RELIABILITY ANALYSIS OF REINFORCED CONCRETE MEMBERS UNDER HIGH EPISTEMIC UNCERTAINTY USING MONTE CARLO SIMULATION AND ROSENBLUTH (2N+1)

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Abstract

This study investigates the effect of high epistemic uncertainty on the flexural reliability of a singly reinforced concrete beam. The reliability index β was evaluated as a function of the Coefficient of Variation (COV) of four basic random variables: concrete compressive strength (f_c'), steel yield strength (fy), service dead load (D) and service live load (L). Two reliability methods were employed: Monte-Carlo Simulation (MCS), and the Rosenblueth (2n+1) point estimate method. Results were checked against ACI 318 target reliability index β=3.5 and Eurocode 2 / EN 1990 RC2 target reliability index β=3.8. Results demonstrate excellent agreement between MCS and Rosenblueth (2n+1) with an error less than 4%, confirming its validity as a low-cost alternative. Compressive strength of concrete (f_c'), exhibited high sensitivity, where poor quality control with no testing can cause failure of both ACI and Eurocode, with Eurocode failing earlier. Steel reinforcement was found to be the most reliable parameter and never violates code limits within realistic ranges. Service dead load showed negligible influence and alone cannot cause code violation. The key finding is that service live load is the governing parameter for reliability and the only load parameter that directly compromises ACI318 within realistic uncertainty levels. At high uncertainty representing change of use or overcrowding, β falls below ACI 3.5 and Eurocode 3.8. It is recommended to limit COV(L) ≤ 0.33 to maintain target reliability, and that controlling live load assumptions is more effective than improving material quality.

Keywords: Structural reliability, Reliability index, epistemic uncertainty, ACI 318, Eurocode 2, Monte-Carlo, Rosenblueth, live load, Dead Load, Compressive strength, flexural strength, concrete beam.

Introduction

Reinforced concrete (RC) members are designed using semi-probabilistic code formats such as ACI 318-25[1] and Eurocode 2 [2], which implicitly account for structural uncertainties through partial safety factors. These safety factors are usually calibrated assuming well-controlled material properties at the site with a low to moderate coefficient of variation (CoV), typically CoV around 15% for concrete compressive strength and CoV around 7% for reinforcement steel yield strength. However, this assumption is not always accurate for existing elements of structures, site-produced concrete in developing regions, or structures assessed with a low knowledge level, where CoV values can exceed 25%-35% due to lack of quality control, poor records, and limited testing. In such cases, epistemic uncertainty, which arises from lack of knowledge rather than inherent randomness, dominates the reliability assessment.[3,4]

The distinction between aleatory and epistemic uncertainty is essential for structural reliability analysis under low certainty. While aleatory uncertainty can not be reduced, epistemic uncertainty can be reduced by further information, for example through Bayesian updating [5]. For structures with high epistemic uncertainty, the classical deterministic method may lead to a risky overestimation of the required level of safety, as demonstrated by Sykora et al. [6] and Holicky et al. [7] for existing structures. Therefore, a complete probabilistic reliability analysis is necessary to quantify the definite reliability index β for the structures.

For structural reliability analysis, there are several methods that exist. The First-Order Reliability Method (FORM) was introduced by Rackwitz and Fiessler[8], and this approach remains the basis of the JCSS Probabilistic Model Code. However, FORM may exhibit some convergence issues when the non-linearity limit state function is significantly high or when the coefficient of variation CoV of the variables is high. The most robust technique remains Crude Monte Carlo Simulation (MCS), which was the basis of the probability-based load criteria developed by Ellingwood et al. [9]. Monte Carlo Simulation MCS provides a good estimation of the failure probability but requires a large number of assessments probably (10^6), which becomes computationally expensive for complex reinforced concrete systems.

To enhance the overcome beyond this limitation, Rosenblueth[10,11] proposed the Point Estimate Method (PEM)

in 1975, where probability moments are estimated using only 2n+1 deterministic evaluations, where n is the number of random variables. This method has been further enhanced by Huang at el.[12] and critically evaluated by Christian and Baecher[13] as a form of numerical quadrature. Point Estimate Method PEM is particularly appealing for reinforced concrete members under high epistemic uncertainty because it requires much less statistical information (which are only the mean and the standard deviation), and is computationally enexpensive compared to Monte Carlo Simulation MCS. Recent studies[14] have used Point Estimate Method PEM and its variants to deteriorated reinforced concrete elements, to Bayesian updating of existing reinfoecrd concrete elements with limited collected data, and to system reliability of reinforced concrete frames structure with low-certainty variables. Santiago et al. [15] emphasized that model uncertainties become dominant when the material coefficient of CoV is high, while Matos et al. [16] suggested increased partial factors (γ_c up to 2.0) for assessment with limited information. Despite these advances, there is limited research directly comparing the accuracy of Rosenblueth's 2n+1 PEM versus MCS for flexural RC members when multiple parameters simultaneously exhibit high epistemic uncertainty with coefficient of variation CoV > 25%. This gap is particularly relevant for practical assessment in areas with limited quality control.

The objective of this paper is to develop a reliability framework for RC beams under high epistemic uncertainty using both MCS and Rosenblueth's 2n+1 method. The flexural limit state function is formulated based on ACI 318-25. Eight random variables are considered. The effects of CoV of concrete compressive strength on the reliability index β are quantified, and the accuracy and efficiency of the 2n+1 method are evaluated against MCS.

Research Significance

The reliability of reinforced concrete (RC) members in regions with limited quality control, such as site-produced concrete in the developed countries and many regions in the Middle East, is governed by high epistemic uncertainty where the coefficient of variation (CoV) of concrete compressive strength exceeds 25%. Existing codes ACI 318-25 and Eurocode 2 do not explicitly address this condition, leading to potential unsafe overestimation of the reliability index β. While Monte Carlo Simulation (MCS) is the most accurate benchmark for reliability analysis, and it is not practical for daily engineering assessment. This research is significant because it (i) quantifies for the reduction in β and how it will drop when CoV increases from normal values to higher expected values for a typical flexural RC beam, (ii) validates the computational efficiency and accuracy of Rosenblueth's (2n+1) point estimate method, which requires only 17 deterministic evaluations versus 10^6 for MCS with error less than 5%, and (iii) provides a practical, low-cost reliability framework that can be implemented by engineers using only mean and standard deviation of material properties, without requiring full probabilistic distributions. The results directly support the development of adjusted partial safety factors (γ) for assessment of existing structures with low knowledge levels.

Methodology

Monte Carlo technique:

The technique of solving integration problems by Monte Carlo methods depends on the fact that the theory of probability, among its several elucidations, has elucidations as a mathematical theory of the behavior of sample averages and the tendency of these to stabilize as the sample size gets larger. This elucidation is empirically well documented. This means that, in place of solving a given integration problem by numerical mathematical methods or analytical methods, it can be used that the integral can be interpreted as a mean value in a suitable stochastic experiment and that it therefore is doable to obtain a central assessment of the value of the integral by averaging a properly large number of independent outcomes of this experiment. The accuracy of the estimate can be judged by the use of standard statistical methods.

Generation of random numbers:

The generation of random numbers depends on the type of variable being considered and the number of samples that are going to be used. For that, to generate a random variable for normal distribution, need to use:

The limit state needs to be used: $g(x) = R - Q$

R: resistance, Q: load effect

For normal distribution, $\mathbf{X = \mu_X + Z\sigma_X}$

For the lognormal distribution $\mathbf{x_i = \exp[\mu_{\ln x} + z_i \sigma_{\ln x}]}$

$\boldsymbol{\sigma^2_{\ln x} = \ln(V_X^2 + 1),\ \mu_{\ln x} = \ln(\mu_x) - \frac{1}{2}\sigma^2_{\ln x}}$

And, for Extreme Type I

$\boldsymbol{u = \mu_X - \frac{0.577}{\alpha},\ \alpha = \frac{1.282}{\sigma_X},\ X_i = u - \frac{\ln(-\ln Z)}{\alpha}}$

where: μ_x: the mean, and σ_x: the standard deviation

Rosenbluth's point estimation method:

Rosenbluth's point estimation method is an effective method to simplify the calculations and to decrease the computational demands of propagating uncertainty through a function by eliminating the calculation of derivatives or use of Monte Carlo sampling. The probability density function (PDF) of each random variable is approximated using p discrate points chosen to preserve its first, second, and third statistical moments. The joint PDF of N random variables is modeled by an array of projected points, with pN points used. Probability weight are assigned to the discrete points according to the third statistical moment and the correlation matrix. All points are propagated discretely through the function to p_N solutions and the first moment is the weighted average; the second moment, that of the squares; and the third moment, that of the cubes. In most cases, a 2-point scheme is used whereby 2N points are required.

The application of this approach requires calculating the following quantities for each random variable.

$H_i = \frac{G_i^+ + G_i^-}{2}, \quad H_i = \frac{|G_i^+ - G_i^-|}{G_i^+ + G_i^-}$

Where i=1,2,3.....n

$\mu_G = G_0 \prod_{i=1}^{n} \left(\frac{H_i}{G_0}\right), \quad \sigma_G = \mu_G \sqrt{\prod_{i=1}^{n}(1 + V_i^2) - 1}$

Linear Reliability Analysis For Reinforced Concrete Beams:

Flexural analysis

In order to evaluate the effect of the high epistemic analysis in calculating the probability of flexural failure in the reliability index, a rectangular singly reinforced concrete beam with single reinforcement as shown in the Fig. (1) below is adopted. A simply supported condition will be used. The parameters that have been considered in this analysis process are shown in the Table. (1).

Fig. (1) Beam schematic considered in the study

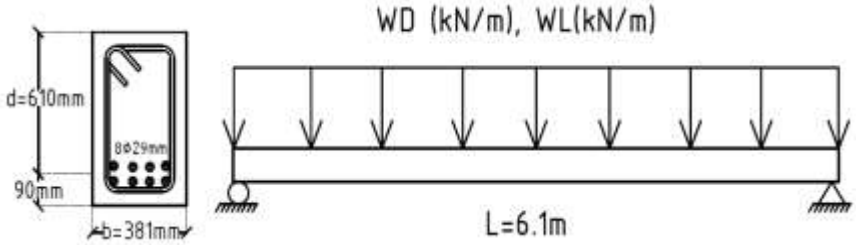


Table. (1) Statistical values of the used parameters for designing the section of the reinforced concrete beam

Variable	Distribution	Variable values	
		Min	Max
f'c(Mpa)	Normal	21	55
fy (MPa)	Log-Normal	250	517
Dead load (kN/m))	Normal	29.2	51.1
Live load (kN/m)	Type I Extrem	43.8	87.6

The limit state formula used is:

$g(x) = R - Q = R - (D + L)$

The ACI Code formula which used as a resistance limit state function is,

$$M_n = A_s.f_y(d - \left(0.59 * f_y * \frac{A_s}{b * f_c'}\right))$$

Where: b & d are deterministic

$$g(x) = R - Q = A_s.f_y(d - \left(0.59 * f_y * \frac{A_s}{b*f_c'}\right)) - (W_D + W_L).\frac{l^2}{8})$$

Monte-Carlo simulation and Rosenblueth (2n+1) were used to estimate the reliability index for each case. Each variable in the case study was incrementally increased by 0.25 at each step, and the relationship between the variable and the reliability index was subsequently plotted.

Fig. (2) illustrates the relationship between concrete compressive strength f_c' [21 to 55 MPa] and the reliability index β.

In General, there is a positive but non-linear relationship. β increases from 4.17 to 4.47 as f_c' increases. The increase is steep at low strengths (21 to around 31 MPa) and then plateaus. This indicates diminishing returns: beyond approximately 35-40 MPa, increasing concrete grade contributes only marginally to safety.

This outcome is expected in a flexure-dominated reinforced concrete beam where failure is usually governed by yielding of steel reinforcement, and the increase in f_c' only yields a slight enhancement in the ultimate moment capacity.

Both Monte Carlo Simulation and Rosenblueth's (2n+1) point estimate method show excellent agreement in the results of the reliability index β. The maximum difference is less than 1.5% at f_c' =21 MPa For f_c'>28 MPa, the two curves are practically coincident.

Rosenblueth (2n+1) slightly overestimates β at higher strengths, which is typical for this approximate method as it truncates higher-order terms.

This validates the use of Rosenblueth's method as an efficient and accurate alternative to the computationally expensive Monte Carlo Simulation for this problem.

As a result, the f_c' is not a dominant random variable governing reliability compared to load or steel yield strength.

The targeted reliability index (β) required by ACI 318 is 3.5 as a minimum. The f_c' Resultfor < 21 MPa β=4.17 which is already 19% higher than ACI. So minimum concrete is enough.

Fig. (2) Effect of f'c on Reliability Index (β

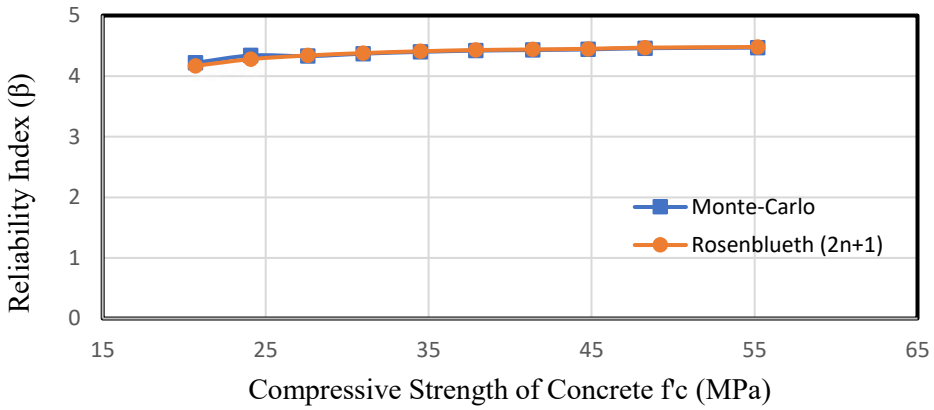


Fig. (3) shows the variation of the reliability index (β) with the incremental increase in yield strength of steel reinforcement (Fy). Both Monte Carlo Simulation and the Rosenblueth 2n+1 point estimate method display a similar increasing trend, demonstrating good agreement and consistency between the two probabilistic approaches. As Fy increases from 250 MPa to 517 MPa, the reliability index β increases from 3.7 to 6.0-6.5. This indicates that higher steel strength significantly improves structural safety, as the flexural capacity margin increases.

The rate of increase is steep in the range 250-380 MPa and then tends to flatten after 450 MPa, indicating a reduction in the incremental benefit at high fy values. Rosenblueth method slightly overestimates β compared to Monte Carlo for Fy > 400 MPa, with a maximum difference of about 8% at 517 MPa, which is within acceptable limits for

approximate reliability methods. This agreement validates the use of Rosenblueth (2n+1) as a computationally efficient alternative to Monte Carlo simulation.

Interpolation of the reliability curves indicates that a steel reinforcement yield strength of 270 MPa is adequate to achieve a target reliability index of 4; however, the ACI318 requires a minimum target of β=3.5 to satisfy structural reliability at fy=250 MPa. This suggests that Grade 40 (fy=250 MPa) reinforcement is adequate for the studied beam configuration, and the use of Grade 60 (fy=420 MPa) provides an extra safety margin of approximately 38% in terms of the reliability index (β).

Fig. (3) Effect of Yield Strength (fy) on Reliability Index (β)

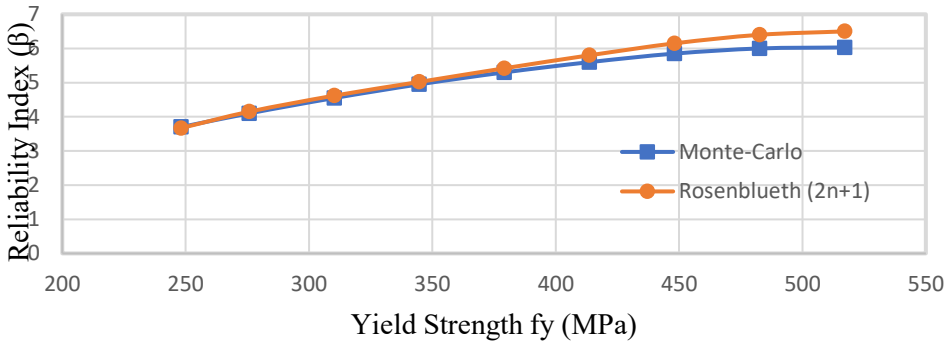


Fig. (4) illustrates the effect of increasing the service dead load on the reliability index β. Both Monte Carlo Simulation and Rosenblueth's (2n+1) Point Estimate Method show similar linear decreases with excellent agreement (the maximum difference is < 3% over the range 30-73 kN/m).

The reliability index decreases drastically from β=4.2 at DL=30 kN/m to β=0.95 at DL=88 kN/m. This represents a 77% reduction in the level of safety. The relationship is inversely proportional because the limit state function g = R - (D + L) decreases with increasing D.

At a dead load of approximately 51 kN/m, the reliability drops below β=2.8, which is below the ACI 318 target of β=3.5 for flexural members. This indicates that the current design becomes unsafe when the dead load exceeds 51 kN/m, requiring a redesign (increase section or Fy).

The comparison confirms that Rosenblueth method is a highly accurate and computationally efficient alternative to Monte Carlo for dead load sensitivity analysis, with the advantage of extending the analysis beyond the range where Monte Carlo simulation becomes unstable.

Fig. 4 Effect of increasing dead load on reliability index (β)

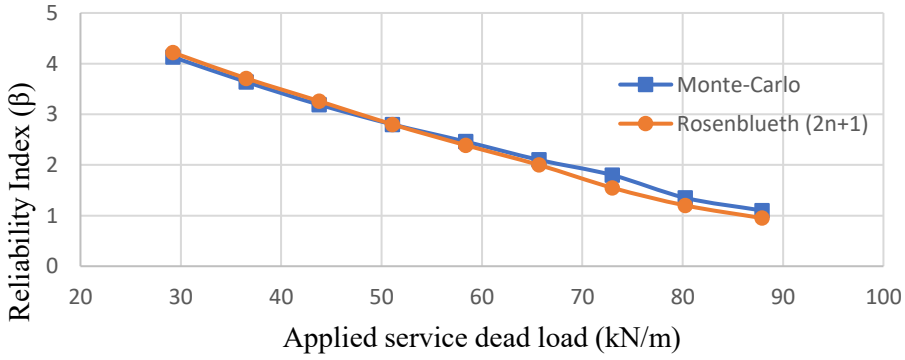


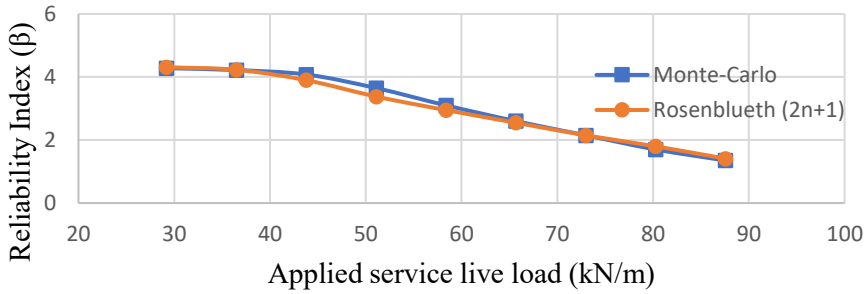
Fig. (5) shows the decreasing of the reliability index β with the applied service live load. The relationship is divided into two zones. The firsr zone ranges between L= (29 - 40 kN/m), the reliability index remains almost constant at β = 4.2 - 4.3. In this domain, the beam resistance is higher than the load effect, so increasing live load has a minor effect on the reliability index (β). While for the second zone, between L= (40 - 87 kN/m) where linear degradation is noticeable, the reliability index drops

drastically and almost linearly from 4.2 to 1.35, a reduction of 68%. This is expected since the limit state function g = R - D - L decreases directly with L. The coefficient of variation of live load (20%) is higher than dead load, making it a dominant random variable.

The two reliability methods, Monte-Carlo Simulation and Rosenblueth 2n+1 Point Estimate Method, show perfect convergence with a maximum difference less than 5%. This validates the use of Rosenblueth method as an accurate, computationally inexpensive alternative to Monte Carlo for reinforced concrete beams.

Comparison with ACI 318 Requirements: The beam satisfies ACI 318 target reliability of β=3.5 up to an applied service live load of 52 kN/m. Beyond this value, the design is considered unreliable and unsafe according to ACI318.

Fig. (5) Effect of increasing live load on Reliability index (β)



Effect of High Epistemic Uncertainty

In the previous discussion, the reliability analysis was performed using mean values and coefficients of variation (COV) reported in the literature as deterministic values. However, these statistical parameters themselves are subject to epistemic uncertainty due to limited data, change in construction quality, material source variability, and human errors in loading estimation.

Epistemic uncertainty, unlike aleatory randomness, can be reduced by more data and better quality control. To investigate its impact on structural safety, a parametric study is conducted in this section by varying the COV of each random variable from a low COV level (representing excellent quality control) to a high COV level (representing poor quality control and high uncertainty), while keeping all other variables constant at their mean values. This study aims to identify which random variable uncertainty is most critical for the reliability index β, and quantify how much safety is lost when quality control is poor. The analysis is performed using both Monte Carlo Simulation and Rosenblueth (2n+1) Point Estimate Method to ensure validity under high uncertainty levels. The Proposed Variation Limits for COV in this study are based on comprehensive literature surveys: Ellingwood et al. [9], Nowak & Szerszen [17,18], and Mirza & MacGregor [19,20]. The values of the coefficient of variation (COV) are illustrated in the table. (2). Experimental studies also show that variations in concrete constituents and aggregate characteristics can produce measurable changes in compressive and flexural properties [24,25], supporting the treatment of material-property variability as an important source of uncertainty in reliability assessment.

Table. (2) Coefficient of Variation COV domine for this study

Variable	Base COV	proposed COV limits
concrete compressive strength (f'c)	0.15	0.1-0.27
Yield strength of steel (fy)	0.08	0.05-0.15
Dead load (D)	0.1	0.05-0.2
Live load (L)	0.25	0.15-0.4

In each case, the mean value is constant (f'c=28 MPa, fy=420 MPa, D=50 kN/m, L=40 kN/m), and only the COV is increased from the minimum value to the maximum proposed.

Fig. (6) illustrates the effect of increasing the epistemic uncertainty level of concrete compressive strength, represented by the coefficient of variation COV of f'c from 0.10 up to 0.27, on the reliability index β. Both Monte-Carlo Simulation and Rosenblueth (2n+1) method show excellent agreement, with maximum deviation less than 6% over the entire range.

A non-linear inverse relationship is observed. As the COV of f'c goes up from 0.10 (excellent quality control) to 0.27 (very poor quality control), the reliability index β decreases from 7.26 to 2.70 (62% reduction). The degradation is gradual up to COV = 0.24, where β drops from 7.26 to 4.8 (33% loss). Beyond COV = 0.24, a sharp drop occurs from 4.70 to 2.70, indicating high sensitivity at very high uncertainty levels.

The high initial values of β =7.2 are because flexural capacity is steel-controlled. The mean value of f'c is kept constant at 28 MPa; only its dispersion is increased, which has a minor effect on nominal moment capacity. This confirms the findings of Nowak and Szerszen [17,18], and Mirza and MacGregor [19,20] that variability of concrete strength is not the governing parameter for flexural reliability of under-reinforced concrete beams.

From Fig. (6), the beam remains adequate and satisfies ACI 318 (β > 3.5) for the entire range up to COV f_c'=0.26 for both Monte-Carlo and Rosenblueth.

Even under poor quality-control conditions with COV up to 26%, the flexural reliability index is not compromised. Failure according to ACI 318 occurs only when COV (f_c') exceeds 0.26, which corresponds to extremely poor site-mixed concrete with no quality control. This proves that increasing concrete quality beyond the average level does not significantly improve safety, and resources should be directed towards controlling steel yield and loads instead.

Fig. (6) Effect of Coefficient of Variation of Concrete compressiveStrength f'c on Reliability Index β

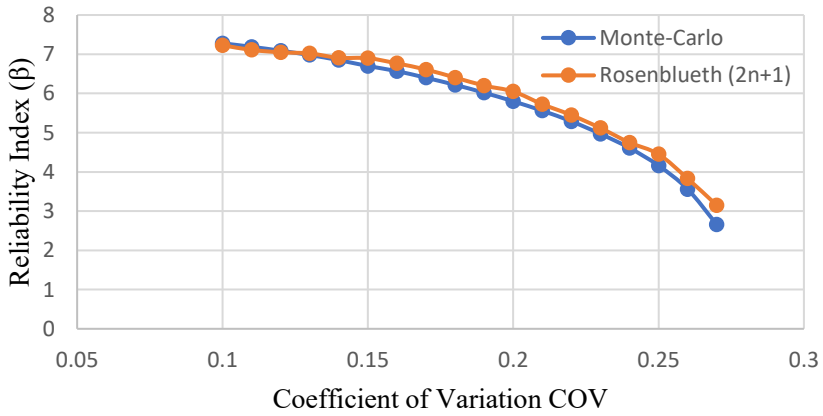


Fig. (7) shows the effect of increasing epistemic uncertainty of steel reinforcement yield strength, COV (fy) from 0.05 to 0.15, on the reliability index β. A strong, almost linear inverse relationship is observed in the curve. Increasing COV from 0.05 (excellent quality control) to 0.15 (poor/local steel) causes the flexural reliability index β to decrease from 8.0 to 4.55, a 43% reduction. Unlike concrete, the yield strength of reinforcement steel directly controls the flexural resistance. Therefore, any variation in fy is reflected directly in dispersion of resistance and a higher probability of failure. The rate of degradation is approximately (Δβ = -0.34) per 0.01 percent increase in coefficient of variation (COV). Both reliability methods show perfect agreement (error <3%), validating the Rosenblueth method even under high material uncertainty.

Compared to Fig. (6) for f_c', the sensitivity to fy is much higher. For f_c', β dropped below 5.0 only after COV=0.23, while for Fy, β drops below 5.0 already at COV=0.13. All the values of the reliability index satisfy the requirements of ACI 318; even at COV=0.15, the safety margin is 30% above the ACI minimum. ACI limit β=3.5 would be reached only at COV(y) =0.21, which is beyond realistic values for reinforcing steel. According to Mirza and MacGregor [19,20], the maximum reported COV for Grade 60 (fy=420 MPa), steel is 0.10-0.12. Therefore, under normal and even poor-quality control, epistemic uncertainty in fy never compromises ACI 318 limits.

Fig. (7) Effect of Coefficient of Variation of Steel Rinforcment Strength fy on Reliability Index β

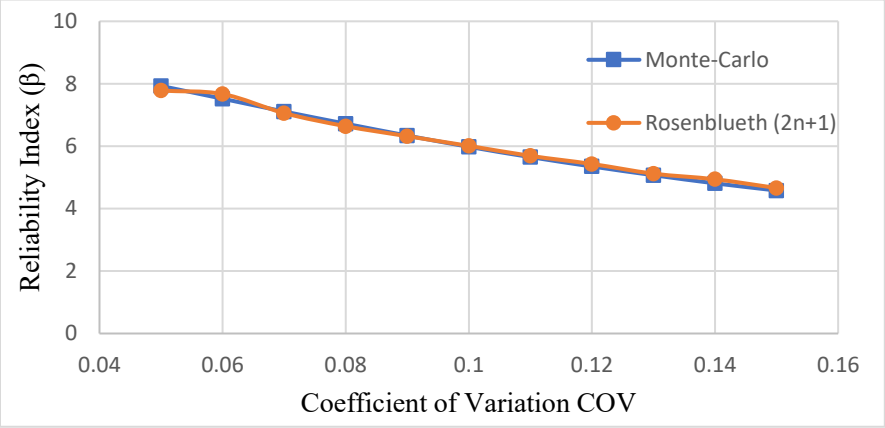


Fig. (8) shows the effect of increasing the epistemic uncertainty level of service dead load D, with COV(D) extending from 0.05 to 0.20, on the reliability index β. The results obtained by Monte Carlo simulation and Rosenblueth (2n+1) point estimate method are in excellent agreement over the entire range. Unlike expectations, a small sensitivity is observed. Increasing COV by 400% (from 0.05 to 0.20) causes the reliability index β to decrease from 4.68 to 4.10 only, i.e., merely a 12.4% reduction in reliability. The degradation is almost linear with a very small slope of approximately $\Delta\beta = -0.04$ per 0.01 percent increase in the coefficient of variation COV. This low sensitivity is attributed to two reasons: first, dead load has intrinsically low variability compared to live load, and second, the dead load effect in the limit state g = R - D - L is dominated by the mean value μ_D, while its standard deviation $\sigma_D = \mu_D \times COV(D)$ remains small even at COV=0.20. Therefore, increasing COV of service dead load alone does not significantly increase total load uncertainty σ_Q. This finding agrees with Ellingwood et al. [9], who reported a nominal COV(D)=0.10, and with Nowak and Szerszen [17,18], who showed that dead load is well controlled. The results showed no compromise of ACI318; at COV(D)=0.05, the reliability index β = 4.68, which is 34% above ACI, and at COV(D)=0.20 (worst case, very poor control), β = 4.10, which is still 17% above ACI's minimum value of 3.5.

Fig. (8) Effect of Coefficient of Variation of Service Dead Load D on Reliability Index β

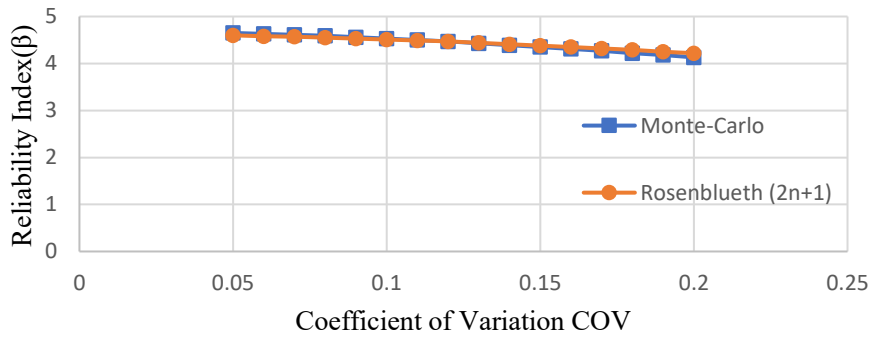
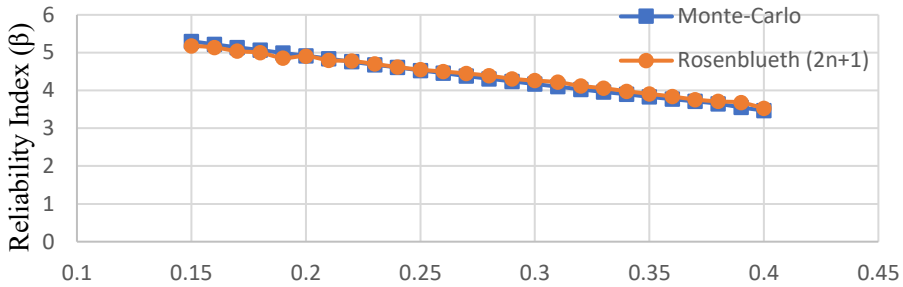


Fig. (9) illustrates the effect of epistemic uncertainty of service live load L, with COV(L) rising from 0.15 to 0.40, on the reliability index β. A pronounced linear inverse relationship is observed between the two variables, with higher sensitivity compared to dead load. Increasing COV(L) from 0.15 (good live load control) to 0.40 (highly uncertain) causes β to decrease from 5.30 to 3.40, which is a 36% reduction. The drop rate is $\Delta\beta \approx -0.076$ per 0.01 percent increase in COV, which is almost double the rate of dead load (0.04), and around triple that of concrete strength. This high sensitivity is because live load has large inherent variability and constitutes a major portion of load effect uncertainty σ_Q. According to Ellingwood et al. [9], nominal COV for live load is 0.25. Increasing it to 0.40 simulates epistemic uncertainty due to changes in building use, overcrowding, or poor load surveys in some developed or rural regions. The result matches Nowak & Szerszen [17,18], who stated that live load is the governing parameter for

flexural reliability. The results in this case compromise the ACI318 requirements for β > 3.5 as well as Eurocode 2, which is β > 3.8 for consequence class 2 (RC2) since Eurocode 2 imposes a more stringent reliability requirement. According to the literature discussed earlier, the maximum realistic coefficient of variation (COV) for live load in office/residential buildings is between 0.32 and 0.40 when including epistemic uncertainty. Therefore, under poor live load control, the beam violates ACI318 and Eurocode 2 requirements and becomes unreliable. This is a serious concern for structures in some developed countries in the world where live loads are often underestimated or building use changes. This proves that even a beam perfectly designed for concrete strength and steel can become unsafe solely due to underestimation or uncontrolled increase in live load, which is a common issue in practice.

Fig. (9) Effect of Coefficient of Variation of Service Live Load L on Reliability Index β



Conclusions

Based on reliability analysis using Monte-Carlo Simulation and Rosenblueth (2n+1) point estimate method for a singly reinforced concrete beam, the effect of high epistemic uncertainty expressed as the coefficient of variation (COV) of basic variables on reliability index β was investigated. The following conclusions can be drawn:

1. The Rosenblueth (2n+1) method shows excellent agreement with Monte-Carlo with an error < 4% for all parameters. It can be used as a low-cost alternative to MCS for epistemic uncertainty analysis.

2. The compressive strength of concrete f_c' showed high sensitivity to epistemic uncertainty. As the uncertainty level of f_c' increased, the reliability index exhibited a sharp and continuous decrease, reflecting the direct influence of concrete quality on flexural capacity. The analysis indicates that under poor quality control conditions, such as sites with absence of concrete testing and uncontrolled mixing ingredients, the reliability can drop below the limits required by both ACI 318 and Eurocode 2. Eurocode 2 was found to be violated earlier than ACI 318 due to its higher target reliability, confirming that compressive strength is a critical parameter when construction control is low.

3. Steel is the most reliable parameter.

Increasing COV for the steel reinforcement (fy) from 0.05 to 0.15 reduces β from 8.0 to 4.55 (43% loss); however, it never fails ACI 318 or Eurocode 2 within a realistic range. Critical COV for ACI failure is > 0.19, which is unrealistic for steel (nominal COV=0.07 per Mirza et al.).

4. Epistemic uncertainty in service dead load alone cannot cause violation of ACI 318. The structure is highly robust against dead load variability. This contrasts with service live load, which is expected to be the dominant factor causing ACI non-compliance. Failure in dead load would require COV > 0.40, which is physically impossible for dead load.

5. Service live load was identified as the governing parameter for reliability and the only load parameter that directly compromises ACI318 within realistic uncertainty levels. The key finding is that ACI318 is clearly compromised. At high levels of epistemic uncertainty representing change of use, overcrowding, or poor load estimation, the reliability index falls below the ACI target. Similarly, Eurocode 2 is compromised even earlier than ACI, as it requires a higher safety level.

6. Practical Recommendation:*

For practical recommendations for construction in developed countries, to maintain target reliability β ≥ 3.8 (Eurocode) and β ≥ 3.5 (ACI318), the following COV limits has to be enforced:

COV(f_c') ≤ 0.20, COV(fy) ≤ 0.10, COV(D) ≤ 0.20, COV(L) ≤ 0.33

Controlling live load assumptions (accurate load survey, preventing change of use) is 3 times more effective than improving concrete quality.

7. ACI 318 load factor for live load (1.6) may be insufficient when epistemic uncertainty COV(L) > 0.35. For structures with high live load uncertainty, Eurocode 2 load factor (1.5) combined with higher β_{target}=3.8 is safer and has to be adopted.

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