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Probabilistic Evaluation of Steel Column Damage under Blast via Simulation Reliability Methods and Gene Expression Programming †

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Abstract: This paper introduces a probabilistic assessment of steel column damage caused by blast loads, utilizing simulation reliability methods and gene expression programming. The research focuses on an H-section steel column and incorporates uncertainties associated with input loads (axial and blast loads) and geometric factors (i.e., maximum slenderness) under various boundary conditions (pinned and fixed supports). The reliability analysis employs three different methods: the point estimate method (PEM), Monte Carlo simulation method (MCS), and Monte Carlo simulation with Latin Hypercube sampling method (MCS-LHS). To establish the reliability analysis, formulas derived from a previous study conducted by the authors using gene expression programming (GEP) are employed. Damage assessment is determined based on a damage index criterion, considering the post-blast residual axial load-bearing capacity of the steel column. The research presents the results in terms of damage probability, considering the different reliability analysis methods and boundary conditions. The findings demonstrate that the PEM effectively estimates the probabilistic response of the steel column with acceptable accuracy and less effort compared to the MCS and MCS-LHS. Furthermore, the MCS-LHS demonstrates higher accuracy in estimating the probability distribution function by utilizing the Latin Hypercube sampling (LHS) method, as compared to the MCS. These findings emphasize the importance of considering uncertainties in calculating the column response under extreme dynamic blast loading.

Keywords: probabilistic evaluation; steel column; monte carlo simulation; latin hypercube sampling; point estimate method; blast load; damage index

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1. Introduction

Significant structural failures often result from damage to columns, necessitating their resilience against diverse dynamic loads, ranging from explosions and impacts to seismic forces and gravity. Comprehending how columns respond under these dynamic conditions is crucial for predicting overall structural performance. Extensive research on dynamic loads, including explosions, has been carried out by military organizations since World War II, with classified findings shaping guidelines for designing structures to withstand such loads [1,2]. These guidelines have relied on simplified methods like Single Degree of Freedom (SDOF) analysis [3,4], but nowadays, complicated finite element modelling by advanced commercial software tools like LS-DYNA [5], ABAQUS [6], etc. is being incorporated into the blast design of structures. From an analytical perspective, two main approaches exist for analysing structural elements or members subjected to sudden dynamic loads: (1) deterministic methods, which employ single values for parameters while disregarding uncertainties, and (2) probabilistic methods, which consider probability density functions for uncertain parameters, offering insights into safety levels and failure mode predictions. The contemporary trend in structural design emphasizes reliability to create cost-effective and safe structures that are resilient to uncertainties. Consequently, the adoption of reliability methods in designing structures subjected to dynamic loads holds significant importance [7–13]. This study aims to assess the probabilistic evaluation of steel columns under blast loads by employing various reliability methods, including Monte Carlo simulation method (MCS) and point estimate method (PEM), and Monte MCS with the assistance of Latin Hypercube sampling method (LHS) as MCS-LHS. The study concludes by estimating the probability density function of steel column failure based on approximate relationships derived from artificial intelligence-based Gene Expression programming (GEP) [14].

2. Blast Loading

An explosion is the rapid release of energy from an explosive source, creating high-pressure, high-temperature gases. This gas expansion immediately elevates ambient pressure to the incident level. Following the explosion, ambient pressure rapidly rises to its peak reflective point and then exponentially decreases until returning to ambient pressure. This sequence includes the positive phase (initial rise) and, over a longer period, the negative phase (gradual decrease). An idealized blast loading is defined as a pressure time history according to Friedlander's equation as follows [15]:

$$P(t) = P_0 + P_{so}\left(1 - \frac{t - t_a}{t^+}\right)\exp\left(-\alpha\frac{t - t_a}{t^+}\right) \tag{1}$$

where P_{so} represents the peak overpressure recorded at t = 0, and P_0 denotes the ambient atmospheric pressure (approximately 101.3 kPa). t^+ indicates the duration of the positive phase, and t^- represents the negative phase duration. Additionally, t_a is the arrival time and α serves as a shape parameter. It is worth mentioning that various formulas from the literature [16] are available to compute these parameters, relying on the scaled distance parameter of the explosion, denoted as Z, defined as $Z = R/W^{1/3}$, where R represents the detonation distance from the structure or structural member, and W signifies the explosive weight. Once the blast load parameter has been computed, its impact should be regarded as a pressure distribution along the height of the steel column, allowing for the subsequent calculation of the structural response in case of maximum midspan displacement, post-blast residual axial capacity, and so on. Subsequently, the column response can be used to determine the damage state of the column under blast loading according to damage criteria based on support rotation, residual axial capacity, and so on. Further details can be found in [14].

3. GEP Formulas

Artificial intelligence techniques are widely used to predict how a system will behave in different situations, making use of previously gathered information about the same system [17,18]. These methods create intelligent connections between the inputs and outputs of a system. One popular artificial intelligence method is GEP, which uses a genetic evolutionary algorithm similar to genetic algorithms and genetic programming for problem-solving [19]. In previous research conducted by the authors of this paper [14], numerous finite element models of H-section steel columns subjected to various blast loading scenarios were analysed. The results of these analyses were then used as a database to extract relationships using GEP for calculating the axial capacity, both initial and post-blast, of H-section steel columns with pinned and fixed end conditions. To perform probabilistic analysis in this study, the GEP1P and GEP1F models were adopted from [14] to calculate the post-blast residual capacity for pinned and fixed end conditions, respectively, and are represented in Equations (2) and (3). Additionally, Equations (4) and (5) are also utilized to determine the axial capacity of the member in the reliability analysis, respectively for pinned and fixed conditions, enabling the calculation of the damage index (DI) based on Equation (6).

$$P_{residual-Pinned} = \frac{0.094(7.66+R)(R-W_{eff})}{7.09-R} + AF_y + 0.46R^3(R-\lambda_{max})(W_{eff}-AF_y)AF_y \cdots \\ +2(W_{eff}-0.32)\lambda_{max}{}^2AF_y{}^3 - 0.33W_{eff}\lambda_{max}{}^2AF_y(3.56+W_{eff}-2P_d) \quad (2)$$

$$P_{residual-Fixed} = -0.036(1.31+W_{eff})(W_{eff}-R) + AF_y + \frac{RAF_y}{R-5.78+4.82W_{eff}(AF_y-2.34)} \cdots \\ +\frac{0.102}{2.43-R+0.5\lambda_{max}-0.5P_d} + \lambda_{max}{}^2AF_y\left(0.2P_d - \frac{0.48W_{eff}}{W_{eff}+R}\right) \quad (3)$$

$$P_{initial-Pinned} = A - A^2\lambda_{max}{}^2 + 0.177F_y + 0.388A(A\lambda_{max}+F_y-1.575) \cdots \\ +0.0176(A-\lambda_{max})(0.0535-A+F_y+F_y{}^2) \quad (4)$$

$$P_{initial-Fixed} = A + \frac{F_y}{5.089-2.605A+F_y} + \frac{4A(F_y-2.018)}{12.878-\lambda_{max}+F_y} \quad (5)$$

$$DI = 1 - \frac{P_{residual}}{P_{initial}} \quad (6)$$

where in the above equations, the parameters W_{eff}, R, λ_{max}, A, F_y, and P_d represent, respectively, the effective weight of the explosive charge in kilograms of TNT, the distance of structural member from the centre of the explosion in meters, the maximum slenderness ratio, the cross-sectional area in mm^2, the yield stress in MPa, and the initial axial load (i.e., dead load) in KPa. It should be noted that W_{eff} equals to $W_{Surface\_burst}$ times 1.8, and $W_{Surface\_burst}$ is the actual charge weight (in kg of TNT) detonated at ground surface or near it. Furthermore, $P_{residual}$ represents the residual axial load-carrying capacity of the column after explosion and $P_{initial}$ signifies the axial load capacity of the column in its undamaged state. Degrees of damage are also categorized into four levels [20]: (i) Low damage (DI = 0–0.2), (ii) Medium damage (DI = 0.2–0.5), (iii) High damage (DI = 0.5–0.8), and (iv) Collapse (DI = 0.8–1.0).

4. Reliability Methods and Uncertainties

In this study, probabilistic analysis is conducted using both MCS and PEM, with an investigation into the impact of the sampling approach on probabilistic outcomes based on LHS. The MCS is employed for reliability analyses, recognized for its simplicity and relatively high accuracy in estimating the probability of failure in general systems. This method has been extensively utilized in studies related to structural reliability under blast loading. On the other hand, the PEM, proposed by Rosenblueth [21], offers a probabilistic estimation technique. It calculates the mean and standard deviation of the desired output by considering a specific number of input points as estimation points. While suitable for problems with a low number of random variables, it becomes less efficient as the number of random variables increases, leading to exponential growth in required input points and computational costs. MCS, despite demanding a significant number of iterations for accuracy, can leverage parallel analyses and the power of modern computing machines to mitigate computational time and cost. Furthermore, to enhance the effectiveness of MCS, researchers have introduced techniques designed to improve the precision of the method like LHS, etc. These methods offer advantages over standard sampling, enabling comparable accuracy with fewer samples or higher accuracy with the same number of samples.

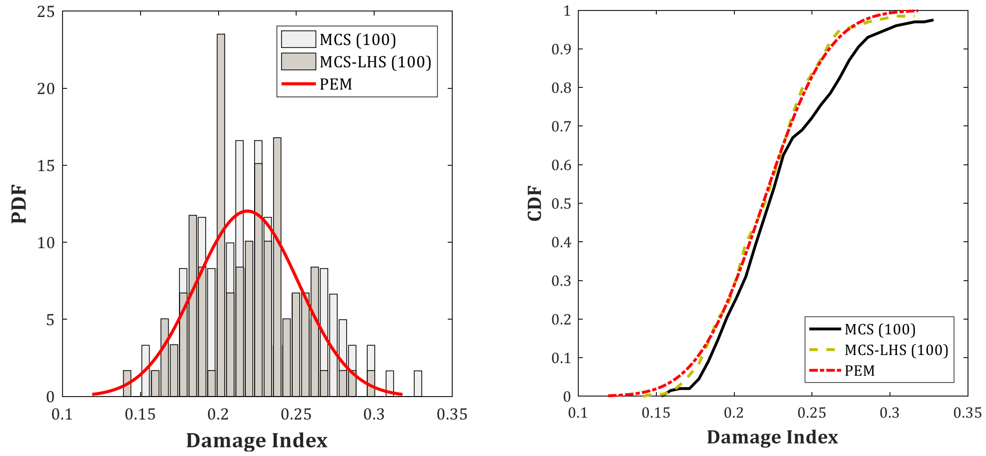
The variables W_{eff}, R, λ_{max}, F_y, and P_d are treated as random variables in the reliability analysis, while parameter A is regarded as a fixed, deterministic value. This is based on the assumption that the steel column used in the reliability analysis is a hot-rolled steel column with a uniform cross-sectional area at all points. Statistical characteristics and uncertainties of these variables are determined using the normal distribution function. For the reliability analysis, an IPB300 steel column measuring 3.6 m in length was utilized, and both pinned and fixed end conditions were investigated. Table 1 provides the statistical properties of the input random variables considered for the reliability analysis.

Table 1. Statistical characteristics of random input parameters.

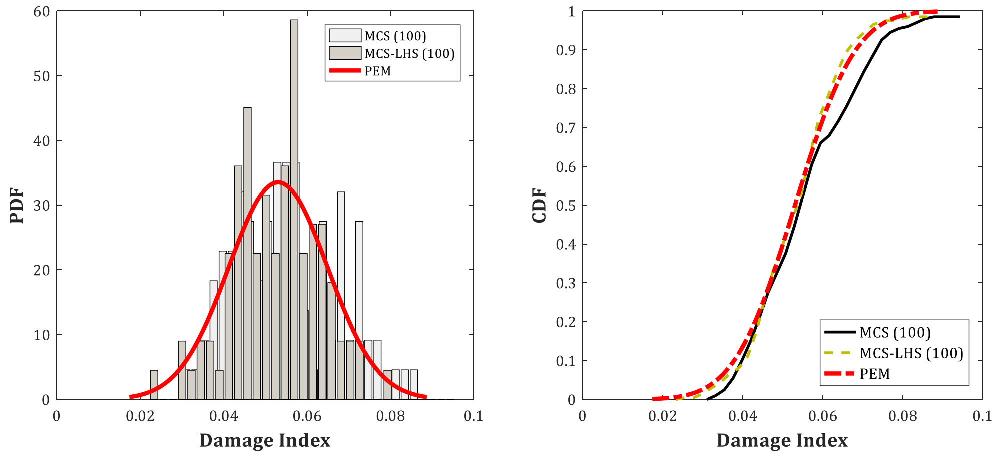
Random Variable	Mean Value (μ)	Coefficient of Variation (COV.)	Standard Deviation (σ)	Minimum Value	Maximum Value
W_{eff} (kg of TNT)	500	0.1	50.0	350.0	650.0
R (m)	10.0	0.1	1.0	7.0	13.0
λ_{max} (Pin)	47.49	0.05	2.37	40.38	54.60
λ_{max} (Fix)	23.74	0.05	1.18	20.20	27.28
F_y (MPa)	240.0	0.06	14.4	196.8	283.2
P_d (KN)	900.0	0.10	90.0	630.0	1170.0

5. Results and Discussion

After implementing the approximate PEM on the provided genetic relationships, the obtained results were compared with those obtained from the MCS and MCS-LHS. The aim of this comparison was to assess the accuracy of the approximate method compared to simulation methods on one hand and to investigate the impact of sampling methods on the MCS output on the other hand. From PEM, the mean and standard deviation of the damage index for pinned condition were calculated as 0.21857 and 0.033164, respectively. For fixed end conditions the mean and standard deviation values of the damage index were obtained as 0.05303 and 0.01188, respectively. After obtaining the mean and standard deviation values of the damage index in both pinned and fixed end conditions using the PEM, the probability distribution function of the damage index can be determined. The probability distribution function of the damage index obtained from the PEM is compared with the probability distribution functions obtained from MCS with 100 simulation and MCS-LHS with 100 simulations are shown in Figure 1. Based on the figure, it can be observed that the PEM provides very good accuracy in estimating the probability distribution function of the damage index compared to the MCS and MCS-LHS. It may be perceived that the PEM is superior; however, it is crucial to note that the PEM is an approximate method and may offer less accuracy for complex problems compared to MCS-based methods. Based on Figure 1, it is observed that the MCS-LHS provides better accuracy in estimating the probability distribution function of the damage index compared to the MCS and offers more accurate results while reducing computational load. In other words, when using the MCS with 100 simulations and the MCS-LHS with 100 random samples, the MCS exhibits more dispersion, whereas the MCS-LHS accurately approximates the cumulative probability distribution function of the damage index (compared to the PEM, which offers acceptable accuracy). Furthermore, further investigations have been carried out (but not presented here) showed that using the MCS-LHS with 100 simulations achieves almost the same accuracy as the MCS with 300 simulations and can significantly contribute to reducing analysis times in reliability analyses with high computational demands.



(**a**) Pinned condition



(**b**) Fixed condition

Figure 1. Comparison of the probability density function and cumulative probability distribution function obtained from the PEM and its comparison with the distribution obtained from the MCS with 100 iterations and the MCS-LHS with 100 iterations for the IPB300 column under both (**a**) pinned and (**b**) fixed conditions.

6. Conclusions

In this study, the response of steel columns to blast loads has been explored, with a particular focus on the implementation of gene expression programming (GEP) formulas to calculate axial capacities in both initial and post-blast conditions as well as damage index criterion. The study further delved into the application of reliability methods, namely the Monte Carlo simulation method (MCS) and the point estimate method (PEM), to assess the probabilistic response of steel columns under blast loads. The MCS, known for its simplicity and accuracy, provided valuable insights, while PEM demonstrated its potential by offering acceptable accuracy, particularly in scenarios with fewer random variables. The integration of Latin Hypercube sampling (LHS) within the MCS as MCS-LHS method significantly enhanced precision, enabling the estimation of probability distribution functions with greater accuracy. The findings underscored the critical role of the MCS-LHS, especially when precision was paramount, even with a reduced number of samples. In other words, the MCS-LHS was able to achieve more accurate results with a smaller number of calculations or simulations, making it a more efficient and reliable choice for assessing structural reliability in scenarios where extreme dynamic forces are at play. The study advances knowledge of structural dynamics and provides a robust framework for assessing damage probability and enhancing the design of resilient structures that consider uncertainties and dynamic forces.

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