

# **Optimal risk-based design of a RC frame under different column loss scenarios**

Lucas da Rosa Ribeiro<sup>1</sup>, André Teófilo Beck<sup>1</sup>, Fulvio Parisi<sup>2</sup>

<sup>1</sup>Dept. of Structural Engineering, University of São Paulo Av Trabalhador São-carlense, 400, 13566-590, São Carlos, SP, Brazil lucasribeiro@usp.br, atbeck@sc.usp.br
<sup>2</sup>Dept. of Structures for Engineering and Architecture, University of Naples Federico II Via Claudio, 21, 80125, Naples, Italy fulvio.parisi@unina.it

Abstract. The sudden loss of a single supporting element in a reinforced concrete (RC) frame can result in disproportionate structural collapse if its design fails to confine the initial damage through resistance mechanisms. Given the significant impact of uncertainties related to material properties and geometric parameters on the behavior of these resisting mechanisms, and considering the high stakes involved in such failure events, risk optimization provides a practical approach to striking the right balance between cost-efficiency and safety. This is demonstrated herein through the optimization of a two-story, four-bay RC frame under two scenarios of column removal at the first floor: middle column and corner column. Design variables include cross-sectional depth, steel rebar areas, and concrete strength of beams and columns. Failure consequences are assessed for both the intact structure (considering beam serviceability, beam bending, shear failure of beams, and flexo-compression failure for the columns) and for both column removal scenarios (involving steel rupture of the top rebar layer at the interface between the beam and adjacent column, shear failure of beams, and flexo-compression failure of the columns). A physical and geometrical nonlinear static analysis is conducted, with sample points subjected to bay pushdown analysis. Material behavior is characterized by an elastoplastic model with isotropic hardening for the steel rebars and the Mazars µ model for the concrete (using the modified Park-Kent model for calibration reference). Failure probabilities are assessed using the Weighted Average Simulation Method, and risk optimization is performed using the Firefly Algorithm. To mitigate the computational cost arising from the nonlinearities and the high number of required sample points, Kriging is employed to generate an accurate metamodel for the limit states and reliability indexes. The optimal conventional design prioritizes resistance against bending failure at the beam ends rather than serviceability failure. Beyond a certain threshold value of local damage probability, an increase in the overall frame robustness is observed for both column loss scenarios, with the most significant improvement occurring for corner column removal. This is attributed to this scenario leading to lower resistance against steel rupture and to keep bending moments at the adjacent column close to zero.

Keywords: kriging, progressive collapse, reinforced concrete, reliability analysis, risk optimization

# 1 Introduction

Progressive collapse happens when an initial member failure triggers the failure of the adjacent elements, in resemblance to a cascade effect, leading to a final failure with a disproportionate higher severity in relation to the initial event. When under multiple hazards, the probability of structural collapse P[C] is given as:

$$P[C] = \sum_{H} \sum_{LD} P[C|LD,H] P[LD|H] P[H]$$
<sup>(1)</sup>

where P[H] is the probability of hazard occurrence; P[LD|H] is the conditional probability of local damage for a given hazard H; and P[C|LD, H] is the conditional probability of collapse for a given LD and H.

This study follows Beck et al. [1, 2], considering P[LD|H] P[H] as the probability of local damage  $P_{LD}$  to combine column loss and intact structure scenarios in a single objective function. The cost-benefit of considering two column removal scenarios in designing a RC frame while considering the realistic nonlinear structural behavior is herein addressed.

## 2 Formulation and implementation

The RC frame considered is shown in Figure 1. Its beams have a span of 4.00 m, cross section width of 20 cm, concrete cover of 2.5 cm, and stirrups with a diameter of 8 mm. Each column has 3.00 m, cross section width of 20 cm, concrete cover of 2.5 cm, and stirrups with diameter of 8 mm spaced by 10 cm. Each member has longitudinal rebars with yielding strength of 510 MPa and modulus of elasticity  $E_s = 210$  GPa. Both dead load and live load are 7.0 kN/m<sup>2</sup>, and an additional 2.0 kN/m due to non-structural components over the beams is considered. Since the floors are one-directional, this leads to a nominal dead load  $D_n$  and live load  $L_n$  of 16 kN/m and 14 kN/m, respectively. The design parameters to be optimized are the mean values of: the beams cross section height, top and bottom beam rebar areas, stirrups spacing in the beams, longitudinal rebar area at the columns, and column cross section height. Hence, every design variable is a random variable. No discontinuities are considered along the elements, and the same beam and column optimal design is attributed to every beam and column, respectively.



Figure 1. Studied frame

### 2.1 Risk optimization

The risk optimization problem follows the formulation proposed by Beck et al. [1, 2] with a total expected cost  $C_{TE}$  adapted to the RC frame studied herein:

$$C_{TE} = C_M + \sum_{i=1}^{NI} k_i C_M P_{fi} + \sum_{j=1}^{NCL} k_j C_M P_{fj} P_{LD}$$
(2)

where  $C_M$  is the manufacture cost; the superscripts *I* and *CL* stands for intact and column loss scenarios, respectively;  $P_{fi}$  is the failure probability of the i-th failure mode. Failure consequences are assessed for the intact structure (considering beam serviceability, beam bending, shear failure of beams, and flexo-compression failure for the columns) and for both column removal scenarios (involving steel rupture of the top rebar layer at the interface between the beam and adjacent column, shear failure of beams, and flexo-compression failure of the columns).

The SINAPI database is adopted to estimate  $C_M$  in R\$, where unencumbered prices for São Paulo regarding the period of July 2023 are considered, and later is converted do  $\in$ . Hence,  $C_M$  is composed by cost of formwork, obtainment of concrete, pouring of concrete, obtainment of steel rebars, and placing of steel rebars. For a given failure mode, the expected cost of failure  $C_{ef}$  is given by the product of a cost multiplier k times  $C_M$  times the probability  $P_f$  that the considered failure mode occurs. Thus, for CL the probability of local damage  $P_{LD}$  also multiplies  $k \times C_M \times P_f$ . The multipliers k are chosen according to the order of severity of each failure [1, 2]. Therefore, k is assumed equal to 10 for serviceability failure, 30 for beam bending failure, 40 for steel rupture at catenary action, and 80 for each fragile and severe failure mode.

CILAMCE-2023 Proceedings of the XLIV Ibero-Latin American Congress on Computational Methods in Engineering, ABMEC Porto – Portugal, 13-16 November, 2023

#### 2.2 Reliability analysis

The Weighted Average Simulation Method (WASM), proposed by Rashki et al. [4], is used herein to estimate the failure probabilities  $P_f$  required to compute the  $C_{TE}$ . This technique is appropriate for optimization problems involving random design variables since the estimation of  $P_f$  depends only on the index function I(x) and the weight index W(x) of the  $n_{sp}$  sample points, with x being the random variable vector. Therefore, changing the mean value of the candidate for optimal design only requires the re-evaluation of the weight index W(x).

$$P_{f} = \frac{\sum_{k=1}^{n_{sp}} I(\mathbf{x}_{k}) W(\mathbf{x}_{k})}{\sum_{k=1}^{n_{sp}} W(\mathbf{x}_{k})}$$
(3)

The uncertainties adopted in this work are addressed in Table 1. A total of 7 million sample points are used to estimate every  $P_f$  for 2000 optimal candidates, which are generated via Latin Hypercube Sampling over the design domain. These optimal candidates are used to elaborate a metamodel for every  $\hat{\beta} = -\Phi^{-1}(\hat{P}_f)$ , reducing even further the computational cost to compose  $C_{TE}$ .

Distribution	Mean (µ)	Standard	Coefficient of	Reference
		deviation ( $\sigma$ )	variation ( $\delta$ )	
Normal	To be optimized*	1 mm	-	[5]
Normal	To be optimized*	-	0.05	[5, 6]
Normal	To be optimized*	-	0.05	[5, 6]
Normal	To be optimized*	-	0.05	Assumed
Normal	To be optimized*	-	0.05	[5, 6]
Normal	To be optimized*	1 mm	-	[5]
Lognormal	To be optimized*	-	0.12	[7, 8]
Lognormal	To be optimized*	-	0.12	[7, 8]
Normal	510 MPa	-	0.05	[6, 8]
Normal	25 kN/m <sup>3</sup>	-	0.05	Assumed
Normal	0.20	-	0.14	[9]
Normal	$1.05 D_n$	-	0.10	[10]
Gumbel	$1.00 L_{m}$	-	0.25	[10]
2411041	$1.00 D_n$		0.20	[*~]
G	0.05 1		0.55	[10]
Gamma	$0.25 L_n$	-	0.55	[10]
Lognormal	1.107	-	0.229	Obtained
	Distribution Normal Normal Normal Normal Normal Lognormal Normal Normal Normal Normal Normal Normal Gumbel Gamma Lognormal	DistributionMean $(\mu)$ NormalTo be optimized* To be optimized*NormalTo be optimized*NormalTo be optimized*NormalTo be optimized*NormalTo be optimized*NormalTo be optimized*NormalTo be optimized*NormalTo be optimized*NormalTo be optimized*LognormalTo be optimized*Lognormal510 MPaNormal510 MPaNormal0.20Normal1.05 $D_n$ GumbelGamma0.25 $L_n$ Lognormal1.107	DistributionMean $(\mu)$ Standard deviation $(\sigma)$ NormalTo be optimized*1 mmNormalTo be optimized*-NormalTo be optimized*-NormalTo be optimized*-NormalTo be optimized*-NormalTo be optimized*-NormalTo be optimized*-NormalTo be optimized*-NormalTo be optimized*-LognormalTo be optimized*-Lognormal510 MPa-Normal0.20-Normal1.05 $D_n$ -Gamma0.25 $L_n$ -Lognormal1.107-	DistributionMean $(\mu)$ Standard deviation $(\sigma)$ Coefficient of variation $(\delta)$ NormalTo be optimized*1 mm-NormalTo be optimized*-0.05NormalTo be optimized*-0.05NormalTo be optimized*-0.05NormalTo be optimized*-0.05NormalTo be optimized*-0.05NormalTo be optimized*-0.05NormalTo be optimized*-0.05NormalTo be optimized*-0.12LognormalTo be optimized*-0.12Lognormal510 MPa-0.05Normal0.20-0.14Normal0.20-0.14Normal0.25 $L_n$ -0.25Gamma0.25 $L_n$ -0.55Lognormal1.107-0.229

Table 1.	Uncertainties	considered

#### 2.3 Structural analysis

In order to estimate the probabilities of failure, a metamodel via kriging is employed [11], which requires the evaluation of a sufficient number of support points by an accurate model of structural analysis. The finite element method based on positions proposed by Coda [12] is used herein, where layered 2D beam elements are adopted.

Each beam is discretized into 3 finite elements with a eight-degree of approximation, and each column into 1 finite elements with the same degree. A total of 15 layers with 1 integration point each is used to discretize the cross-sections, being 13 layers for the concrete core and one for each steel reinforcement. An uniaxial model with isotropic hardening is used to represent the elastoplastic behavior of the longitudinal rebars, while  $\mu$ -Model [13] is used to represent the damage evolution and the unilateral behavior of the concrete. Stirrups cannot be explicitly considered, but its influence on the ductility of the confined concrete is regarded by considering the resulting uniaxial curve from the Modified Park-Kent Model [14] to calibrate the parameters of the  $\mu$ -Model.

Two structural analysis are carried out for every sample point: one for the intact structure (I), where an increasing uniform load is applied over each beam, and one for the column loss scenario (CL), where the uniform load is increased only over the beams directly affect by the column removal. Due to the symmetry in the structural geometry and loading conditions, only half of the structure is modelled for both scenarios.

## **3** Results

The following results were obtained considering 2500 support points for metamodeling the structural response (thus the limit states), which allowed the obtainment of 15 million sample points to guarantee the estimative of additional 2500 support points for metamodeling the reliability indexes of each failure mode considered. Firefly algorithm [16] was used for the risk optimization (40 fireflies, 100 iterations + auxiliary extensive search). Table 2 shows the optimal design for every value of  $P_{LD}$  ranging from  $P_{LD}^{min} = 5\text{E-6}$  [1, 2] until  $P_{LD} = 1.0$ .

Variable	Middle column loss scenario			Corner column loss scenario
$P_{LD}$	$5 \times 10^{-6}$	$10^{-2}$	1	$5 \times 10^{-6}$ $10^{-2}$ 1
$h_B \ (mm)$	424	466	492	424 449 498
$A_B$ (cm <sup>2</sup> )	3.30	3.30	8.01	3.30 3.30 11.84
	(~3 <b>\$</b> 12)	(~3\phi12)	(~4\oplus16)	(~3\phi12) (~3\phi12) (~3\phi22)
$A_T$ (cm <sup>2</sup> )	6.66	10.02	8.47	6.67 10.54 11.55
	(~4\phi14)	(~4\phi18)	(~4\oplus17)	(~4\phi14) (~4\phi14) (~3\phi22)
$s_t \text{ (mm)}$	200	110	106	200 106 105
$h_{\mathcal{C}}$ (mm)	300	300	300	300 300 367
$A_C$ (cm <sup>2</sup> )	4.60	4.60	6.91	4.60 9.97 9.00
	(~4 <b>\oplus12</b> )	(~4\oplus12)	(~4\oplus15)	$(\sim 4\phi 12)$ $(\sim 4\phi 18)$ $(\sim 4\phi 17)$
$f_{c_B}'$ (MPa)	45.0	32.8	45.0	45.0 42.5 43.2
$f_{c}'_{c}$ (MPa)	30.0	36.7	44.4	30.0 37.6 40.2
$\mathcal{C}_M \left( \mathbf{\epsilon} \right)$	3724.36	4307.07	4912.88	3724.63 4817.17 5966.90
$C_{TE} (\mathbf{E})$	3760.10	4396.07	5079.74	3760.37 5131.24 6048.47

Table 2. Optimal values for each design variable according to  $P_{LD}$ 

Optimal conventional scenario is guided by bending failure at the beam ends (negative moments), with optimal reliability index of ~3.4 and an increased top reinforcement (Figure 2a and 2b). Since the beam has a small length (4 m), this optimal detailing leads to a much greater reliability index for the beam serviceability failure (maximum vertical displacement).

Table 2 shows, for the studied frame, that the adopted formulation results in greater overall robustness for corner column loss scenarios (increased cross-section depth, greater reinforcement area, greater concrete strength, and reduced stirrup spacing at the beams). According to the nonlinear structural analysis, the ultimate load for steel rupture after sudden loss of a corner column is found to be 75% of this corresponding value for middle column loss. This is possibly due to the lack of an efficient Vierendeel action (small number of storeys), which reduces the amount of alternative load paths for this case. Hence, more material has to be allocated in order to provide a similar optimal reliability index of ~3.4 against this failure mode (Figure 2a and 2b). Figure 2d shows that the expected cost of steel rupture grows faster for the corner column loss scenario.



Figure 2. Optimal reliability indexes x  $P_{LD}$ 

Optimal beam detailing against steel rupture for the middle column scenario provides a similar reliability index for shear failure. However, the additional strength against steel rupture for loss of a corner column leads to a shear resistance considerably increased in terms of the actual shear demand (optimal reliability index of ~5.9, Figure 2b). Besides, Figures 2c and 2d shows that shear failure is the first column loss scenario failure mode to be addressed. The greater increase in expected cost of shear failure happens due to the optimal conventional design not being able to withstand the significantly increased shear demand after a sudden column removal.

Middle column removal leads to both axial forces and bending moments at the adjacent columns significantly increased, so a greater loading demand is observed for this scenario (optimal reliability index of ~4.1). Bending moments at the adjacent column for corner column removal are significantly smaller, so loading demand is smaller and mostly due to axial forces. Nonetheless, optimal column design for this scenario has greater robustness in order to decrease the column horizontal drift, simultaneously assisting to mitigate premature steel rupture, reducing the bending moment demand and increasing column strength. In this case, the optimization algorithm shows that ensuring a near zero probability of adjacent column failure is more cost-effective.

# 4 Conclusions

This manuscript shows how the behavior of the optimal design for the considered RC frame suddenly changes after the consideration of two column loss scenarios starts to have a positive cost-benefit. The optimal conventional design prioritizes resistance against bending failure at the beam ends rather than serviceability failure. Beyond a certain threshold value of local damage probability, an increase in the overall frame robustness is observed for both column loss scenarios, with the most significant improvement occurring for corner column removal. This is attributed to this scenario leading to lower resistance against steel rupture and to keep bending moments at the adjacent column close to zero.

Acknowledgements. Funding of this research project by Brazilian agencies CAPES (Brazilian Higher Education Council), CNPq (Brazilian National Council for Research, grant n. 306373/2016-5), joint FAPESP-ANID (São Paulo State Foundation for Research - Chilean National Agency for Research and Development, grant n. 2019/13080-9) and FAPESP (grant n. 2019/23531-8 and grant n. 2021/12884-7).

**Authorship statement.** This section is mandatory and should be positioned immediately before the References section. The text should be exactly as follows: The authors hereby confirm that they are the sole liable persons responsible for the authorship of this work, and that all material that has been herein included as part of the present paper is either the property (and authorship) of the authors, or has the permission of the owners to be included here.

## References

[1] A. T. Beck, L. R. Ribeiro, and M. Valdebenito. Risk-based cost-benefit analysis of frame structures considering progressive collapse under column removal scenarios. *Engineering Structures*, vol. 225, pp. 111295, 2020.

[2] A. T. Beck, L. R. Beck, M. Valdebenito, and H. Jensen. A. Risk-based design of regular plane frames subject to damage by abnormal events: a conceptual study. Journal of Structural Engineering, 148, 1, 04021229, 2021.

[3] Comité Euro-International du betón. Model Code 2010 – Final draft, vol. 1. CEB bulletin n. 53. March 2012.

[4] M. Rashki, M. Miri, and M. A. Moghaddam. A new efficient simulation method to approximate the probability of failure and most probable point. *Structural Safety*, vol. 39, pp. 22-29, 2012.

[5] JCSS. Probabilistic Model Code. Joint Committee on Structural Safety. Published online. 2001.

[6] A. T. Beck. Confiabilidade e Segurança das Estruturas. 1ª ed, Elsevier Editora Ltda, Rio de Janeiro, 2019.

[7] D. Wisniewski, P. J. S. Cruz, A. A. Henriques, and R. A. D. Simões. Probabilistic models for Mechanical properties of concrete, reinforcing steel and pre-stressing steel. *Structure and Infrastructure Engineering*, vol. 8(2), pp. 111-123, 2012.

[8] F. Parisi, M. Scalvenziz, and E. Brunesi. Performance limit states for progressive collapse analysis of reinforced concrete framed buildings. *Structural Concrete*, vol. 20, pp. 68-84, 2019.

[9] Y. Shi, and M. G. Stewart. Spatial reliability analysis of explosive blast load damage to reinforced concrete columns. *Structural Safety*, vol. 53, pp. 13-25, 2015.

[10] B. Ellingwood, and T. V. Galambos. Probability-based criteria for Structural design. Struct Saf, vol. 1, pp. 15-26, 1982.

[11] H. M. Kroetz. Otimização estrutural sob incertezas: métodos e aplicações. Thesis, Universidade de São Paulo, 2019.

[12] H. B. Coda. O método dos elementos finitos posicional: sólidos e estruturas- não linearidade geométrica e dinâmica, 1st ed. São Carlos: EESC-USP, vol. 1, 2018.

[13] J. Mazars, F. Hamon, and S. Grange. A new 3D damage model for concrete under monotonic, cyclic and dynamic loadings. *Materials and Structures*, vol. 48, pp. 3779-3793, 2015.

[15] R. Park, M. J. N. Priestley, and W. D. Gill. Ductility of square-confined concrete columns. *Journal of Structural Engineering*, ASCE, vol. 108, n° ST4, pp. 929-950, 1982.

[15] V. Dubourg. Adaptive surrogate models for reliability analysis and reliability-based design optimization. Thesis, Université Blaise Pascal, 2011.

[16] X. S. Yang. Nature-Inspired Metaheuristic Algorithms. UK: Luniver Press, 2008.

[17] L. R. Ribeiro, H. M. Kroetz, F. Parisi, and A. T. Beck. Optimal risk-based design of a RC frame under column loss scenario. In Proc., *14th International Conference on Applications of Statistics and Probability in Civil Engineering*. Dublin, Ireland, July 9-13, 2023.

[18] L. R. Ribeiro, A. T. Beck, and F. Parisi. Risk optimization of a RC frame under column loss scenario. In Proc., *XLIII Ibero-Latin-American Congress on Computational Methods in Engineering*. Foz do Iguaçu, Brazil, November 21-25, 2022.