Quantifying Uncertainty in Steel Member Reliability via Global Sensitivity Indices

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Abstract: - The study presents a comprehensive global sensitivity investigation focusing on the failure probability in torsion-loaded thin-walled steel members with uncertainties in material, geometric, and loading parameters. Two distinct sensitivity measures are scrutinised: one formulated through variance analysis of a binary failure outcome and the other based on discrete entropy. Total-effect indices, encompassing all interaction orders, are employed to assess variable importance. The results indicate that the long-term variable load significantly influences the uncertainty in structural reliability, while material and geometric parameters play a secondary role. The entropy-based measure accentuates the distinction between dominant and less influential inputs, while the variance-based approach captures a broader sensitivity structure. The findings underscore the impact of the selected sensitivity metric on input ranking and its implications for reliability assessment.

Key-Words: - Global sensitivity analysis, Structural reliability, Failure probability, Entropy index, Variance index, Torsional loading, Thin-walled steel member.

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1 Introduction

Global sensitivity analysis (GSA) provides an effective framework for quantifying the impact of uncertain input parameters on model responses across the entire input space. Within the context of civil engineering, where nonlinearities, imperfections, and variability in material and geometric properties are significant components of computational models, GSA offers a comprehensive understanding of the factors influencing limit states and failure probabilities. In contrast to local methods that rely on partial derivatives at nominal values, GSA methods can assess both individual and interactive effects of uncertainties on model output. In recent years, GSA has been increasingly integrated into probabilistic design and reliability analysis, particularly for steel structures, where failure modes such as buckling, ultimate deformation, and fracture are sensitive to random variability in input parameters.

Recent advancements in GSA have significantly enhanced the probabilistic evaluation of structural reliability in steel structures. A variance-based global sensitivity analysis was performed to evaluate the in-plane buckling resistance of steel arches, with yield stress and geometric parameters identified as the main contributors to variability in buckling strength, [1]. First-order GSA was applied to moment-resisting steel frames with shape-memory alloy bolts under blast loads, [2]. It was found that uncertainties in material strength and bolt properties significantly influence reliability, [2]. Sobol indices were used to assess the tensile resistance of stainless-steel beams, showing that yield strength was the dominant source of resistance variability, followed by geometric parameters, [3].

A Monte Carlo-based reliability analysis of a steel frame with semi-rigid joints demonstrated that geometric imperfections and connection stiffness significantly influence the buckling failure probability, [4]. The system reliability of steel trusses with correlated member capacities and loads was investigated, and sensitivity measures were used to identify critical components that contributed to structural failure, [5]. The progressive collapse behaviour of steel sandwich-plate structures was analysed, showing that member stiffness and rib configuration significantly affected collapse sensitivity and redundancy, [6].

Design optimisation considering reliability for steel–concrete composite beams was conducted using Monte Carlo (MC) sampling, implicitly capturing the global sensitivity of material and geometric parameters during the optimisation process, [7].

A probabilistic framework was developed that integrated MC simulation, Sobol sensitivity indices, and three surrogate models–Kriging, PRSM, and ANN–for evaluating the failure probability of a two-storey steel frame with moment-resisting connections subjected to heavy vehicle collision, [8]. Vehicle mass, velocity, and yield strength were identified as the dominant contributors to structural failure, [8]. A global sensitivity analysis approach was presented using polynomial chaos expansions (PCE), enabling efficient quantification of input importance with respect to the full output distribution rather than a single summary statistic, [9].

In addition to model-based reliability analyses, sensitivity studies have also been conducted at the system level. For example, order statistics have been applied to assess the sensitivity of k-out-of-n systems with load-sharing effects, demonstrating how system reliability depends on the distributional properties of component lifetimes, [10].

The present study builds upon these foundations by applying GSA to steel structures characterised by random geometric imperfections and uncertain material properties. A finite element model (FEM) is utilised for simulating the structural response under torsional loading. The primary objective is to identify and compare the influence of geometric characteristics, material yield strength, and cross-sectional properties on the ultimate load-carrying capacity. The results highlight critical aspects of the dominant sources of uncertainty and support a reliability-oriented design approach for steel structures.

2 Sensitivity Analysis Frameworks

In structural engineering, sensitivity analysis (SA) methods are essential for identifying how uncertain parameters affect model outputs. Variance-based methods, such as Sobol's indices, are widely used due to their ability to quantify both main and interaction effects. An effective approach that transforms a sensitivity problem into a single uncertainty propagation process was proposed, [11]. This method, implemented with the Univariate Reduced Quadrature (URQ) technique, exhibits high accuracy for linear problems and sufficient efficiency for nonlinear models, while significantly reducing the computational cost compared to traditional MC methods, [11].

To address challenges posed by medium-dimensional input spaces and computationally expensive model evaluations, Hübler proposed a two-tiered approach, [12]. First, a metamodel-based dimensionality reduction is performed, subsequently followed by the application of stochastic collocation to estimate Sobol sensitivity indices. This method extends the applicability of GSA to structural models characterised by arbitrary input distributions and has been validated in structural reliability applications, [12].

When dealing with dependent or correlated input variables, classical SA techniques often lose interpretability. A comprehensive framework that combines dependency modelling with variance-based and derivative-based GSA was developed, [13]. This framework accommodates dependent variables and multivariate outputs, introduces derivative-based upper bounds for total sensitivity indices, and extends Morris' method to accommodate dependent inputs, thereby facilitating refined screening and ranking of influential parameters, [13].

For models where the subject of interest is defined by extreme values, such as maximum displacements or critical loads, conventional SA methods may not be suitable. A conceptually straightforward approach was proposed for extreme-based problems, [14]. This approach sequentially fixes one parameter and evaluates the variation of the response optimum, thereby providing sensitivity insight without explicitly defining input distributions. This method is computationally efficient and well suited for reliability-based design tasks, [14].

The scope of GSA was expanded to stochastic hybrid simulation, in which part of the structure was subjected to physical testing while the remainder was numerically simulated, [15]. A surrogate model based on the generalized lambda distribution was developed to approximate the hybrid system's response and compute Sobol's indices for the quantiles of interest, [15]. This approach effectively captures uncertainty in substructure responses without requiring repeated evaluations, thereby making it computationally feasible for dynamic testing frameworks, [15].

A GSA method based on Cliff's Delta, a distribution-free effect size indicator originally designed for ordinal datasets, was introduced to assess structural reliability without assumptions about the distributions of resistance and load. By comparing paired samples of load action (F) and resistance (R) random realizations, this method quantifies the probability of structural success ($R>F$) and provides first- and higher-order sensitivity indices. Although computationally expensive, this approach improves the precision of failure probability estimates in nonlinear FEM simulations, [16].

2.1 Sensitivity Analysis of Reliability

Failure probability-oriented sensitivity analysis has emerged as a relatively recent discipline within the field of stochastic structural mechanics. Its primary objective is to quantify the reliability of structural systems. In this context, Sobol-type decompositions applied to the failure probability P_f use a binary response function, defined as $1_{F>R}$, which yields one if the load F exceeds the resistance R, and zero otherwise. The first two statistical moments of this binary indicator describe the mean value P_f and its variance.

$$E(1_{F>R}) = P_f \tag{1}$$

$$V(1_{F>R}) = (1 - P_f) \cdot P_f \tag{2}$$

The decomposition of $V(1_{F>R})$ underpins reliability-oriented Sobol sensitivity analysis, [17], [18]. However, the study [19] showed that conventional GSA using the variance of model outputs and GSA in terms of P_f may yield significantly different results. Notably, variance-based measures applied to small failure probabilities P_f typically produce very low first-order indices and a high proportion of higher-order interaction effects, complicating interpretability.

Discrete entropy was introduced in [19] as an alternative sensitivity measure, yielding a comparatively higher proportion of first-order sensitivity indices and thus providing clearer interpretability. Despite these differences in sensitivity index decomposition, both approaches yield similar total-effect indices and consistent variable rankings in reliability analysis.

Entropy-based metrics are widely used in information theory and signal processing for system optimization and model selection, [20], [21]. However, their application in GSA and structural reliability remains limited. This study applies discrete entropy to decompose sensitivity indices related to structural failure probability, which differs from conventional uses of entropy in engineering.

Based on these findings, further numerical studies are being conducted using finite element models of real structural members to investigate these sensitivity measures and their capability to reflect the influence of random input variables on P_f. Nevertheless, several theoretical challenges persist, including the definition of appropriate domains and ensuring non-negativity. Although entropy lacks some mathematical properties inherent to variance (e.g., additivity), it offers certain advantages and may complement variance-based measures in reliability sensitivity assessments.

Within the generalized framework, the symbol Q denotes the selected sensitivity measure, with Q^V representing variance-based indices and Q^H entropy-based ones.

$$Q^V(P_f) = (1 - P_f) \cdot P_f \tag{3}$$

$$Q^H(P_f) = -P_f \cdot \ln(P_f) - (1 - P_f) \cdot \ln(1 - P_f) \tag{4}$$

Equation (4) represents the discrete entropy of the Bernoulli random variable describing structural failure. This entropy quantifies the uncertainty associated with the binary outcome of failure or survival, reaching its maximum at P_f=0.5 and vanishing as P_f approaches 0 or 1.

Similar to Equation (3), Equation (4) provides a symmetric and bounded measure that peaks at P_f=0.5 and vanishes as P_f approaches 0 or 1. The decomposition of entropy-based sensitivity indices follows a procedure analogous to variance-based Sobol decomposition. First-order and higher-order sensitivity indices are computed by sequential conditioning of entropy on the input variables. This allows for quantifying both the direct and interaction effects of input variables on the uncertainty in structural reliability.

Primary indices S_i, second-level terms S_{ij}, along with higher-order components S_{ijk},… quantify the individual and interactive contributions of input factors to overall uncertainty in model output, measured by variance or entropy.

$$S_i = \frac{Q(P_f) - E(Q(P_f | X_i))}{Q(P_f)} \tag{5}$$

$$S_{ij} = \frac{Q(P_f) - E(Q(P_f | X_i, X_j))}{Q(P_f)} - S_i - S_j \tag{6}$$

These contributions collectively sum to unity, enabling systematic interpretation of structural reliability with respect to P_f.

$$\sum_i S_i + \sum_i \sum_{j>i} S_{ij} + \sum_i \sum_{j>i} \sum_{k>j} S_{ijk} + \ldots + S_{123\ldots M} = 1 \tag{7}$$

A detailed illustrative example of the index decomposition and its numerical implementation, including tabular results, is provided in [19].

The total-effect index S_{Ti} aggregates both the main effect of a variable and all its interactions. Compared to full higher-order decompositions, total-effect indices are computationally less intensive and are often sufficient for identifying influential factors.

$$S_{Ti} = 1 - \frac{Q\left(E\left(P_f \mid X_{\sim i}\right)\right)}{Q\left(P_f\right)} \quad (8)$$

It should be noted that the estimation of sensitivity indices is computationally demanding, particularly for low failure probabilities. In engineering design practice, target reliability levels often correspond to P_f=7.2 · 10^{-5}, presenting a significant challenge for conventional estimation techniques. Monte Carlo-based GSA is constrained by the need for a large number of simulations, which is further exacerbated by the necessity of nested loops to generate realizations of F, R, and the binary response $1_{F>R}$.

2.2 GSA of P_f in Torsion

The torsion-loaded closed thin-walled member was selected as a benchmark problem due to the availability of an exact closed-form solution for stress verification, the practical importance of torsion in thin-walled structures, and the limited research on torsional reliability problems.

An analysis is performed on the reliability of thin-walled closed steel member under torsional loading. The study investigates the influence of random input variables affecting resistance and loading on the failure probability P_f. A numerical case study is presented to compare sensitivity indices based on discrete entropy [19] with those derived from the variance of a binary failure-success random variable following the Bernoulli distribution, [17], [18]. The goal of the presented case study is to find out a GSA of P_f, where the limit state function is defined as $Z=R-F$. Failure occurs if $R<F$.

The steel member is subjected to constant torque along its length, and the cross-section remains uniform. Failure is prevented if the torsional shear stress does not exceed the von Mises yield limit. In the idealized case of a sharp-cornered thin-walled section, the von Mises condition reduces to the material's shear yield strength, and the torsional resistance is given by formula:

$$M_R = f_y \cdot 2 \cdot A_k \cdot t\,, \quad (9)$$

where f_y is the yield strength, A_k is the area enclosed by the midline of the thin-walled closed section, and t is the wall thickness. The simplified formula for torsional resistance in Equation (9) is based on classical assumptions for thin-walled closed sections. It assumes that the shear stresses are constant across the wall thickness and act tangentially along the midline of the cross-section. The resultant shear flow q [N/m] is considered constant along the closed midline, satisfying equilibrium conditions.

For the investigated box-shaped section, the correlation between this simplified resistance model and the resistance obtained from FEM simulation is 0.99, Figure 1.

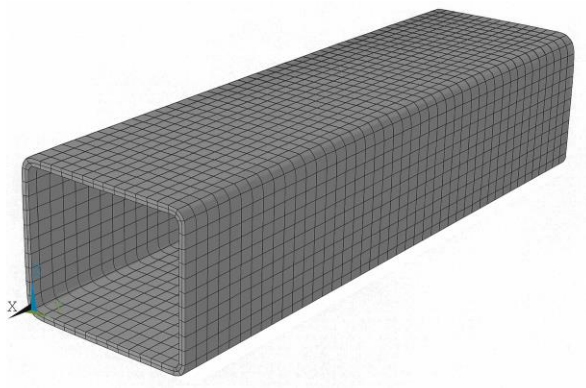

Fig. 1: FE Mesh of Thin-Walled Box Section

The computational model was developed using ANSYS Mechanical APDL 2024 R1 (ANSYS Inc., 2024), employing the SHELL181 element. To efficiently manage the extensive number of random realizations required for the reliability and sensitivity analysis, the process was integrated with Ansys optiSLang 2024 R1 (ANSYS Inc., 2024).

The finite element model assumes a geometrically linear elastic response and perfect symmetry of the structure and loading. The torsional moment is applied via pairs of concentrated forces acting in the mid-surfaces of the thin-walled plates near the free edges, ensuring pure torsion with negligible bending effects. Symmetry conditions are applied to reduce the model size. Rotation around the centroidal axis is restrained by fixing the displacements at corner nodes located at the intersection of the model and its symmetry plane. This prevents rigid-body rotation while allowing natural deformation of the cross-section at the free edges. Additional boundary conditions are applied to ensure static determinacy while allowing cross-sectional warping and out-of-plane displacements to remain unconstrained.

The wall thickness is defined directly as a parameter of the SHELL181 elements, which avoids the need for through-thickness discretization. The mesh was refined to ensure sufficient element density along the structural dimensions. This modelling approach is well-suited for thin-walled members, and the applied mesh satisfies common guidelines for accurate stress evaluation in shell-based FEM analyses.

The structural resistance is treated as a function of three basic physical parameters: yield strength f_y, web thickness t_w, and section width b. The probabilistic properties of these variables are based on long-term experimental investigations, [22]. In this study, the random variables f_y, t_w, and b are modelled as normally distributed with the following mean values and standard deviations:

Yield strength f_y is characterized by an average of 297.3 MPa and a standard deviation of 16.8 MPa. Web thickness t_w has a mean of 8.0 mm with a standard deviation of 0.37 mm. Section width b has a mean of 180.0 mm and a standard deviation of 0.79 mm.

The normal distribution was adopted for all input parameters, following conventional assumptions in stochastic modelling of geometrical imperfections, [23], [24]. For material properties, normal distributions are widely used to represent the yield strength of structural steel, as confirmed by several studies, [25], [26], [27]. Although log-normal distributions could also be considered, the normal distribution is generally accepted and provides a practical basis for the present analysis.

The loading is composed of a permanent component G and a long-term variable component Q, corresponding respectively to the mean values m_G=20kNm, σ_G=2 kNm and m_Q=57 kNm σ_Q=20 kNm. While the first four variables (i.e., f_y, t_w, b, and G) are assumed to follow normal distributions, the long-term load Q is modelled using a Gumbel-max distribution, [28].

The failure probability P_f was estimated using numerical integration [19], which offers sufficient accuracy for small values such as $P_f \approx 1 \cdot 10^{-5}$, including conditional failure probabilities $P_f | X_i$, $P_f | X_i, X_j$, etc. Expected values E[$\cdot$] were computed using a MC simulation with 100,000 outer samples. In contrast, the direct MC estimation of P_f proved insufficiently accurate, prompting the exploration of surrogate models tailored for the GSA of reliability.

The convergence of the estimated sensitivity indices at small failure probabilities (e.g., $P_f \approx 1 \cdot 10^{-5}$) was addressed by performing parallel computations using multiple CPU cores. Each sensitivity index was obtained as the arithmetic mean of several independent estimates, each computed with different pseudo-random sequences. This approach reduces sampling variability and improves the numerical stability of the estimated indices.

Confidence intervals for the computed sensitivity indices were not explicitly evaluated. However, the results are based on a large MC sample of 100,000 outer realizations, ensuring numerical stability. Given the clear dominance of the long-term variable load Q in all sensitivity rankings, the qualitative conclusions of the analysis are not affected by sampling uncertainty.

A total of 31 sensitivity indices were computed based on the five input variables provided in Table 1.

Table 1. Input random quantities

Parameters	Mean value	St. deviation
G	20 kNm	2 kNm
Q	57 kNm	20 kNm
f_y	297.3 MPa	16.8 MPa
t_w	8 mm	0.37 mm
b	180 mm	0.79 mm

All input random variables in Table 1 are assumed statistically independent. This assumption is consistent with experimental findings [22], where only weak correlation was observed between yield strength f_y and wall thickness t_w, allowing it to be neglected, [3]. Both GSA approaches employed here require input independence, which is reasonably satisfied. Including this weak correlation would have negligible impact on the sensitivity ranking, where the dominant influence of the long-term variable load Q clearly prevails.

The results of the GSA of P_f are presented in Figure 2 and Figure 3. The dominant influence of Q is evident from both graphs. The indices shown in the Figure 2 are based on Equation (3), while the indices shown in the Figure 3 are based on Equation (4).

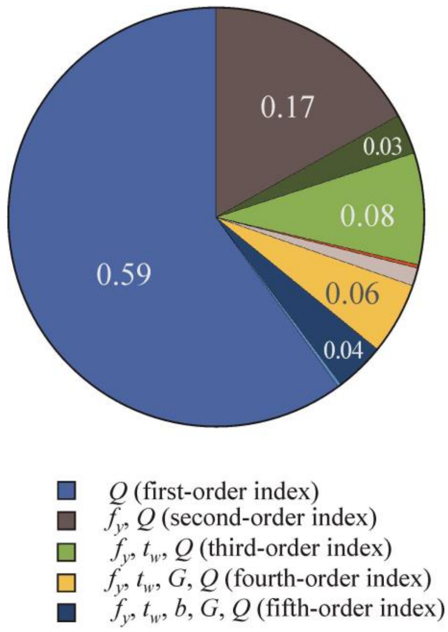

Fig. 2: Contribution of Q to Failure Probability (Variance-Based)

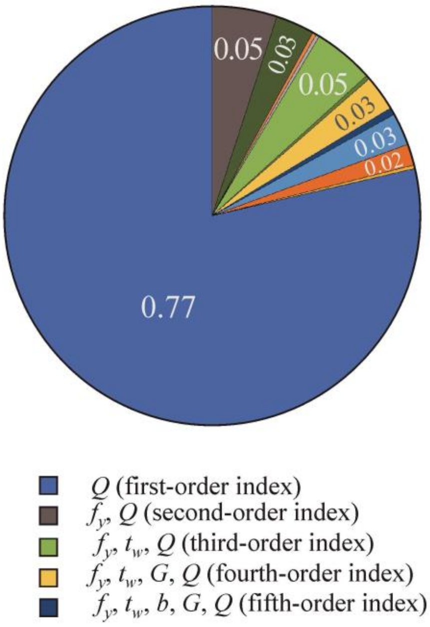

Fig. 3: Contribution of Q to Failure Probability (Entropy-Based)

The case study demonstrates the importance of the selected sensitivity measure in assessing structural reliability using global sensitivity indices derived from two importance measures.

3 Sensitivity Index Ranking and Interpretation

Two distinct sensitivity measures were applied to evaluate the relative importance of five random input variables: yield strength f_y, web thickness t_w, section width b, dead load G, and sustained variable load Q. As detailed in Equation (3), the first measure is based on the variance related to the binary failure function. Conversely, the second measure employed the entropy of the Bernoulli distribution, given in Equation (4). In both cases, indices representing total effects were computed to capture the complete contribution of each variable, encompassing all interactions. The total indices were obtained by summing all partial sensitivity indices across all orders, i.e., the main effect together with all higher-level interaction terms in which a given variable appears.

This summation approach was adopted to ensure consistency and interpretability of the sensitivity results. It is fully consistent with the variance-based sensitivity measure, as the variance decomposition inherently follows an additive structure. Consequently, the total effect index equals the sum of the first-order and all higher-order interaction indices involving the variable. While Equation (8) provides an alternative method to compute total indices, its validity is strictly tied to the variance-based framework, where such decomposition holds exactly. In contrast, for the entropy-based measure, Equation (8) may not yield total indices equivalent to the sum of partial indices, due to the non-additive nature of entropy. Nevertheless, Equation (8) remains a useful tool for estimating the overall influence of variables under certain conditions, especially when the focus is on capturing global effects rather than decomposing specific interaction contributions.

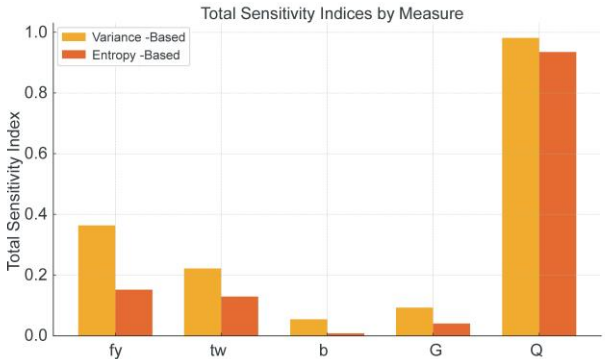

Fig. 4: Total Sensitivity Indices for Input Variables

The results presented in Figure 4 demonstrate a consistent leading influence of the variable Q, representing the long-term variable load, which exhibits the highest total-effect index under both sensitivity measures: 0.981 for the variance-based and 0.934 for the entropy-based approach. This clearly indicates that uncertainty in long-term loading significantly influences the variability of the structural failure probability. This dominance can be attributed to both the high mean value and the relatively large standard deviation associated with Q, along with its Gumbel distribution, which introduces heavier tails compared to the Gaussian-distributed inputs.

For completeness, Table 2 and Table 3 report the numerical values of the first-order and total-effect indices, respectively. These tables complement the graphical results presented earlier by providing precise values for all indices, including the very small first-order indices of less influential variables, which are not clearly visible in the bar charts due to their small magnitude.

Table 2. First-order indices

Parameters	Variance - based	Entropy - based
f_y	0.001520	0.023523
t_w	0.000989	0.016649
b	0.000008	0.000404
G	0.000066	0.002010
Q	0.590108	0.770021

Table 3. Total-effect indices

Parameters	Variance - based	Entropy - based
f_y	0.363250	0.152153
t_w	0.222237	0.128906
b	0.054227	0.008588
G	0.093141	0.040273
Q	0.981368	0.934351

Yield strength f_y and web thickness t_w are the next most influential variables, although their importance is substantially lower and more sensitive to the choice of sensitivity measure. Under the variance-based formulation, f_y reaches a total index of 0.363 and t_w 0.222. In contrast, the entropy-based analysis yields considerably reduced values of 0.152 and 0.129, respectively. This suggests that entropy-based indices tend to compress the relative differences among moderately influential variables, leading to a steeper sensitivity gradient favouring the dominant variable. This behaviour is related to the mathematical properties of entropy. While the variance function has a constant derivative near P_f=0, the derivative of entropy tends to infinity as P_f approaches zero. As a result, entropy-based indices are inherently more sensitive to small changes near low failure probabilities, which leads to a stronger emphasis on the dominant variables and a sharper reduction of relative differences among the others.

Section width b and permanent load G exhibit low total-effect indices across both formulations (below 0.1 in all cases). This indicates that their contributions to P_f are minor and that potential simplifications or fixed-value assumptions could be considered in reduced-order modelling.

A key insight from this comparison is the observed robustness of the dominant variable Q across both sensitivity metrics. However, the remaining variables exhibit a pronounced dependence on the selected measure. While variance-based indices offer more nuanced differentiation among secondary inputs, entropy-based indices may serve as effective tools for isolating the primary source of failure uncertainty. These findings highlight the methodological impact of sensitivity measures on variable ranking and suggest that the choice of index should reflect the analytical objective—whether comprehensive input screening or targeted identification of dominant contributors.

Total-effect indices remain effective for systems with strong interactions, and combining multiple sensitivity metrics can clarify structural reliability under uncertainty. However, both variance- and entropy-based methods require sufficiently large datasets to characterize input randomness, which is difficult for long-term stochastic loads or when data are limited.

In such cases, methods from uncertainty theory, such as the uncertainty Bayesian rule, model inputs as uncertain variables and estimate reliability from limited observations via posterior uncertainty distributions, [29]. Though methodologically different, these approaches offer a practical option for reliability analysis with scarce data.

4 Conclusion

This study presented a global sensitivity evaluation of the failure probability P_f for a thin-walled steel member subjected to torsional loading, considering random variations in material properties, geometry, and loading. Two distinct importance measures were investigated: one based on the variance of the binary failure indicator and the other on the entropy of the Bernoulli distribution. Furthermore, total-effect sensitivity indices were computed to comprehensively assess the influence of each input variable along with all interaction effects.

The results consistently identified the long-term variable load Q as the dominant factor influencing the structural reliability, regardless of the selected sensitivity measure. This observation corroborates the robustness of Q's impact, which stems from both its high variability and heavy-tailed Gumbel distribution. Secondary variables such as yield strength f_y and web thickness t_w exhibited moderate influence, while section width b and permanent load G made only minor contributions in all scenarios.

The entropy-based sensitivity measure exhibited a tendency to diminish the relative importance of less influential variables, resulting in a steeper sensitivity profile centred around the dominant input. This property may be advantageous in screening applications, where prompt identification of key parameters is critical. In contrast, the variance-based approach preserved finer distinctions among secondary inputs, potentially facilitating more detailed reliability studies.

The findings emphasise the importance of selecting a sensitivity measure that aligns with the objectives of the analysis. While both methods yielded consistent rankings for the most influential variable, the choice of metric influenced the interpretation of subordinate factors. This insight is particularly relevant in reduced-order modelling, model calibration, or uncertainty prioritization.

Future research may focus on the use of surrogate models to further reduce computational demands, particularly in cases involving very low failure probabilities. The strong dominance of the long-term variable load Q tends to overshadow the effects of other random variables, whose influence mainly appears through interactions with Q. Future research will focus on quantile-based global sensitivity analysis, which can separately evaluate the effects of random input variables on the design quantiles of load and resistance. Since the variability of material and geometric properties is generally lower than that of Q, it is more appropriate to analyse the load and resistance sides separately, rather than jointly, following the limit state design principles defined in EN 1990. The future work will thus aim to apply global sensitivity analysis to the design quantiles of load and resistance, supporting more targeted reliability assessments.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

The authors wrote, reviewed and edited the content as needed and verifies that none utilised artificial intelligence (AI) tools were used. The authors take full responsibility for the content of the publication.

References:

[1] Nguyen, T.H., Global Sensitivity Analysis of In-Plane Elastic Buckling of Steel Arches, *Engineering, Technology & Applied Science Research*, Vol. 10, No. 5, 2020, pp. 6476–6480. https://doi.org/10.48084/etasr.3833.

[2] Weli, S.S., Vigh, L.G., Blast Reliability Assessment and Sensitivity Analysis of Steel MRFs Equipped with NiTi SMA Bolts, *Engineering Structures*, Vol. 286, 2023, pp. 1–12. https://doi.org/10.1016/j.engstruct.2023.116137.

[3] Omishore, A., Global Sensitivity Analysis of Ultimate Limit States of Stainless Steel Structural Members, *IOP Conference Series: Materials Science and Engineering*, Vol. 1203, No. 2, 2021, pp. 1–7. https://doi.org/10.1088/1757-899X/1203/2/022142.

[4] Tran, N.L., Nguyen, T.H., Reliability Assessment of Steel Plane Frame's Buckling Strength Considering Semi-Rigid Connections, *Engineering, Technology & Applied Science Research*, Vol. 10, No. 1, 2020, pp. 5099–5103. https://doi.org/10.48084/etasr.3231.

[5] Kubicka, K., Radoń, U., The System Reliability of Steel Trusses with Correlated Variables, *Archives of Civil Engineering*, Vol. 70, No. 2, 2024, pp. 163–178. https://doi.org/10.24425/ace.2024.149857.

[6] Zeng, W., Luo, J., Xiao, J., Resistance to Progressive Collapse Performance Analysis of Steel Open-Web Sandwich Plate Structure, *Archives of Civil Engineering*, Vol. 66, No. 3, 2020, pp. 281–303. https://doi.org/10.24425/ace.2020.134398.

[7] Nguyen, T.H., Le, V.D., Vu, X.H., Nguyen, D.K., Reliability-Based Design Optimization of Steel-Concrete Composite Beams Using Genetic Algorithm and Monte Carlo Simulation, Engineering, Technology & *Applied Science Research*, Vol. 12, No. 6, 2022, pp. 9766–9770. https://doi.org/10.48084/etasr.5366.

[8] Sadeghi, A., Kazemi, H., Samadi, M., Reliability and Reliability-based Sensitivity Analyses of Steel Moment-Resisting Frame Structure Subjected to Extreme Actions, *Frattura ed Integrità Strutturale*, Vol. 57, 2021, pp. 138–159. https://doi.org/10.3221/IGF-ESIS.57.12.

[9] Novák, L., On distribution-based global sensitivity analysis by polynomial chaos expansion, *Computers and Structures*, Vol. 267, 2022, pp. 1–18. https://doi.org/10.1016/j.compstruc.2022.106808.

[10] V. Rykov, N. Ivanova, D. Kozyrev, T. Milovanova, On Reliability Function of a k-out-of-n System with Decreasing Residual Lifetime of Surviving Components after Their Failures, *Mathematics*, Vol. 10, No. 22, 2022, pp. 4243. https://doi.org/10.3390/math10224243.

[11] Chen, X., Molina-Cristóbal, A., Guenov, M. D., Riaz, A., Efficient method for variance-based sensitivity analysis, *Reliability Engineering & System Safety*, Vol. 181, No. 1, 2019, pp. 97–115. https://doi.org/10.1016/j.ress.2018.06.016.

[12] Hübler, C., Global sensitivity analysis for medium-dimensional structural engineering problems using stochastic collocation, *Reliability Engineering & System Safety*, Vol. 195, No. 1, 2020, pp. 1–14. https://doi.org/10.1016/j.ress.2019.106749.

[13] Lamboni, M., Kucherenko, S., Multivariate sensitivity analysis and derivative-based global sensitivity measures with dependent variables, *Reliability Engineering & System Safety*, Vol. 212, No. 1, 2021, pp. 1–13. https://doi.org/10.1016/j.ress.2021.107519.

[14] Nogal, M., Nogal, A., Sensitivity method for extreme-based engineering problems, *Reliability Engineering & System Safety*, Vol. 216, No. 1, 2021, pp. 1–10. https://doi.org/10.1016/j.ress.2021.107997.

[15] Tsokanas, N., Zhu, X., Abbiati, G., Marelli, S., Sudret, B., Stojadinović, B., A global sensitivity analysis framework for hybrid simulation with stochastic substructures, *Frontiers in Built Environment*, Vol. 7, No. 1, 2021, pp. 1–15. https://doi.org/10.3389/fbuil.2021.778716.

[16] Kala, Z., Global sensitivity analysis of structural reliability using Cliff Delta, *Mathematics*, Vol. 12, No. 13, 2024, pp. 1–18. https://doi.org/10.3390/math12132129.

[17] Li L., Lu Z., Feng J., Wang B., Moment-independent importance measure of basic variable and its state dependent parameter solution, *Structural Safety*, Vol.38, No.1, 2012, pp. 40–47. https://doi.org/10.1016/j.strusafe.2012.04.001.

[18] Wei P., Lu Z., Hao W., Feng J., Wang B., Efficient sampling methods for global reliability sensitivity analysis, *Computer Physics Communications*, Vol.183, No.8, 2012, pp. 1728–1743. https://doi.org/10.1016/j.cpc.2012.03.014.

[19] Kala, Z., New importance measures based on failure probability in global sensitivity analysis of reliability, *Mathematics*, Vol.9, No.11, 2021, pp. 2425. https://doi.org/10.3390/math9192425.

[20] A. Bazzi and M. Chafii, "Mutual Information Based Pilot Design for ISAC," *IEEE Transactions on Communications*, 2025.

[21] A. Bazzi, D. T. M. Slock, and L. Meilhac, "Detection of the Number of Superimposed Signals Using Modified MDL Criterion: A Random Matrix Approach," *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2025.

[22] Melcher J., Kala Z., Holický M., Fajkus M., Rozlívka L., Design characteristics of structural steels based on statistical analysis of metallurgical products, *Journal of Constructional Steel Research*, Vol.60, No.5–6, 2004, pp. 795–808. https://doi.org/10.1016/S0143-974X(03)00144-5

[23] S. Shayan, K.J.R. Rasmussen, H. Zhang, On the modelling of initial geometric imperfections of steel frames in advanced analysis, *Journal of Constructional Steel Research*, Vol. 98, No. 1, 2014, pp. 167–177. https://doi.org/10.1016/j.jcsr.2014.02.016.

[24] D. Jindra, Z. Kala, J. Kala, Probabilistically Modelled Geometrical Imperfections for Reliability Analysis of Vertically Loaded Steel Frames, *Journal of Constructional Steel Research*, Vol. 217, 2024, pp. 108627. https://doi.org/10.1016/j.jcsr.2024.108627.

[25] T. Sakai, M. Nakajima, K. Tokaji, N. Hasegawa, Statistical distribution patterns in mechanical and fatigue properties of metallic materials, *Journal of the Society of Materials Science*, Japan, Vol. 46, No. 6, 1997, pp. 63–74. https://doi.org/10.2472/jsms.46.6Appendix_63.

[26] Z. Sekulski, Statistical properties of the yield strength of normal strength hull structural steel plates, *The Annals of "Dunărea de Jos" University of Galati, Fascicle XI – Shipbuilding*, Vol. 42, 2019, pp. 55–64. https://doi.org/10.35219/AnnUGalShipBuilding.2019.42.08.

[27] M. De Stefano, R. Nudo, G. Sara, S. Viti, Effects of randomness in steel mechanical properties on rotational capacity of RC beams, *Materials and Structures*, Vol. 34, 2001, pp. 92–99. https://doi.org/10.1007/BF02481557.

[28] Kala Z., Reliability analysis of the lateral torsional buckling resistance and the ultimate limit state of steel beams with random imperfections, *Journal of Civil Engineering and Management*, Vol.21, No.8, 2015, pp. 902–911. http://dx.doi.org/10.3846/13923730.2014.971130.

[29] C. Zhang, Y. Wang, Reliability Evaluation Based on Uncertain Bayesian Rule, *WSEAS Transactions on Mathematics*, Vol. 22, 2023, pp. 55–63. http://dx.doi.org/10.37394/23206.2023.22.7.

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

- A. Omishore participated in the evaluation of sensitivity indices, contributed to selected sections of the manuscript, and assisted with its revision.
- L. Puklický carried out the finite element modelling, conducted the numerical simulations, and contributed to writing and revising the manuscript.
- Z. Kala formulated the concept, performed the global sensitivity analysis, supervised the finite element modelling, interpreted the results, and contributed to writing and revising the manuscript.

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Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.