

Advances in Numerical Methods and Computational Techniques Across Engineering Disciplines: From Numerical Simulation to Intelligent and Data-Driven Engineering

Carlos Llopis-Albert^{1,*}, Shouzhen Zeng² and Carlos Alberto Devece Carañana³

¹ Institute of Mechanical Engineering and Biomechanics (I2MB), Department of Mechanical Engineering and Materials, Universitat Politècnica de València, Camino de Vera, s/n, 46022, Valencia, Spain

² School of Business, Ningbo University, Ningbo, China

³ Department of Business Organization, Universitat Politècnica de València (UPV), Camino de Vera s/n, 46022, Valencia, Spain

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¹Institute of Mechanical Engineering and Biomechanics (I2MB), Department of Mechanical Engineering and Materials, Universitat Politècnica de València, Camino de Vera, s/n, 46022, Valencia, Spain

²School of Business, Ningbo University, Ningbo, China

³Department of Business Organization, Universitat Politècnica de València (UPV), Camino de Vera s/n, 46022, Valencia, Spain

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1 Introduction

Numerical methods constitute one of the cornerstones of contemporary engineering and applied science. For decades, advances in mathematical modelling, computational resources, and numerical algorithms have enabled researchers to investigate increasingly complex systems involving nonlinear phenomena, multiphysics interactions, uncertainty, and large-scale datasets. What began as a set of mathematical techniques for approximating solutions to differential equations has evolved into a multidisciplinary ecosystem that supports design, analysis, optimization, prediction, and decision-making across virtually every engineering field.

This transformation has been driven by several factors. First, the continuous increase in computational power has enabled the development of high-fidelity numerical simulations capable of reproducing complex physical phenomena with unprecedented accuracy. Second, advances in computational mechanics, computational fluid dynamics, optimization, and high-performance computing have expanded the range of engineering systems that can be modelled and analysed computationally. Third, the emergence of machine learning and artificial intelligence has created new opportunities for integrating data-driven methodologies with traditional physics-based numerical frameworks [1–3].

*Correspondence: Carlos Llopis-Albert (cllopisa@upvnet.upv.es). This is an article distributed under the terms of the Creative Commons BY-NC-SA license

As a consequence, modern numerical methods increasingly operate within broader computational environments where simulation, optimization, uncertainty quantification, machine learning, and decision-support methodologies coexist. This trend is particularly evident in the growing field of scientific machine learning, which seeks to combine the predictive capabilities of machine learning with the interpretability and robustness of physics-based models. Recent developments in physics-informed neural networks and related methodologies demonstrate how numerical methods and machine learning are progressively converging toward unified computational paradigms capable of addressing complex scientific and engineering challenges [4].

Simultaneously, new paradigms such as digital twins are redefining the role of computational models in engineering practice. Rather than serving merely as offline analysis tools, numerical models are increasingly integrated with sensor data, optimization algorithms, and predictive analytics into dynamic computational environments capable of supporting real-time engineering decisions. Digital twins have become one of the most influential concepts in Industry 4.0, providing a framework for connecting physical assets and virtual models throughout their operational lifecycle [5–8].

Moreover, uncertainty quantification has emerged as a critical research area as engineering decisions become increasingly dependent on computational predictions. Engineering systems are inevitably affected by uncertainty arising from model assumptions, parameter variability, measurement errors, and operational conditions. Consequently, the development of uncertainty-aware computational methodologies has become essential for ensuring the reliability and trustworthiness of numerical simulations [9].

These developments are reshaping the landscape of computational engineering. Numerical methods are no longer viewed solely as tools for solving mathematical equations but as integral components of intelligent computational ecosystems capable of supporting the complete engineering process. Recent research in renewable-energy systems, for example, illustrates how advanced numerical modelling, optimization techniques, and intelligent control strategies can be combined to improve system performance and resilience under increasingly challenging operating conditions [10]. Similarly, coupled CFD-FEM frameworks are demonstrating the potential of integrated computational methodologies for achieving enhanced performance, durability, and sustainability in complex mechanical systems [11]. The emergence of digital twin-based optimization approaches further reinforces this trend by connecting numerical simulation, optimization, and real-time decision support within unified computational environments [12].

Against this backdrop, the Special Issue *Advances in Numerical Methods and Computational Techniques Across Engineering Disciplines* was launched to provide an interdisciplinary forum for disseminating innovative developments in numerical methodologies and computational engineering. The aim was to bring together theoretical advances, methodological innovations, and practical applications capable of contributing to the continued evolution of computational science and engineering.

The resulting collection of papers highlights the diversity and vitality of contemporary numerical research. The six accepted contributions span renewable energy systems, underwater image enhancement, mining engineering, grey system theory, petroleum engineering, computational geometry, and engineering education. At first glance, these topics may appear disconnected. A closer examination reveals key methodological threads, demonstrating how numerical methods are increasingly integrated with optimization, intelligent computing, and decision-support strategies across diverse engineering domains. This progressive transformation of numerical instruments from traditional simulation tools into comprehensive computational frameworks supporting analysis, optimization, prediction, and

decision-making forms the intellectual foundation of this editorial and offers valuable insights into emerging directions for future research.

2 Overview of the Special Issue

The Special Issue was conceived as a platform for presenting recent advances in the development, improvement, and application of numerical methods across diverse engineering disciplines. Particular emphasis was placed on contributions that combined methodological innovation with practical relevance, illustrating how computational techniques can address real-world engineering challenges.

The six published papers represent a diverse yet coherent collection of contributions reflecting several of the most significant directions currently driving computational engineering research. Although the application domains vary substantially, ranging from renewable energy and mining engineering to image processing and petroleum engineering, the methodologies employed share a common reliance on advanced computational techniques, numerical modelling, optimization strategies, and data-driven analysis.

From a methodological perspective, the contributions can be grouped into three broad categories.

The first category comprises advanced computational modelling and numerical simulation. This group includes the works of [13–15], which employ CFD, geomechanical simulations, and numerical integration techniques, respectively, to investigate complex engineering systems.

The second category encompasses intelligent computational approaches and data-driven methodologies. Ref. [16] exemplify this direction through the development of a deep-learning framework for underwater image enhancement, illustrating the growing integration of artificial intelligence into computational engineering workflows.

The third category focuses on optimization and decision-support frameworks operating under uncertainty. Refs. [17,18] employ grey system theory, clustering methodologies, and grey relational analysis to support classification, evaluation, and engineering decision-making processes.

Although representing different domains, these contributions collectively reveal many of the transformations currently occurring across computational science and engineering. The works demonstrate how numerical methods increasingly serve not only to reproduce physical behaviour but also to support optimization, classification, prediction, design, and strategic decision-making.

In this sense, the Special Issue provides more than a collection of individual case studies. Taken together, the papers offer a representative snapshot of the evolving role of numerical methods within modern engineering research and highlight the progressive convergence among simulation, artificial intelligence, optimization, and decision-support methodologies.

3 Computational Modelling and Numerical Simulation

A major theme emerging from the Special Issue is the continuing importance of numerical simulation as a fundamental tool for investigating, understanding, and optimizing engineering systems. Despite the increasing popularity of data-driven approaches, physics-based simulation remains the backbone of computational engineering because of its ability to provide detailed insights into system behaviour and support informed engineering decisions.

One notable example is provided by [13], who investigated the aerodynamic performance of a vertical-axis wind turbine incorporating an inner cylindrical deflector. Using computational fluid dynamics simulations, the authors analysed the influence of the deflector on flow behaviour and

turbine performance, demonstrating how numerical methods can support the development of more efficient renewable-energy technologies. Their work illustrates the continuing relevance of CFD as one of the most powerful tools for analysing complex fluid-flow phenomena and guiding performance-driven engineering design.

Beyond renewable-energy applications, numerical simulation also plays a critical role in geomechanical engineering. Ref. [14] examined the stability of composite bearing structures within room-and-pillar goafs subjected to repeated mining activities. Through advanced numerical modelling, the authors analysed the structural response of mining systems under complex loading conditions and provided valuable insights into mechanisms affecting long-term stability. Such studies highlight the capacity of numerical methods to address engineering problems where direct experimental investigation is often impractical, prohibitively expensive, or unsafe.

A different perspective on numerical methodologies is offered by [15], who developed an interactive computational framework integrating vector calculus and numerical integration techniques for the design and analysis of complex three-dimensional surfaces. The proposed MATLAB-based environment combines mathematical rigour, computational efficiency, and graphical visualization to facilitate engineering analysis and education. The results demonstrate how numerical methods can simultaneously support practical engineering applications and educational innovation.

The significance of these three contributions extends beyond their individual application domains. Collectively, they illustrate the versatility of modern simulation methodologies and their ability to support engineering research across widely different contexts. More importantly, they demonstrate that numerical simulation continues to evolve beyond traditional prediction tasks toward integrated frameworks capable of supporting design, optimization, visualization, and decision-making.

This trend is consistent with recent developments in computational engineering and sustainable-energy research, where coupled numerical frameworks increasingly combine multiple modelling techniques and optimization methods. For example, recent CFD-FEM coupled frameworks for wind turbine gearbox design have demonstrated the benefits of integrating fluid mechanics, structural analysis, and multi-objective optimization within unified computational environments [11]. Similarly, advanced grid-forming wind turbine architectures incorporating hybrid energy-storage strategies further illustrate how numerical simulation is becoming an essential component of modern control, optimization, and resilience-oriented design methodologies [10].

Consequently, while artificial intelligence and data-driven techniques are attracting increasing attention, the contributions presented in this Special Issue confirm that high-fidelity numerical simulation remains a foundational pillar of computational engineering. Rather than being replaced by emerging methodologies, simulation is increasingly serving as a central component of integrated computational ecosystems combining modelling, optimization, artificial intelligence, and decision support.

4 Intelligent Computational Approaches and Data-Driven Engineering

One of the most transformative developments in computational engineering during the last decade has been the convergence between traditional numerical methods and artificial intelligence. While numerical modelling has historically relied on first-principles formulations derived from physics, modern computational frameworks increasingly incorporate machine learning, deep learning, and data-driven methodologies to enhance prediction accuracy, computational efficiency, and adaptability.

This evolution has given rise to emerging paradigms such as scientific machine learning and physics-informed machine learning, which seek to combine the strengths of data-driven approaches with the robustness and interpretability of physics-based models [3].

Within the Special Issue, this trend is exemplified by the contribution of [16], who proposed MTNet, a multi-task underwater image enhancement framework based on Retinex theory and deep learning. The proposed methodology addresses one of the major challenges in underwater imaging: severe image degradation caused by light absorption, scattering effects, color distortion, and low contrast. By integrating multiple learning tasks within a unified computational architecture, the framework achieved significant improvements in image quality while preserving structural details and visual consistency.

Although underwater image enhancement belongs to the field of computer vision, the methodological implications of this study extend far beyond image processing. The work illustrates how intelligent computational systems increasingly complement traditional numerical methodologies by extracting information from complex datasets that may be difficult to describe through purely physics-based models. In this sense, the contribution reflects a broader transition occurring throughout computational science and engineering, where modelling and data are no longer viewed as competing paradigms but as complementary sources of information.

The growing relevance of this convergence is evident across multiple engineering domains. Scientific machine learning has emerged as a rapidly developing field that combines numerical simulation, machine learning, optimization, and computational science within unified frameworks capable of addressing problems characterized by high dimensionality, limited data availability, or computational complexity [1,2]. Similarly, physics-informed machine learning approaches integrate governing equations directly into learning algorithms, reducing dependency on large datasets while preserving consistency with established physical principles [3,4].

From a computational perspective, the integration of machine learning with numerical methodologies provides several advantages. First, data-driven models can accelerate simulations through surrogate modelling and reduced-order representations, thereby decreasing computational costs for complex engineering analyses. Second, machine-learning techniques can support parameter identification, model calibration, anomaly detection, and predictive maintenance tasks that complement traditional numerical simulation. Third, hybrid approaches can improve robustness when dealing with uncertain, incomplete, or noisy data environments.

These capabilities are increasingly influencing engineering applications ranging from fluid mechanics and energy systems to structural health monitoring and advanced manufacturing. In fluid mechanics, for example, machine-learning techniques are now being applied for flow reconstruction, turbulence modelling, reduced-order modelling, and optimization of complex flow systems [2]. More broadly, scientific machine learning is becoming a key enabling technology for next-generation computational engineering environments capable of integrating heterogeneous information sources into coherent predictive frameworks [1].

The growing interaction between numerical methods and artificial intelligence can also be observed in renewable-energy research. Modern computational frameworks no longer focus exclusively on system simulation but increasingly incorporate optimization, control, forecasting, and adaptive decision-making capabilities. Recent research on grid-forming wind turbines, for instance, demonstrates how advanced numerical modelling and intelligent control strategies can be integrated to improve the resilience and frequency-support capabilities of converter-dominated power systems

[10]. Such developments illustrate how computational engineering is moving toward intelligent systems capable of simultaneously modelling physical processes and supporting operational decisions.

Despite these advances, important challenges remain. One major concern is interpretability. While machine-learning models often achieve impressive predictive performance, their decision-making processes may be difficult to understand, particularly in safety-critical engineering applications. Consequently, there is growing interest in hybrid frameworks that preserve physical interpretability while exploiting the flexibility of data-driven methodologies [3]. Related challenges include generalization, robustness, uncertainty quantification, and the integration of heterogeneous data sources.

From the perspective of the Special Issue, the work of [16] therefore represents more than an isolated application of deep learning. It reflects a wider transformation affecting virtually all areas of computational engineering. Numerical methods are increasingly evolving toward intelligent computational environments where simulation, optimization, learning, and decision-making operate as interconnected components rather than independent processes.

This transition is likely to accelerate in the coming years as developments in machine learning, scientific computing, and high-performance computing continue to mature. The future of computational engineering will almost certainly involve deeper integration between numerical modelling and artificial intelligence, resulting in computational systems capable of learning from data while remaining grounded in physical reality. In this context, intelligent computational methodologies should not be viewed as replacements for numerical methods but rather as their natural extension within the broader framework of modern engineering science.

5 Grey Systems, Optimization and Engineering Decision-Making

A distinctive characteristic of this Special Issue is the strong presence of contributions devoted to grey system theory, clustering methodologies, and computational decision-support frameworks. While numerical simulation traditionally focuses on reproducing and analysing physical phenomena, many contemporary engineering problems require an additional layer of complexity: the ability to make informed decisions under uncertainty, incomplete information, heterogeneous datasets, and multiple competing objectives. In such contexts, grey systems theory continues to provide a valuable set of mathematical and computational tools capable of supporting engineering decisions when conventional deterministic or statistical approaches may be insufficient.

Within the Special Issue, Ref. [17] addressed this challenge through a comprehensive investigation of indicators-coupled grey relational analysis (ICGRA) models for panel data. Their work employed extensive numerical simulations to analyse the robustness of several existing grey relational models under different indicator arrangements. The study revealed important limitations associated with the instability of relational rankings when indicators are reordered and proposed improved formulations based on averaging procedures and deep modelling strategies. The optimized approaches significantly enhanced clustering performance and achieved classification accuracies comparable to those obtained using machine-learning techniques. This contribution illustrates how numerical simulation itself can be used not only to solve engineering problems but also to evaluate and improve the reliability of analytical methodologies.

The importance of this work extends beyond the specific context of panel data analysis. Engineering systems increasingly generate multidimensional datasets containing temporal, spatial, operational, and environmental information. Extracting meaningful relationships from these datasets requires robust computational frameworks capable of identifying patterns and supporting decision-making

even when information is incomplete or uncertainty is present. The work of [17] demonstrates how grey relational analysis can continue evolving to address these challenges while maintaining the flexibility that has characterized grey system methodologies since their inception.

A complementary perspective is provided by [18], who proposed an integrated framework combining grey clustering and grey relational analysis for drill-bit selection in petroleum engineering. The proposed methodology incorporated geological information, rock mechanical properties, drillability indicators, and operational performance metrics to optimize the selection of drilling equipment. Numerical evaluations and field applications demonstrated substantial improvements in drilling efficiency and operational performance. Beyond its direct industrial relevance, this work illustrates the broader capacity of computational decision-support frameworks to transform large quantities of heterogeneous engineering information into actionable decisions.

The common element linking these two contributions is the central role of uncertainty. Engineering decisions are frequently made in environments where information is incomplete, measurements are imperfect, and future conditions remain only partially known. Grey systems theory was originally developed to address precisely these situations, occupying an intermediate position between fully known and completely unknown systems. Consequently, grey methodologies remain particularly useful in many modern engineering applications, especially when the available information is insufficient to support purely statistical or data-intensive approaches.

The relevance of grey system methodologies is further reinforced by contemporary developments in intelligent decision-support systems. Modern engineering environments increasingly require computational tools capable of integrating simulation outputs, experimental data, operational information, expert knowledge, and optimization objectives within unified decision frameworks. Grey relational analysis, clustering techniques, aggregation operators, and multi-criteria evaluation methodologies represent important components of such frameworks and continue to evolve alongside advances in computational intelligence and data analytics.

From a broader perspective, the works of [17,18] highlight a significant transformation occurring within numerical methods research. Traditionally, numerical techniques were primarily concerned with accurately approximating the behaviour of physical systems. Today, however, numerical methodologies are increasingly expected to support engineering decisions, evaluate alternatives, rank scenarios, optimize designs, and manage uncertainty. The boundary between simulation and decision support is therefore becoming progressively less distinct.

This trend is also visible in other areas represented in the Special Issue. The CFD analyses reported by [13] ultimately aim to support energy-system design decisions. The geomechanical simulations of [14] contribute directly to safety-related decisions in mining operations. Similarly, the computational framework developed by [15] supports both engineering design decisions and educational applications. In each case, numerical methods function not merely as predictive tools but as instruments enabling more informed engineering choices.

The growing importance of optimization further reinforces this evolution. Engineering systems increasingly involve multiple and often conflicting objectives, including performance, cost, reliability, sustainability, energy efficiency, and environmental impact. Advanced optimization methodologies provide a means of balancing these objectives while navigating complex design spaces. Recent studies in renewable-energy systems and sustainable engineering design illustrate this tendency, where coupled simulation–optimization frameworks are being employed to identify configurations that simultaneously improve technical performance and sustainability indicators [11].

Consequently, one of the clearest messages emerging from this Special Issue is that decision-support capabilities are becoming an essential dimension of numerical methods research. Whether through grey systems, optimization techniques, machine-learning algorithms, or integrated computational frameworks, modern numerical methodologies increasingly contribute not only to understanding engineering systems but also to determining how those systems should be designed, managed, and operated. This shift from simulation-oriented computation toward decision-oriented computation represents one of the most significant transformations currently shaping the future of computational engineering.

6 Emerging Trends across Engineering Disciplines

Beyond the specific contributions of the individual papers, the Special Issue reveals several cross-cutting trends that reflect broader transformations currently occurring in computational engineering research. These trends not only connect the six published articles but also provide insight into the future evolution of numerical methods and computational technologies across engineering disciplines.

Collectively, these contributions illustrate a broader evolution in computational engineering, wherein numerical methods are no longer confined to the traditional task of approximating mathematical solutions. Instead, they increasingly function as core components of integrated computational ecosystems that combine simulation, data analysis, optimization, uncertainty management, and decision support, thereby redefining both the scope and the impact of the field.

6.1 From Simulation to Decision Support

Historically, the principal objective of numerical methods was to reproduce the behaviour of engineering systems through mathematical models. While this objective remains fundamental, modern computational engineering increasingly requires methodologies that go beyond descriptive simulation and actively support engineering decisions.

This transition is evident throughout the Special Issue. The computational fluid dynamics framework developed by [13] is ultimately intended to guide design decisions aimed at improving wind-turbine performance. Similarly, the geomechanical simulations presented by [14] provide quantitative information supporting safety assessments and operational planning in mining systems. The works by [17,18] move even further toward decision support by directly addressing classification, ranking, optimization, and equipment-selection problems. Finally, the computational environment proposed by [15] supports engineering design choices through interactive modelling and numerical evaluation.

In all these cases, computational methods are not merely generating results; they are generating information that enables decisions. This distinction is increasingly important because many engineering challenges involve selecting among multiple alternatives under technical, economic, environmental, and operational constraints. As a consequence, future numerical methodologies will likely be judged not only by their predictive accuracy but also by their ability to support robust and transparent decision-making processes.

The growing integration of simulation and decision support is closely linked to advances in optimization, machine learning, uncertainty quantification, and computational intelligence. Together, these developments are transforming numerical methods into essential components of modern engineering-management and planning frameworks.

6.2 *Convergence of Numerical Methods and Artificial Intelligence*

Perhaps the most visible trend in contemporary computational science is the convergence between traditional numerical modelling and artificial intelligence.

For many years, numerical simulation and machine learning evolved largely as separate disciplines. Numerical methods relied on mathematical models derived from physical principles, whereas machine-learning algorithms extracted patterns directly from data. Today, however, the distinction between these approaches is becoming increasingly blurred. Scientific machine learning, physics-informed neural networks, surrogate modelling, reduced-order modelling, and hybrid computational frameworks are creating a new generation of methodologies that combine both perspectives [3,4].

The contribution of [16] reflects this transition by employing deep-learning techniques to solve a complex image-enhancement problem. More broadly, the contributions illustrate how crucial it is to integrate computational modeling, optimization, data analysis, and intelligent strategies across engineering. Even studies traditionally rooted in numerical simulation now increasingly rely on advanced optimization and data-driven workflows.

This convergence offers several important benefits. Machine-learning models can accelerate numerical simulations, identify hidden relationships in large datasets, improve parameter estimation, and support real-time predictions. Conversely, numerical methods provide physical consistency, interpretability, and robustness that purely data-driven approaches often lack. The combination of these strengths is expected to become one of the dominant paradigms in computational engineering during the coming decade.

Future research will likely focus on developing computational frameworks capable of learning from data while preserving physical realism and engineering interpretability. Such developments will be particularly important in safety-critical domains, where reliability and explainability remain essential requirements.

6.3 *Validation, Reliability and Trustworthiness*

Another common feature shared by the contributions of this Special Issue is the strong emphasis placed on validation.

As computational methods become increasingly influential in engineering decision-making, confidence in model predictions becomes a critical issue. Engineering practitioners and decision-makers require not only accurate predictions but also evidence that computational results are reliable, reproducible, and robust under varying conditions.

Each contribution addresses this challenge in different ways. Ref. [13] validated numerical predictions through systematic aerodynamic analyses. Ref. [14] examined structural responses under realistic mining conditions. Ref. [16] employed quantitative performance metrics for image enhancement. Refs. [17,18] validated their methodologies through numerical experiments and practical engineering applications. Ref. [15] demonstrated the consistency of their framework through comparisons between analytical and numerical solutions.

This shared focus reflects a broader trend within computational engineering research. As models become more sophisticated and influential, validation is no longer viewed as a secondary task but as a central component of methodological development. Future computational frameworks will increasingly need to incorporate systematic validation protocols, uncertainty analysis, sensitivity assessments, and reproducibility strategies.

Closely related to validation is the issue of trustworthiness. The integration of artificial intelligence into engineering systems introduces new challenges associated with interpretability, robustness, and explainability. Consequently, future research must seek a balance between predictive power and transparency. Hybrid methodologies that combine physical principles with data-driven techniques may offer particularly promising solutions to this challenge.

6.4 *Interdisciplinary Computational Engineering*

A particularly noteworthy aspect of the Special Issue is its interdisciplinary character.

The six published contributions address problems ranging from wind-energy systems and under-water image enhancement to mining engineering, panel-data analysis, petroleum engineering, and computational geometry. Despite these differences, similar computational principles appear across all studies. Numerical modelling, optimization, data analysis, simulation, and computational decision support serve as common methodological foundations connecting otherwise distinct engineering disciplines.

This observation illustrates one of the most significant developments in modern engineering research: computational methodologies increasingly transcend disciplinary boundaries. Techniques originally developed in one field are rapidly adapted and applied in others. Computational fluid dynamics, machine learning, optimization algorithms, finite element methods, and digital-twin technologies are now routinely employed across a wide spectrum of applications.

Such interdisciplinarity creates important opportunities. First, it accelerates methodological innovation through knowledge transfer between domains. Second, it enables researchers to address increasingly complex problems requiring expertise from multiple disciplines. Third, it encourages the development of general computational frameworks with broad applicability.

The Special Issue itself demonstrates the value of this interdisciplinary perspective. By bringing together contributions from multiple fields, it highlights common challenges and shared opportunities that may not be apparent when disciplines are considered in isolation.

6.5 *Sustainability and Intelligent Engineering Design*

A final trend emerging from the Special Issue relates to sustainability and intelligent engineering design.

Engineering systems are increasingly expected to satisfy not only technical performance requirements but also environmental, economic, and societal objectives. As a result, computational methodologies are becoming essential tools for balancing multiple competing criteria during design and operation.

The renewable-energy applications addressed by [13], as well as recent research on grid-forming wind turbines and advanced energy-management strategies, exemplify this tendency [10]. Similarly, coupled CFD-FEM optimization frameworks developed for wind-turbine gearbox design demonstrate how integrated computational approaches can simultaneously improve efficiency, durability, and sustainability [11].

These developments point toward a future where computational engineering increasingly supports sustainable design processes through multi-objective optimization, lifecycle analysis, predictive maintenance, and energy-efficiency assessments. Rather than optimizing single performance indicators, future methodologies will increasingly address broader sustainability objectives involving resource consumption, environmental impact, reliability, and resilience.

The emergence of digital twin technologies further reinforces this trajectory; although not directly addressed in the papers comprising this Special Issue, they represent a natural extension of several computational paradigms discussed herein by providing robust frameworks for the continuous monitoring, evaluation, and optimization of engineering systems throughout their lifecycle. Recent work on digital twin-based design optimization for wind-turbine gearboxes illustrates how these technologies can integrate numerical simulation, optimization, and real-time decision support within a unified environment [12].

Taken together, these developments suggest that sustainability and intelligent engineering design will become central drivers of future computational research. Numerical methods will remain fundamental to this process, but their role will increasingly extend beyond simulation toward supporting adaptive, resilient, and sustainable engineering systems.

In summary, the six contributions published in this Special Issue collectively reveal a computational landscape undergoing rapid transformation. Numerical methods are evolving from isolated simulation tools into integrated computational ecosystems that connect modelling, machine learning, optimization, uncertainty management, sustainability assessment, and decision support. These trends provide the foundation for the future research directions discussed in the following section.

7 Future Perspectives and Research Challenges

The contributions published in this Special Issue not only demonstrate the current capabilities of numerical methods and computational techniques but also highlight several research directions that are likely to shape the future of computational engineering. Although the methodologies presented address diverse application domains, common challenges emerge regarding computational efficiency, model reliability, uncertainty management, data integration, and decision support. Addressing these challenges will require continued advances in mathematics, computer science, engineering, and artificial intelligence.

7.1 Scientific Machine Learning and Physics-Informed Computational Frameworks

Although the contributions included in this Special Issue do not directly address physics-informed machine learning, this rapidly growing field exemplifies how contemporary computational science merges traditional numerical modeling with modern machine-learning techniques to exploit both physical knowledge and observational data [3].

Physics-informed neural networks represent one of the most visible manifestations of this trend. By embedding governing equations, boundary conditions, and physical constraints directly into training procedures, these methods offer the possibility of reducing data requirements while improving physical consistency and interpretability [3,4]. Such approaches are particularly attractive in engineering applications where obtaining large experimental datasets may be costly, time-consuming, or even impossible.

Future research is expected to focus on improving scalability, robustness, and computational efficiency while extending scientific machine learning to increasingly complex multiphysics systems. Issues such as model generalization, extrapolation beyond training domains, uncertainty estimation, and integration with high-fidelity simulations remain open challenges that will likely receive substantial attention in the coming years.

For numerical methods researchers, the key challenge will not be replacing physics-based models with machine learning but rather creating hybrid frameworks capable of exploiting the strengths of both approaches.

7.2 *Digital Twins and Real-Time Computational Engineering*

Although digital twins are not directly addressed by the contributions included in this Special Issue, they represent a natural future extension of several computational paradigms discussed throughout the published works, particularly those involving numerical simulation, optimization, monitoring, and decision support.

The growing interest in digital twins represents another major direction for future research. Digital twins are increasingly viewed as comprehensive virtual representations of physical systems that integrate numerical simulation, sensor data, optimization algorithms, machine learning, and predictive analytics within a unified computational environment [5–7].

The significance of digital twins extends well beyond real-time visualization. Their true value lies in the possibility of creating continuously updated computational models capable of supporting monitoring, prediction, optimization, maintenance scheduling, and operational decision-making. As sensor networks, communication technologies, and computational resources continue to improve, digital twins are expected to become increasingly important across manufacturing, energy systems, transportation, infrastructure, and industrial operations.

From the perspective of this Special Issue, digital twins can be viewed as a natural evolution of several themes represented by the published works. High-fidelity simulations such as those developed by [13,14], intelligent computational frameworks such as MTNet [16], and optimization-oriented approaches such as those proposed by [17,18] all constitute essential building blocks of future digital-twin ecosystems.

Particularly relevant in this regard is the development of digital twin-based optimization frameworks for complex engineering systems. Recent work on digital twin-enabled design optimization of wind-turbine gearboxes demonstrates how simulation, optimization, and decision support can be integrated within a single computational architecture [12]. Such approaches illustrate the potential of digital twins to bridge the gap between numerical analysis and industrial decision-making.

However, significant challenges remain. Digital twins require robust methods for model updating, data assimilation, uncertainty management, computational efficiency, and cyber-physical integration. Solving these problems will require sustained collaboration between researchers working in numerical methods, artificial intelligence, information technologies, and domain-specific engineering disciplines.

7.3 *Uncertainty Quantification and Trustworthy Computational Predictions*

As computational models exert increasing influence on engineering design and operation, the ability to quantify uncertainty is becoming a fundamental requirement rather than an optional feature.

Engineering decisions are inevitably affected by uncertainties arising from material properties, boundary conditions, manufacturing tolerances, environmental variability, measurement errors, and modelling assumptions. While numerical simulations may provide highly accurate predictions under idealized conditions, real-world engineering systems often operate in environments characterized by significant uncertainty.

Consequently, future numerical methodologies must increasingly incorporate uncertainty quantification as an integral component of the modelling process. Advances in metamodeling, surrogate

modelling, stochastic simulation, sensitivity analysis, and probabilistic design optimization are providing powerful tools for addressing these challenges [9].

The importance of uncertainty management is particularly evident in complex engineering systems involving multiple interacting physical processes. In such cases, traditional deterministic analyses may fail to capture the full range of possible system behaviours, potentially leading to overconfidence in computational predictions.

Furthermore, the integration of machine learning introduces additional sources of uncertainty associated with training data, model architectures, and generalization capabilities. As a result, future research must address both physical uncertainty and algorithmic uncertainty to ensure trustworthy computational predictions.

The growing emphasis on uncertainty-aware methodologies is likely to become one of the defining characteristics of next-generation numerical methods.

7.4 High-Performance Computing and Large-Scale Simulation

Advances in numerical methods have always been closely linked to advances in computational power. The increasing availability of high-performance computing (HPC) resources continues to expand the range of engineering problems that can be addressed through numerical simulation.

Large-scale CFD, finite-element analyses, multiphysics simulations, and optimization studies routinely involve millions or even billions of computational degrees of freedom. Such simulations generate unprecedented opportunities for understanding complex engineering systems while simultaneously creating new computational challenges.

Future developments will likely be characterized by increasing use of heterogeneous computing architectures, parallel algorithms, cloud computing infrastructures, and distributed simulation frameworks. These technologies will enable more detailed simulations, faster optimization cycles, and deeper integration of simulation with real-time decision support.

Importantly, high-performance computing is expected to play a central role in enabling many of the developments discussed previously, including scientific machine learning, digital twins, uncertainty quantification, and real-time engineering analytics.

Consequently, numerical methods research must continue to address issues of computational scalability, algorithmic efficiency, memory management, and parallelization strategies.

7.5 Sustainable, Resilient, and Intelligent Engineering Systems

Another major direction emerging from the Special Issue concerns the growing importance of sustainability and resilience as engineering objectives.

Traditional engineering optimization often focused primarily on technical performance measures such as efficiency, strength, speed, or cost. Contemporary engineering practice increasingly demands broader objectives encompassing environmental impact, resource efficiency, sustainability, robustness, resilience, and lifecycle performance.

Numerical methods are uniquely positioned to support this transition because they provide the ability to evaluate multiple design alternatives before physical implementation. Computational frameworks can help identify solutions that simultaneously satisfy technical, environmental, and economic requirements.

The renewable-energy applications represented within and beyond this Special Issue illustrate this trend. Numerical optimization strategies for wind-energy systems increasingly seek to improve not only performance but also reliability, maintainability, sustainability, and operational resilience. Recent developments combining CFD, FEM, optimization, and energy-system modelling demonstrate how integrated computational approaches can contribute directly to sustainable engineering design [10,11].

Similarly, resilience-focused approaches are becoming increasingly important in converter-dominated power systems, industrial infrastructures, transportation networks, and manufacturing systems. Numerical methodologies capable of supporting resilience-oriented design and operation are therefore expected to become a major research focus in the coming years.

7.6 Challenges and Limitations

Despite the rapid evolution of numerical and computational methods, their increasing integration also introduces significant challenges. High-fidelity numerical simulations can remain computationally demanding, particularly for multiphysics problems, large-scale systems, and applications requiring repeated simulations for optimization or uncertainty quantification. At the same time, data-driven models depend strongly on the quality, representativeness, and availability of training data. Their performance may deteriorate when applied outside the conditions covered by the training datasets, raising concerns about extrapolation, robustness, and transferability.

The integration of physics-based and data-driven approaches introduces additional methodological challenges. Hybrid models must reconcile different sources of uncertainty, assumptions, and model errors, while maintaining computational efficiency and physical consistency. Their increasing complexity can also make validation, reproducibility, interpretability, and uncertainty quantification more difficult. These issues become particularly relevant when computational models are used to support safety-critical or high-consequence engineering decisions, where predictive accuracy alone may not be sufficient to establish confidence in the results.

Future progress should therefore focus not only on developing more powerful computational methods, but also on establishing rigorous frameworks for model verification and validation, uncertainty quantification, reproducibility, and trustworthy deployment. The challenge is ultimately to develop computational systems that are not only accurate and efficient, but also robust, interpretable, and sufficiently transparent to support reliable engineering decisions.

7.7 Toward Autonomous Engineering Systems

Perhaps the most ambitious long-term vision emerging from current developments is the creation of autonomous engineering systems capable of continuously monitoring, analysing, predicting, optimizing, and adapting their behaviour.

Such systems would integrate many of the core elements discussed throughout this editorial, seamlessly combining high-fidelity numerical simulation, machine learning and artificial intelligence, uncertainty quantification, optimization methodologies, digital twins, sensor networks, and real-time decision-support frameworks.

In this context, numerical methods will continue to constitute the computational foundation upon which future intelligent engineering systems are built. Their role, however, will increasingly extend beyond simulation toward enabling adaptive, predictive, and autonomous system behaviour.

While considerable scientific and technological challenges remain before such visions become fully realized, the contributions presented in this Special Issue clearly indicate that many of the

necessary building blocks already exist. Advances in simulation, artificial intelligence, optimization, and computational decision support are progressively converging toward integrated computational ecosystems capable of supporting increasingly sophisticated engineering functions.

In summary, the future of numerical methods will likely be characterized by deeper integration, greater interdisciplinarity, stronger connections with artificial intelligence, and an expanding role in decision-making and system autonomy. The research directions outlined above provide a roadmap for future developments and highlight the continuing importance of numerical methods as a driving force in engineering innovation.

8 Conclusions

The papers collected in this Special Issue reflect the diversity and continued evolution of numerical methods across contemporary engineering disciplines. Although the contributions address different application domains and employ distinct computational approaches, they collectively underline the central role that numerical methodologies continue to play in understanding, designing, optimizing, and managing increasingly complex engineering systems.

Rather than pointing toward a single dominant methodology, the published works illustrate the growing complementarity between computational modelling, numerical simulation, optimization techniques, data analysis, and decision-support frameworks. This convergence is progressively expanding the scope of computational engineering and enabling new forms of interdisciplinary research and technological innovation.

The contributions also highlight a broader evolution in the role of numerical methods. Beyond their traditional function as tools for analysing physical phenomena, numerical methodologies are increasingly integrated into larger computational environments that support design exploration, performance assessment, optimization, and informed decision-making. At the same time, the continued development of these approaches will depend on addressing challenges related to validation, uncertainty quantification, computational efficiency, interpretability, and reproducibility.

Looking ahead, advances in scientific machine learning, hybrid physics-data modelling, digital twins, and intelligent decision-support systems are expected to create new opportunities for extending the capabilities of numerical methods. While these emerging paradigms are not directly represented by all the contributions included in this Special Issue, they provide a broader context within which many of the published developments can be understood and further expanded.

Ultimately, the future of computational engineering will depend not only on advances in individual methods, but also on the effective integration of complementary computational paradigms. The convergence of simulation, optimization, data-driven techniques, and intelligent computational frameworks is likely to remain a defining characteristic of future research and innovation across engineering disciplines.

As Guest Editors, we sincerely thank all authors, reviewers, and members of the editorial team whose contributions made this Special Issue possible. We hope that the studies presented herein will stimulate further research, encourage interdisciplinary collaboration, and contribute to the continued advancement of numerical methods and computational techniques in engineering.

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