradicts and strongly supports the alternative hypothesis (SCUDINO [8]). In hypothesis testing, the following fundamental definitions apply:

1 - Null Hypothesis ($H0$): the random variable fits the candidate distribution;

2 - Alternative Hypothesis ($H1$): The random variable does not fit the candidate distribution.

In this formulation of the problem, two types of errors can occur: a Type I error, which is the probability of rejecting $H0$ when it is true; and a Type II error, which is the probability of accepting $H0$ when it is false.

3.3.2. Anderson-Darling Test

This test compares the empirical cumulative distribution function of the sample data with the expected distribution if the data were normal. If this observed difference is sufficiently large, the test will reject the null hypothesis of normality for the population (RYAN; JOINER [9]).

$$AD = n \int_{-\infty}^{\infty} \frac{\left(S(x)-F(x)\right)^2}{F(x)\left(1-F(x)\right)} dF(x) \quad (4)$$

Onde:
F(x) = Theoretical cumulative distribution
S(x) = Empirical cumulative distribution
n = Sample size

3.3.4. Significance Level and p-Value

The significance level (α) is specified before sample collection and hypothesis definition to ensure that the choice of hypothesis does not influence the selection of the candidate distribution. This value is usually chosen between 0.01 and 0.05, corresponding to confidence levels of 99% and 95%, respectively, to make the correct decision (SCUDINO [8]).

The p-value represents the probability that the theoretical test statistic is equal to or more extreme than the observed value, assuming the null hypothesis is true. The simplest way to make the correct decision is to compare the p-value of the hypothesis test with the chosen significance level. If the p-value is smaller than α, the null hypothesis is rejected (TORMAN, COSTER, and RIBOLDI [7]); otherwise, the null hypothesis is accepted. The p-value ranges from 0 to 1, with lower values providing stronger evidence against the null hypothesis.

3.3.5. Structural Reliability

The reliability of a structure is defined as the probability that the structure will not fail in performing its functions (Beck [10]). Reliability analysis can be applied to both new structures and existing ones. Depending on the level of available information, there are different methods to approach reliability, according to Madsen et al. [11] and Lopez [12].

Thus, the present study will consider the Failure Probability Method, where probability distributions are specified, and the probability of failure is calculated, satisfying the following condition:

$$P_f \leq P_{f\ adm} \quad (5)$$

3.4.3. Monte Carlo Simulation

Monte Carlo simulation is a statistical method involving the generation of a large number of random values for each random variable. From these values, the behavior function (simulated model) is evaluated, and its results are then observed (JACOBONI; REGGIANI [13]).

Different probability distributions are used for the independent variables, such as Normal, Log-Normal, Exponential, Gamma, and Weibull (JACOBONI; REGGIANI [13]).

In the case of structural reliability analysis, this means that each randomly generated variable will form a vector ui={X1, X2,..., Xn} of random variables. The behavior function is then evaluated as G(ui). If it is violated (G(ui) ≤ 0), the structure or element does not meet the required minimum conditions. The experiment is repeated many times, and each time a new vector ui={X1, X2,..., Xn} is generated. Finally, if a number n of experiments is conducted, the probability of failure is approximately given by:

$$P_f \approx \frac{n(G(u_i) \leq 0)}{N} \quad (6)$$

Where n(G(ui) ≤ 0) is the number of times the behavior function has values G(ui)≤0, and n is the number of evaluations of the behavior function required for the desired accuracy.

For this methodology, the beta index is calculated using the following expression:

$$\beta = \Phi^{-1}(1 - P_f) \quad (7)$$

Where Φ^{-1} is the inverse of the standard normal cumulative distribution function.

4. Methodology

To evaluate neighborhood factors from pressure coefficients, Lavôr [4] generated experimental data of instantaneous pressures in the Joaquim Blessmann atmospheric boundary layer wind tunnel, located at the Construction Aerodynamics Laboratory of the Federal University of Rio Grande do Sul.

Figure 2 shows the positions adopted for this research.

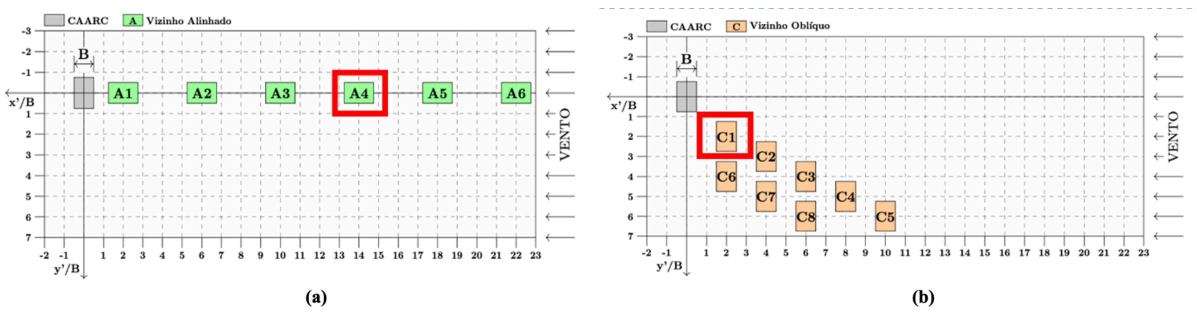


Figure 2 – (a) Aligned Neighbor (C0V90_A4) and (b) Oblique Neighbor (C0V0_C1). Source: Lavôr [4]

From these records, goodness-of-fit tests (Anderson-Darling) were conducted to determine which distribution best fits each case, where the condition of the isolated CAARC has a lognormal distribution, and the CAARC + neighbor conditions exhibit a normal distribution. Subsequently, the respective mean and standard deviation values were obtained. Based on these, the Monte Carlo methodology was applied, and 3,000,000 simulations were performed for each configuration under study (isolated CAARC and CAARC + neighbor).

The drag force perturbation index ($\Delta\beta$) was obtained through the difference between the simulations conducted for the isolated CAARC and the CAARC + neighbor, followed by the calculation of Beta according to Equation (7). This index represents how the wind flow varies with the change and positioning of these neighbors.

In the results presented below for each positioning, in addition to the isolated CAARC positioned at 0º, analyses will be performed for the aligned neighbor "A4" and oblique neighbor "C1" (Figure 2) to show how the drag force perturbation index behaves in the presence of neighbors with different positions.

5. Results

The study included the isolated CAARC, CAARC + neighbor A4, and CAARC + neighbor C1. In the result legends, the case of the isolated CAARC is represented by _ISO, while the situations with the neighbor at the locations are referred to as _A4 and _C1. V0 indicates that the largest façade of the neighbor is perpendicular to the wind direction (neighbor at 0°), while V90 indicates that the smallest façade of the neighbor is perpendicular to the wind (neighbor at 90°). Additionally, for each case, a top view of the buildings is provided, showing the cases studied and their corresponding legends, for both the isolated CAARC and cases with neighbors, according to the neighbor's location and angle.

In the histograms, the x-axis represents the coefficients obtained from the tests conducted by Lavôr [4], and the y-axis represents the frequency of occurrence of the data.

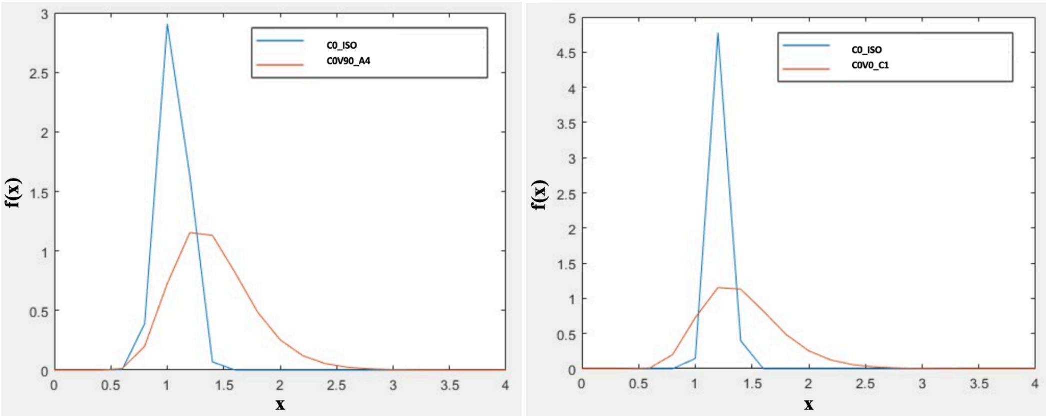
The mean values and standard deviations refer to the drag force data obtained through the tests conducted by Lavôr [4].

5.4.1. Analysis

Table 1 presents the results obtained for the mean, standard deviation, and drag force perturbation index ($\Delta\beta$) after applying Monte Carlo simulations, and Figure 3 displays the distribution graphs and intersections for each case studied.

Analyzing the results (Table 1), it is observed that the case C0V90_A4 has a higher index ($\Delta\beta$) compared to the case C0V0_C1, while the oblique neighbor (C0V0_C1) shows a lower index (Δβ) when compared to the case C0V90_A4.

It can be observed that the further the mean value of the CAARC + neighbors condition deviates from the isolated CAARC (Figure 3), the higher the drag force perturbation index (Δβ). Consequently, a higher beta value (Table 1) indicates greater perturbation.



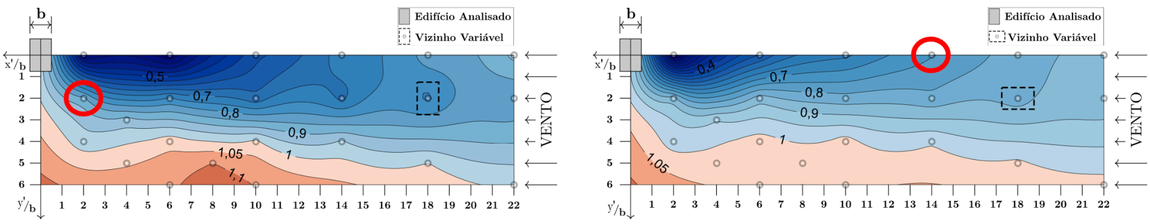
(a) (b)

Figure 3 – (a) Distributions for C0V90_A4 and (b) Distributions for C0V0_C1

Table 1 - Results

	C0_ISO	C0V90_A4	C0V0_C1
MÉDIA (μ)	1,41279832	1,05535272	1,21686138
DESVIO PADRÃO (σ)	0,12971322	0,1243306	0,08179319
ÍNDICE DE PERTURBAÇÃO DA FORÇA DE ARRASTO (Δβ)		0,9621	0,4610

Although there is perturbation in the drag force in the cases studied, it is noted that there is no significant deviation of the means for CAARC + neighbors compared to the isolated CAARC, resulting in low (Δβ) values. Consequently, this generates protective effects for the instrumented CAARC supporting the studies conducted by Lavôr [4] (Figure 4), where it is possible to see that the cases C0V0_C1 (oblique) and C0V90_A4 (aligned) are located in a protective area (blue) with Interference Factor values of 0.85 and 0.75, respectively.



(a) (b)

Figure 4 – Highlight for Interference Factor of (a) oblique and (b) aligned neighbors. Source: Lavôr [4]

6. Conclusions

Considering the means of the cases studied, the highest value occurs for the isolated building, followed by the oblique neighbor C0V0_C1, and finally, the aligned neighbor C0V90_A4. It is observed that there was a reduction in values, indicating oscillation around the mean values of the isolated CAARC (C0_ISO), demonstrating that there is perturbation in the drag force, varying in intensity depending on the position of these neighbors.

Comparing the concepts of structural reliability and the drag force perturbation index ($\Delta\beta$) obtained, it is evident that there is a difference between the commonly used reliability and the approach proposed in this study. The perturbation index obtained through reliability will have a different interpretation than usual, where a higher beta value indicates greater perturbation. As distributions become more similar, the beta value tends to approach zero, and it is even possible to obtain negative beta values, which can be attributed to changes in wind flow.

In summary, it can be considered that the closer ($\Delta\beta$) is to zero, the lower the drag force perturbation, and vice versa. A value of ($\Delta\beta$) further from zero indicates greater drag force perturbation and suggests that the positioning might not be as safe.

It is important to note that the pressure coefficients used in the analyses are dimensionless, and due to the use of similarity theory, the data obtained can be applied to real models, making all established criteria valid.

Thus, the results confirmed that the presence of neighbors, regardless of positioning, significantly affects the obtained data and the drag force perturbation index ($\Delta\beta$) proposed in this study, offering insights that can help predict the behavior of tall buildings subjected to wind loads in the presence of neighboring structures.

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