

Editorial

Computational Methods in Structural Engineering: Current Advances and Future Perspectives

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Abstract

This brief editorial introduces the Special Issue “Computational Methods in Structural Engineering”. This Special Issue brings together recent advances in computational approaches—including finite element modeling, machine learning applications, stochastic analysis, and high-precision numerical methods—highlighting their increasing influence on the analysis, design, and assessment of modern structural systems. The published contributions cover topics such as the nonlinear finite element method (FEM) for structural response under extreme loading, advanced plate and composite modeling, explainable AI for material characterization, machine learning for predictive performance modeling, data-driven signal processing for structural health monitoring, and stochastic analysis of dynamic inputs. Through this collection of studies, this Special Issue underscores both the opportunities and the challenges of applying advanced computational methods to enhance the resilience, efficiency, and understanding of structural engineering systems.

Keywords: structural engineering; computational methods; finite element method; machine learning; explainable AI; structural health monitoring



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1. Introduction

Structural engineering has undergone a profound transformation with the rapid advancement and widespread availability of computers. In the past, engineers relied on hand calculations and simplified models, but modern computational methods have now become indispensable in structural analysis and design [1]. The finite element method (FEM), in particular, emerged as a cornerstone of this revolution, providing the “computational workhorse” for simulating complex structures and physics [2]. Introduced in the mid-20th century, the FEM is regarded as one of the most significant engineering advances of the last century, fundamentally changing how engineers model and design structures [3,4]. By discretizing structures into elements, the FEM enables rigorous analysis of stresses, deformations, and failure mechanisms in everything from bridges and high-rise buildings to aerospace and offshore structures. Its development also gave rise to the field of computational mechanics, integrating physics, numerical methods, and computer science in engineering [2]. The result has been a paradigm shift: many structural engineering problems once intractable or oversimplified can now be tackled with high fidelity, leading to safer and more efficient designs in practice [1].

Equally transformative has been the rise of computational optimization techniques in structural engineering [5–7]. Optimization algorithms allow engineers to automatically search for designs that minimize the weight, cost, or environmental impact, while satisfying the safety constraints. Early applications involved sizing or shape optimization, but the field truly accelerated with topology optimization—a method that optimizes the material layout within a design space. Topology optimization techniques, pioneered in the 1980s and 1990s, have enabled the creation of lightweight yet strong structural forms by removing unnecessary material [8]. Bendsøe and Sigmund’s foundational work introduced general methods to optimize structural layouts, achieving minimum-weight designs without compromising performance [8,9]. Over the past two decades, numerous advances have made such techniques more powerful and practical [5,10]. Comprehensive surveys have shown that modern topology and shape optimization methods—ranging from gradient-based approaches to evolutionary algorithms—are now successfully applied to real-world structures across domains such as aerospace engineering and civil infrastructure [5,6]. These computational design tools improve the efficiency and material usage in structures and also open up innovative architectural forms that would be impossible to realize via manual trial and error [11].

In parallel, performance-based design has emerged as a modern paradigm, particularly in earthquake [12,13] and fire engineering [14], in which structures are iteratively engineered to meet explicit performance targets (e.g., life safety or immediate occupancy) under extreme loads. Such design approaches rely heavily on nonlinear finite element simulations and probabilistic analyses, which are only feasible thanks to today’s computational power [14,15]. Advanced numerical models also tackle complex materials and geometries. For instance, refined finite element formulations allow the analysis of composite structures and unconventional shapes that exhibit behaviors beyond the scope of classical beam or plate theory. From multi-directional functionally graded materials to long-span free-form shells, computational methods provide the means to predict structural responses with confidence where analytical solutions are unavailable [16].

In recent years, the rapid development of machine learning (ML) and artificial intelligence has further expanded the computational toolkit of structural engineers. ML techniques are now being used as powerful supplements (and sometimes alternatives) to physics-based simulations in various structural applications [17,18]. In the last decade, there has been a boom in implementing data-driven models for tasks such as structural health monitoring, damage detection, predictive modeling of structural behavior, and even design automation [17,19,20]. Unlike traditional programs written from first principles, ML algorithms can learn complex nonlinear relationships directly from data—a capability especially useful for problems where accurate analytical modeling is difficult [21]. For example, researchers have trained neural networks and ensemble methods to predict structural responses (deflections, stresses, failures) under loads, bypassing more time-consuming finite element analyses in specific scenarios [17]. Likewise, ML-driven models have achieved remarkable accuracy in estimating material properties (e.g., concrete strength, bond capacity of novel materials) by mining large experimental datasets [22,23]. These approaches can handle high-dimensional data (e.g., vibration signals, monitoring sensor streams) and filter out noise or detect patterns that elude conventional methods [17,24]. While data-driven models do not replace the need for fundamental mechanics, they complement traditional simulations—for instance, hybrid approaches use ML as fast surrogates for costly computations or to optimize structural systems in real time [25]. The net effect is that structural engineering is becoming more predictive and adaptive [17]. Of course, challenges remain in ensuring the reliability, interpretability, and adequate training of these models, but

ongoing research is quickly advancing the integration of AI into structural engineering workflows [24].

Structural health monitoring (SHM) deserves special mention as one of the most active areas of computational innovation in structural engineering. Modern SHM frameworks combine vibration-based testing, dense sensor networks, and advanced data analytics to assess the integrity and performance of structures in real time [26]. With the integration of machine learning, SHM systems can process high-dimensional and noisy monitoring data, enabling more reliable detection of anomalies and early identification of damage [21,22]. These advances support the development of predictive maintenance and early-warning systems that enhance the safety, resilience, and lifecycle management of critical infrastructure [27]. The inclusion of SHM-related contributions in this Special Issue reflects its growing significance in bridging advanced computational methods with practical asset management.

Another frontier in computational structural engineering lies in the advancement of stochastic methods and high-precision numerical techniques. Real-world structures are inherently affected by uncertainties in loads, materials, and environmental conditions, which makes uncertainty quantification and probabilistic modeling essential [28]. Modern approaches such as reliability-based design [29], stochastic dynamic analysis [30], and covariance evaluation provide rigorous tools to capture the variability and assess the structural safety under realistic time-varying conditions. In parallel, progress in high-precision numerical methods has expanded the accuracy and stability of classical formulations, allowing engineers to tackle nonlinear, multi-scale, and multi-physics problems with greater fidelity [31,32]. Together, these developments highlight how computational innovation—both in handling uncertainty and in refining numerical precision—continues to broaden the scope and reliability of structural engineering analysis.

Motivated by these advancements, this Special Issue, “Computational Methods in Structural Engineering”, was conceived to showcase recent developments and applications at the forefront of the field. The call for papers solicited contributions across a wide range of topics—including finite element analysis, optimization techniques, dynamic simulation, novel numerical methods for materials and forms, and machine learning applications—reflecting the broad impact of computation in modern structural engineering. The response to the call has been satisfactory, leading to eight high-quality peer-reviewed papers that collectively showcase some of the most relevant research trends. These contributions span from high-fidelity nonlinear finite element modeling of structural failure under extreme loads to data-driven approaches for processing structural response signals and predicting structural performance, to advanced analytical and numerical techniques for innovative materials and systems. In the following sections, we summarize each contribution to this Special Issue, emphasizing its context and key findings within the broader evolution of computational structural engineering.

2. Contributions

Thango et al. (Contribution 1) investigate the failure response of masonry walls subjected to blast loading using nonlinear finite element analysis (FEM). Masonry structures, widely used in many regions, are highly vulnerable to extreme dynamic loads such as explosions. The authors employ advanced nonlinear FEM models to simulate the blast-induced behavior of masonry walls, capturing complex phenomena including the material nonlinearity, cracking, and progressive failure. The study provides detailed insights into how different parameters, such as loading intensity and boundary conditions, influence wall performance under blast effects. The findings highlight the capability of computational modeling to replicate failure mechanisms that are otherwise difficult to observe experi-

mentally due to safety and cost constraints. This contribution emphasizes the importance of nonlinear FEM in understanding structural resilience under extreme events, offering valuable guidance for protective design and retrofitting strategies.

Damikoukas and Lagaros (Contribution 2) propose the MLDAR model, a machine learning-based framework for denoising structural response signals generated by ambient vibration testing. Structural health monitoring (SHM) often relies on ambient vibration data, but such signals are prone to noise, which can hinder accurate modal identification and damage detection. Traditional filtering methods, such as Fourier or wavelet transforms, have been widely used to address this issue; however, modern machine learning techniques increasingly outperform them. In this work, the authors develop a denoising method that integrates ML algorithms to separate meaningful structural response components from background noise. Their results show that the proposed MLDAR model significantly improves the signal clarity compared to conventional filtering approaches, enabling more reliable extraction of modal parameters. By enhancing the quality of vibration-based data, this study contributes to more robust SHM applications and demonstrates the effectiveness of data-driven approaches in complementing traditional signal processing. The work underscores the growing role of machine learning in improving data quality for structural assessment and monitoring.

Domaneschi et al. (Contribution 3) address the challenge of evaluating covariance in linear structural systems subjected to non-stationary random inputs. Many real-world structural systems are influenced by time-varying dynamic loads, such as earthquakes, wind gusts, or traffic, where classical stationary assumptions no longer hold. The authors propose a numerical method for efficiently computing covariance responses under such non-stationary excitations, providing a valuable tool for uncertainty quantification and reliability analysis. The framework allows for the accurate characterization of structural response statistics without resorting to prohibitively large Monte Carlo simulations. Applications of the method demonstrate its potential for analyzing the safety and serviceability of engineering structures under realistic loading conditions. This contribution reinforces the importance of advanced stochastic analysis in structural engineering, offering a computationally efficient approach to assess performance under complex and uncertain environments.

Bakas (Contribution 4) investigates using Taylor polynomials under high arithmetic precision as universal function approximators. The study revisits the classical concept of Taylor series expansion and explores its potential in modern computational contexts, particularly where high numerical precision is required. By employing advanced numerical techniques, the work demonstrates that Taylor polynomials can serve as reliable universal approximators, effectively capturing complex nonlinear behaviors with enhanced stability and accuracy. This approach offers a promising alternative to more computationally intensive approximation schemes, such as spectral or mesh-based methods, particularly in cases where analytical solutions are intractable or conventional numerical techniques may suffer from precision loss. This contribution highlights how fundamental mathematical tools, combined with high-precision computing, can provide robust and efficient approximation strategies for diverse engineering and scientific applications.

Hadji et al. (Contribution 5) focus on the buckling and free vibration behavior of multi-directional functionally graded (FG) sandwich plates, analyzed using refined plate theories under various boundary conditions. Functionally graded sandwich plates, which combine the advantages of FG materials and sandwich structures, are increasingly studied for their superior mechanical performance in aerospace, civil, and mechanical applications. The authors employ advanced refined plate models to capture the effect of material gradation in multiple directions, allowing for a more realistic representation of the stiffness and mass

distribution. Their analysis explores how different boundary conditions influence both the critical buckling loads and natural frequencies of these innovative structures. The findings provide valuable insights into the stability and dynamic characteristics of FG sandwich plates, emphasizing the importance of considering material gradation patterns in both directions. This research extends the applicability of computational modeling to advanced composite structures and contributes to the broader field of multi-scale modeling of innovative structural systems.

Ababu et al. (Contribution 6) present a study on the use of machine learning algorithms to develop predictive models for estimating the maximum deflection of horizontally curved steel I-beams. Curved I-beams are widely used in bridges and other infrastructures where alignment requires nonlinear geometry. Still, their structural response under loading is significantly more complex than straight beams. Accurate traditional analytical or numerical methods can be computationally intensive and require specialized expertise. In this work, the authors apply supervised ML algorithms to experimental and simulation datasets, creating models that accurately predict the maximum deflections. The study highlights the efficiency of data-driven approaches in capturing the nonlinear relationships inherent in curved beam mechanics. Beyond predictive accuracy, the results demonstrate the potential of ML-based surrogates to reduce the computational costs in design and assessment processes. This contribution illustrates how modern data science can complement classical structural mechanics, offering engineers faster and more accessible predictive tools for complex structural elements.

Mahmoudian et al. (Contribution 7) investigate the use of explainable boosting machine (EBM) models to predict the bond strength of fiber-reinforced polymer (FRP) rebars embedded in ultra-high-performance concrete (UHPC). The bond strength between FRP reinforcement and concrete is a key factor influencing the structural performance, durability, and service life, especially given the increasing use of FRP bars as corrosion-resistant alternatives to steel. In this study, the authors apply EBM, a state-of-the-art machine learning approach that combines predictive power with interpretability, allowing the identification of the most influential parameters affecting bond strength. The model demonstrates excellent predictive accuracy compared to traditional regression methods and provides transparent insights into the relative importance of input variables such as the concrete compressive strength, rebar surface characteristics, and embedment length. By offering accurate predictions and clear explanations of the underlying data-driven relationships, the work advances the integration of trustworthy AI tools in structural engineering practice. This contribution is particularly valuable for guiding design decisions and developing future design codes involving FRP-reinforced UHPC structures.

Hamdia (Contribution 8) presents a study on the application of a numerical homogenization method to evaluate the effective converse flexoelectric coefficients of composite materials. Flexoelectricity, a size-dependent electromechanical coupling phenomenon, is particularly significant in small-scale materials, where strain gradients can induce electric polarization. This work employs a computational framework to bridge the gap between microscale material behavior and effective macroscale properties, enabling accurate prediction of converse flexoelectric coefficients. The study emphasizes the versatility of numerical homogenization techniques in handling complex material microstructures, which are often challenging to address analytically. The results highlight the capacity of this approach to capture essential electromechanical interactions, providing insights into the design and optimization of advanced multifunctional materials. The findings expand the understanding of flexoelectric phenomena and open opportunities for developing innovative smart structures and devices where electromechanical coupling plays a central role. This contribution

underscores the growing role of computational homogenization in linking material science with structural engineering applications.

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