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COMPUTATIONAL NUMERICAL INTEGRATION OF REAL AND COMPLEX MULTIVARIABLE FUNCTIONS: AI-INTEGRATED METHODS AND APPLICATIONS IN MODERN ENGINEERING

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ABSTRACT:
Computational numerical integration is fundamental to real and complex multivariable problems that define the modern artificial intelligence (AI) based decision models. With the increasing data intensity, nonlinearity, and dimensionality of engineering systems, the efficiency of numerical integration methods is of paramount importance for enhancing the numerical accuracy, optimization performance, uncertainty quantification, and predictable reliability of engineering systems. The mathematical principles of numerical integration are reviewed, and deterministic, stochastic, adaptive and hybrid integration techniques in the context of AI-based computational frameworks are explored. A particular focus is on applications in engineering, such as computational fluid dynamics, energy management, digital twin, control engineering, and large-scale engineering simulations, among others. Combining numerical methods with machine learning, probabilistic modelling, and intelligent optimization allows efficient analysis of complex engineering systems and robust and data-driven decision making. The scalability and efficiency of engineering decision models is discussed in relation to recent advancements of high-performance computing, GPU acceleration, parallel processing, digital twins, and explainable AI. High computational complexity, numerical instability, high-dimensional processing, scalability and model interpretability are thoroughly discussed as key challenges. Lastly, new trends that feature AI-driven adaptive integration, intelligent optimization, real-time simulation, and self-governing computational systems are emphasized. In conclusion, the combination of advanced numerical techniques and AI offers a solid stepping stone towards the creation of accurate, scalable, and intelligent decision-support systems that can tackle increasingly complex engineering challenges and facilitate next-generation industrial automation and technological innovations.

KEYWORDS: Computational Numerical Integration; Artificial Intelligence; Multivariable Functions; Engineering Optimization; AI-Based Decision Models.

1. INTRODUCTION

Computational numerical integration is an essential part of modern scientific and engineering computation, especially when no analytical solution exists or it can be calculated easily. Nonlinear behaviour, multiple parameter dimensions, uncertainty of operating conditions, and a vast amount of data continuously generated are becoming increasingly characteristic of engineering systems. Numerical integration is the mathematical background needed to approximate integrals that appear in the modelling, optimization, uncertainty analysis, simulation and decision making of systems. With the development of artificial intelligence (AI), its role has been expanded further, redefining traditional engineering methods with intelligent modelling, automated analysis, prediction, and decision support based on data. The AI-driven evolution of industrial engineering is ushering in an era of more responsive and computationally intelligent solutions to complex engineering challenges, as well as new fields for the application of computation in design, production, control and optimization (Akman & Azkeskin, 2025).

Multivariable functions are of special importance, as many processes in engineering involve multiple interacting variables. Applications of real-valued multivariable formulations are common in optimization, structural analysis, fluid dynamics, energy systems, thermal processes and mechanical modelling; applications of complex-valued formulations are common in problems involving oscillatory behaviour, frequency domain analysis, electromagnetic systems, control and signal processing. When the dimension and the complexity of a model are increased, conventional analysis integration becomes increasingly restrictive, creating the need for efficient deterministic, stochastic, adaptive, and hybrid numerical integration techniques. This becomes even more prominent as AI is now being used in conjunction with the fundamental engineering disciplines to deal with computational problems involving interconnected physical variables, nonlinear relationships, large data sets, and complex decision spaces.

Combining the capabilities of numerical computation and AI offers potential benefits for enhancing both computational performance and engineering decision-making processes. Machine learning algorithms can be used beyond conventional numerical techniques to learn complex relationships among systems, to build surrogate models, to help with adaptive computation, and to help in optimization. In contrast, numerical methods offer mathematical tools to compute values needed by probabilistic models and simulations, optimization routines, and uncertainty-aware AI systems. This complementary relationship is very applicable in the field of intelligent mechanical systems, where AI, computational simulation, and engineering design can work in tandem to facilitate next-generation applications, which require higher levels of automation, efficiency, and sustainability (Brinda, 2025). This integration is therefore relevant to engineering design optimization, finite element analysis (FEA), computational fluid dynamics (CFD), structural health monitoring, robotics, autonomous systems and signal processing.

With the advent of data-driven AI, the demand for computational systems that can handle heterogeneous and multidimensional data has grown significantly. In the present era, AI methods are widely used across various fields of application, including predictive modelling, intelligent optimization, pattern recognition, automated decision making and multi-disciplinary data analysis, showing their capabilities to complement mathematical/computational methods (Mahanta et al., 2026). Within the engineering domain, this convergence is reinforced by Internet of Things (IoT) enabled sensing, digital twins, high computing power, parallel processing and real-time computational architectures. These technologies open the way for the continuous collection of data and intelligent analysis, and the numerical integration is a key to connect mathematical models, physical simulation, sensor data and decisions based on artificial intelligence.

In this regard, this review is aimed at taking a look at computational numerical integration of real and complex multivariable functions in an AI oriented engineering view. Specifically, deterministic, stochastic, adaptive, and hybrid integration strategies and their relationship to modern AI algorithms have been highlighted. Their relevance to engineering optimization, FEA, CFD, structural health monitoring, robotics, autonomous systems, signal processing and engineering environments equipped with IoT is critically discussed in addition to computational challenges and emerging research opportunities.

Objectives:

- To critically review deterministic, stochastic, adaptive, and hybrid numerical integration methods for real and complex multivariable functions, considering their accuracy, computational efficiency, scalability, and suitability for engineering problems.
- To examine the integration of numerical integration techniques with AI algorithms for engineering design optimization, FEA, CFD, structural health monitoring, robotics, autonomous systems, and signal processing.
- To evaluate the emerging role of AI-integrated numerical methods in IoT-enabled systems, digital twins, and high-performance computational environments, while identifying current challenges and future research directions.

2. Mathematical Foundations and Numerical Integration Methods

2.1 Real and Complex Multivariable Integration

Multivariable integration provides the mathematical basis for analysing engineering systems governed by several interacting variables. For a real-valued function $f: \mathbb{R}^d \to \mathbb{R}$, a multidimensional integral over a domain Ω can be expressed as

$$I = \int_{\Omega} f(\mathbf{x}) d\mathbf{x}$$

where x=x1,x2,…,xd represents the input variables. Such formulations occur frequently in engineering design optimization, finite element analysis (FEA), computational fluid dynamics (CFD), uncertainty analysis, structural mechanics, and dynamic-system modelling. When analytical solutions are unavailable, numerical integration provides approximate solutions through weighted evaluations of the function.

Complex multivariable functions extend these concepts to quantities containing real and imaginary components. They are particularly important in signal processing, electromagnetic analysis, vibration, wave propagation, communication systems, and frequency-domain modelling. Their increasing incorporation into AI-assisted engineering models creates a need for numerical methods capable of efficiently handling nonlinear, oscillatory, and multidimensional behaviour.

2.2 High-Dimensional Integration and the Curse of Dimensionality

Numerical integration problems become very challenging as the number of dimensions grows. When n integration points are required in each of d dimensions, a conventional tensor-product approach requires approximately n^d function evaluations. This is known as the curse of dimensionality and is a problem which is growing increasingly critical. It has a special relevance for engineering optimization, uncertainty quantification, digital twins and AI models with many design variables, uncertain parameters and/or sensor measurements. Problems of high dimensionality in engineering are therefore of increasing significance and scalable approaches like stochastic sampling, sparse grids, adaptive integration, dimensionality reduction and surrogate modelling are becoming increasingly important (Llorente et al., 2020).

2.3 Deterministic Numerical Integration Methods

Deterministic methods approximate integrals using predefined integration points and

$$I \approx \sum_{i=1}^{N} w_i f(\mathbf{x}_i),$$

where wi and xi represent the weights and integration points, respectively. Common approaches include the trapezoidal rule, Simpson's rule, Gaussian quadrature, multidimensional cubature, arc integration. These techniques provide reproducible results and can achieve high accuracy for sufficiently smooth functions.

Gaussian quadrature is particularly important in engineering because it can achieve high accuracy with relatively few function evaluations. It is extensively applicable to FEA for evaluating element matrices and vectors and is also relevant to structural mechanics, thermal analysis, CFD, and engineering applications. However, conventional deterministic methods become increasingly expensive in high-dimensional spaces motivating the development of sparse and more computationally efficient formulations.

2.4 Stochastic Numerical Integration Methods

Stochastic methods estimate integrals through sampling and are particularly useful for high-dimensional and uncertain systems. Monte Carlo integration represents a fundamental approach:

$$I_N = \frac{1}{N} \sum_{i=1}^{N} f(\mathbf{x}_i).$$

Its dependence on sampling rather than dense multidimensional grids makes it attractive for uncertainty quantification, reliability analysis, Bayesian modelling, and high-dimensional engineering optimization.

Importance sampling, stratified sampling, variance-reduction techniques, and quasi-Monte Carlo methods can further improve computational performance. In engineering, these methods are valuable for uncertainty propagation in FEA and CFD, reliability-based design, probabilistic structural assessment, and autonomous decision systems. AI algorithms can additionally guide sampling toward computationally informative regions, thereby improving efficiency.

2.5 Adaptive Numerical Integration Methods

The idea of adaptive numerical integration is to allocate the computational resources dynamically, based on the behaviour of the integrand locally. The regions which show rapid variation, nonlinearity and singularities or large approximation errors are refined and regions of relative smoothness are refined less. This can make the computation more efficient whilst maintaining a required accuracy.

Adaptive strategies prove to be especially helpful when using FEA near stress concentrations, nonlinear regions and CFD around boundary layers, shocks and strong flow gradients. AI can also be used to improve adaptive integration by forecasting potentially troublesome areas, improving the refinement, and learning the convergence behaviour. These AI-driven adaptivity capabilities have potential for simulation systems that are computation-intensive and in real-time engineering systems.

2.6 Hybrid and AI-Assisted Numerical Integration

Hybrid integration combines complementary numerical strategies to balance accuracy, robustness and computational efficiency. These include the deterministic-stochastic combination, adaptive Monte Carlo techniques and classical numerical methods using machine-learning models. These methods are useful when the engineering problem in question has a combination of determinate and stochastic parameters and/or the problem is of a different complexity in different parts of the computational space.

Intelligent sampling, surrogate modelling, error prediction and automated method selection are a few additional concepts that are expanded upon by AI-assisted hybrid methods. Machine-learning algorithms can approximate numerically costly functions or indicate where further numerical evaluations are needed. Physics-informed models can also be used to integrate the physics with data-driven learning. The potential applications of these approaches are great in the fields of FEA, CFD, structural health monitoring, robotics, autonomous systems and digital twins.

2.7 Accuracy, Convergence, Stability, and Computational Complexity

Numerical integration techniques are characterized by their accuracy, convergence, numerical stability and complexity. Deterministic methods typically give a pretty accurate solution for smooth problems of relatively low dimension but can be costly when the dimension is raised. With stochastic approaches, the dimensional scalability is higher but will need large sample sizes to obtain accurate estimates. Adaptive methods focus computational resources where they are most needed, and hybrid methods attempt to leverage the strengths of several methods.

The trade-offs are especially critical when numerical integration is used multiple times in an engineering optimization, FEA, CFD, real-time monitoring, robotic control, or digital-twin simulation. The use of AI-assisted method selection, surrogate modelling, parallel processing and adaptive computation can decrease the computational demands without sacrificing the numerical reliability. Therefore, while mathematical accuracy is a major factor in determining the choice of an appropriate integration strategy, dimensionality, uncertainty, computational resources and real-time requirements of the engineering application should also be considered.

3. Integration of Numerical Methods with Artificial Intelligence

3.1 Machine Learning-Assisted Numerical Integration

Combination of machine learning (ML) and numerical methods is an efficient tool for solving high dimensional and nonlinear engineering problems. There are many applications such as optimization and simulation where conventional numerical integration needs many function evaluations. The learning of relationships between system inputs and numerical response by the ML models can be used to reduce repetitive computations and helps in faster engineering decisions. These smart computing algorithms are becoming more applicable in process optimization and improvement, and resource-efficient engineering applications at the industrial level (Asih et al., 2025).

ML can also be used for numerical integration, for example to predict error and guide selection of parameters, to determine which variables are influencing the result, and to guide adaptive allocation of computational resources. AI should not be used to replace existing numerical techniques but, rather, should be used to enhance the efficiency of the computations without sacrificing the order of accuracy needed for engineering analysis.

3.2 Deep Learning and Surrogate Modelling

Deep learning models can model complex nonlinear relationships between data obtained numerically or experimentlly. High fidelity simulation results can be used to train neural networks that can serve as surrogate models to provide fast approximations without repeatedly running high-fidelity and expensive simulations. This capability is very helpful in iterative design optimization, uncertainty analysis, and large engineering simulations. The prediction and computational characterization of complex engineering materials and systems are increasingly being achieved using AI-driven modelling, highlighting the potential of data-driven methods in complementing traditional mathematical modelling (Rai et al., 2026). However, the training information and validation of surrogate models to reliable numerical solutions is needed to ensure that they are accurate and generalizable.

3.3 Bayesian and Probabilistic AI Approaches

Material properties, measurements, environmental and operating parameters are often associated with uncertainties in engineering systems. These uncertainties are captured in the form of probability distributions using the Bayesian and probabilistic approaches; numerical integration is needed to compute posterior distributions, expected quantities, and measures of uncertainty. Probabilistic modelling and AI allow for the prediction and decision making with uncertainty. Despite the significant progress that machine-learning approaches have made towards the modelling of complex physical processes, data quality, uncertainty, generalization, and efficiency are important issues (Yaseen, 2023). These approaches are especially pertinent to the fields of reliability assessment, SHM, engineering optimization and autonomous decision systems.

3.4 AI-Guided Adaptive Integration and Intelligent Sampling

AI can be used to improve adaptive numerical integration by determining areas where more detailed calculations are needed. Machine learning algorithms can guide the numerical evaluations towards the areas which make the greatest contribution to the accuracy and predict the local complexity or approximation error. This helps to minimize unnecessary calculations, while at the same time retaining accurate numerical solutions. Intelligent sampling can also help to enhance stochastic integration, by choosing more representative sampling sites. Applications where the number of computational resources is limited like Monte Carlo integration, uncertainty quantification, nonlinear engineering simulations, and real-time computational applications can benefit from these approaches.

3.5 Intelligent Optimization and Hybrid AI–Numerical Models

In engineering design, numerical integration and the use of AI-based optimization are intricately linked due to the often-repeated numerical evaluations of the objective and constraint functions. Intelligent optimization algorithms can be used to search the multidimensional design space; adaptive numerical strategies can focus the computational resources on promising solutions. This combination is useful for multi-objective design optimization, process control and engineering-system optimization. In addition, hybrid AI–numerical frameworks involve the application of deterministic, stochastic or adaptive approaches along with machine learning and surrogate modelling. Physics-informed methods can be used to integrate governing equations, boundary conditions, and physical constraints into AI models, enhancing the alignment of the models with engineering principles. These hybrid schemes show great promise in the fields of FEA, CFD, autonomous systems, robotics, IoT (Internet of Things) digital twins and structural health monitoring, where they offer a balance of computational efficiency, adaptability, and numerical reliability. The major AI approaches integrated with numerical computation and their engineering relevance are summarized in Table 1. The interaction between numerical integration methods, AI algorithms, and engineering decision-making is illustrated in Figure 1.

Table 1. AI Approaches Integrated with Numerical Computation in Engineering

AI/Computational Approach	Role in Numerical Computation	Main Advantage	Engineering Relevance	Reference

Machine learning-assisted computation	Learns relationships between numerical inputs and system responses	Reduces repeated computational evaluations	Industrial optimization and computational engineering	Asih et al., 2025
AI-driven predictive modelling	Develops data-driven representations of complex physical/material systems	Improves rapid prediction and model exploration	Materials modelling and engineering design	Rai et al., 2026
ML-based process modelling	Models nonlinear and multidimensional physical processes	Supports prediction and computational decision-making	Hydrological and complex engineering systems	Yaseen, 2023
Surrogate modelling	Replaces selected expensive simulations with learned approximations	Reduces simulation time	FEA,CFD,optimization, digital twins	Rai et al., 2026
AI-guided adaptive integration	Identifies regions requiring greater numerical refinement	Improves computational efficiency	Adaptive FEA, CFD and uncertainty analysis	Llorente et al., 2020
Physics-informed AI	Integrates governing physical relationships into learning models	Improves physical consistency	Multiphysics and engineering simulations	Mogra et al., 2025

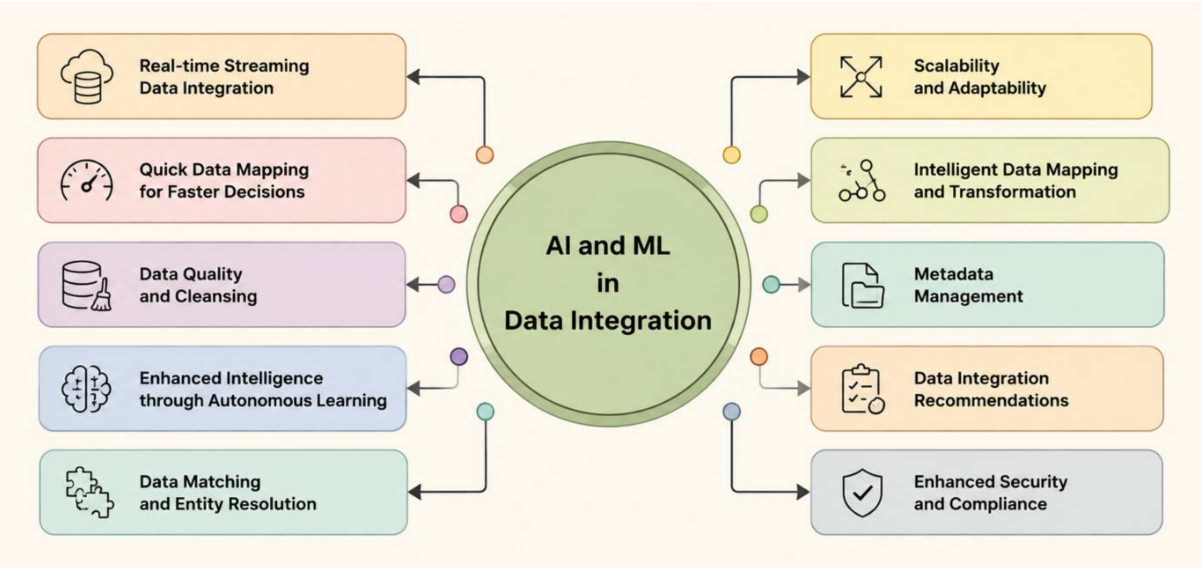

Figure 1: Framework for Integration of Numerical Methods with Artificial Intelligence

4. Applications in Engineering Design, Finite Element Analysis, and Computational Fluid Dynamics

4.1 AI-Assisted Engineering Design Optimization

Optimization problems in engineering design often have multiple constraints, nonlinear objective functions and large design spaces, in which a large number of design evaluations need to be repeatedly performed. Numerical integration can be used for calculation of performance measures, expected responses and objective functions, whilst AI can speed up the design-space exploration and find promising solutions. In engineering systems, AI-driven optimizations are being more adopted to enhance the system's performance and efficiency through predictive modelling and intelligent control in complex systems (Alhazmi, 2026). In the field of architecture and engineering, this integration showcases AI's ability to enhance design processes, making them more efficient, sustainable, and innovative (Almaz et al., 2024). To minimize the time needed for iterative evaluation, computational design frameworks are becoming more commonplace combining simulation, optimization and AI. The selection of parameters and automation of the design process can be aided by AI-driven computational design, especially when traditional optimization methods would involve a lot of simulations (Nashaat & Elzeni, 2025). This functionality renders the use of AI–numerical integration as being especially pertinent to multi-objective and reliability-based engineering design.

4.2 Reliability-Based and Multi-Objective Optimization

Optimization of engineering designs must often be done under multiple and potentially conflicting requirements, where there may be uncertainty of the load, material, operating condition and the environment. Numerical integration can be used to calculate expected performance and uncertainty, whereas stochastic methods can be used to make a probabilistic reliability assessment. Through AI-driven optimization, designs can then be found that optimize for performance, reliability, cost and sustainability. These methods become more and more relevant in various specialties of engineering. In the field of petroleum production engineering, AI is being integrated into prediction and optimization tools and processes for decision-making in sustainability, which includes complex operational variables (Khalili & Abbasi, 2026). The use of AI in pavement engineering also shows potential for more opportunities in data-driven pavement performance prediction, design assessment, and infrastructure optimization (Ramadan et al., 2026).

4.3 Numerical Integration and AI in Finite Element Analysis

One of the most significant of the numerical integration applications in computational engineering is finite element analysis (FEA). Numerical evaluation of integrals over the finite element domains is often necessary for computing element matrices and vectors; Gaussian quadrature is typically an efficient method for many finite element formulations. Problems with nonlinear behaviour or multiple physics can be more costly to integrate since the material behaviour, geometry and coupled physical responses need to be calculated multiple times. Combining AI and computational mechanics can enable the possibility of faster simulations, approximating complex constitutive relationships, and better prediction of engineering responses. The use of AI-enhanced computational mechanics is also starting to be explored in fields like geotechnical engineering, where data-driven approaches can complement traditional numerical modelling techniques for complex physical systems (Liu et al., 2024). In the field of finite element analysis, the potential of AI-driven Multiphysics FEA is another area that stands out for its ability to analyse complex engineering systems that involve multiple physics efficiently and effectively (Mogra et al., 2025).

4.4 Adaptive Integration and Computational Modelling in FEA

The adaptive integration and refinement strategies are significant in cases with a high variation of the structural responses over the computational domain. In areas with stress concentrations, nonlinear behaviour, geometric irregularities or material behaviour that changes quickly, more numerical resolution can be used. Adaptive procedures, in conjunction with AI, may be able to detect areas that need to be refined and lessen unnecessary computation in more uniform areas. All these capabilities are applicable to the modelling of complex materials and structures. These are just a few examples of how AI is applied to concrete technology; more advances in intelligent computational methods are likely to emerge as the industry evolves and new challenges arise. Such models, together with adaptive numerical methods, can be used to aid efficient analyses of systems of engineering where the computations are intensive.

4.5 Numerical Integration and AI-Assisted Computational Fluid Dynamics

The use of computational fluid dynamics (CFD) heavily depends on the numerical discretization and integration of governing equations to describe different physical phenomena of fluid flow, heat transfer and mass transport. To compute fluxes, source terms, temporal evolution, and other quantities in a discretized flow domain, numerical integration needs to be performed. Adaptive strategies may enhance the efficiency by focusing the computational resolution in regions of strong gradient, boundary layer, interfaces or other complex flow features. AI can be used to learn the relationship between flow parameters and responses of the system, which helps to obtain a reduced order or surrogate model of the computationally expensive CFD model. These AI-driven methods can minimize repetitive evaluations of high-fidelity simulations during optimization and real-time decision making. This overall trend is reflected in engineering applications where intelligent models are becoming increasingly coupled with simulation and computational analysis for prediction and performance assessment.

4.6 Uncertainty Quantification in Engineering Simulations

Uncertainty quantification becomes crucial to assess the reliability of the predictions obtained from FEA, CFD and engineering design models. The propagation of variability in properties, boundary conditions, geometric parameters, operating conditions, and data from measurements through simulations can affect the predicted responses. Stochastic integration, Monte Carlo and related stochastic methods can be used to quantify these uncertainties and adaptive/surrogate methods can help the associated computation. This approach of combining numerical simulation with AI thus offers a promise for uncertainty-aware engineering analysis in the future. Hybrid approaches can be used to combine numerical reliability with data-driven prediction, without treating AI as a substitute for physics-based computation. In design optimization, FEA, CFD, material modelling and other applications, it can increase the efficiency of the computations, while retaining the physical information required for confident engineering decision making. The applications of AI-integrated numerical frameworks in engineering design optimization, FEA, and CFD are presented in Table 2.

Table 2. Applications of AI–Numerical Frameworks in Engineering Design, FEA, and CFD

Engineering Area	Numerical/Computational Role	AI Contribution	Major Benefit	Reference
Engineering optimization	Evaluation of multidimensional objectives and system responses	Predictive optimization and intelligent control	Improved efficiency and design decisions	(Alhazmi, 2026)

Architectural and engineering design	Simulation and computational design assessment	AI-assisted design generation and evaluation	Efficiency, sustainability and creativity	(Almaz et al., 2024)
Concrete/material engineering	Numerical simulation and performance modelling	Data-driven prediction and performance estimation	Improved material assessment	(Funda Akbulut et al., 2026)
Petroleum engineering	Computational modelling of production systems	Prediction and optimization	Enhanced operational and sustainability performance	(Khalili & Abbasi, 2026)
Computational mechanics	Physics-based numerical modelling	AI-enhanced prediction and approximation	Faster analysis of complex systems	(Liu et al., 2024)
Multiphysics FEA	Finite-element simulation of coupled dynamic systems	AI-supported multiphysics modelling	Reduced computational burden and improved prediction	(Mogra et al., 2025)
Computational design	Iterative design-space evaluation	AI-supported design workflows	Faster computational design exploration	(Nashaat & Elzeni, 2025)
Pavement engineering	Computational performance assessment	AI-based prediction and modelling	Improved infrastructure design and maintenance	(Ramadan et al., 2026)

5. Applications in Structural Health Monitoring, Robotics, Autonomous Systems, and Signal Processing

5.1 Numerical Integration in Structural Response and Vibration Analysis

In structural dynamics, numerical integration is the key process for solving time-dependent equations of motion to estimate the displacement, velocity, acceleration, and vibration responses. Deterministic and adaptive integration methods may be used to ensure a correct assessment of the structural behaviour when the loading is dynamic, and stochastic methods are suitable when there is uncertainty in the material parameters, loads and/or environment. These numerical outputs can also serve as a computational basis for AI models in order to detect abnormal structural behaviour and predict possible deterioration. Real-time sensors and intelligent computational models are increasingly being used to support structural monitoring. Predictive failure analysis with sensor fusion can enhance the evaluation of critical engineering parts by constantly monitoring the operating conditions and detecting early signs of failure with the help of artificial intelligence (Fazle et al., 2023). The synergy of numerical analysis, sensing and AI is a crucial underpinning to condition-based infrastructure management.

5.2 AI-Based Structural Health Monitoring and Predictive Maintenance

In recent years, there is a growing trend of combining sensor data with AI to perform structural health monitoring (SHM) for detecting structural damage, assessing the state of the system and implementing predictive maintenance. Dynamic response quantities and probabilistic information can be processed with numerical integration and machine-learning models can be used to recognize deterioration or abnormal operation patterns. Prognostics and health-management are also shifting from traditional statistical models to more advanced models that incorporate artificial intelligence (AI) for more sophisticated degradation and remaining-life predictions (Zhuang et al., 2026). This applies to power and infrastructure systems as well. By leveraging AI for fault detection, data processing, predictive modelling, and optimization can be combined to identify abnormal operating conditions and enhance the reliability of the system (Liu et al., 2025). The move from data perception to intelligent prediction and control also highlights the need for a fusion of computational modelling and AI-driven monitoring and decision-making in power-system stability applications (Zhang et al., 2025).

5.3 Robotic Dynamics, Trajectory Estimation, and Control

Continuous numerical evaluation of dynamic equations for position, velocity, acceleration, and forces, and for the states of the systems is required in robotic systems. Thus, numerical integration can be used for trajectory generation, motion prediction, feedback control and dynamic simulation. Adaptive approaches can be useful in situations where the environment in which the robots are operating is variable, and AI can enhance the optimization of trajectories and develop control strategies that can intelligently respond to unknown or uncertain conditions. The use of numerical calculation and AI is more significant for autonomous robotic platforms, the decisions of which need to be made under an extreme real-time constraint. Numerical models can generate physically meaningful estimates of systems behaviour and learning algorithms can be used for perception, planning, adaptation and control.

5.4 Sensor Fusion and State Estimation

In the present context of modern intelligent engineering systems, multiple sensors are typically used which continuously produce a heterogeneous set of measurements. These observations can be fused together to achieve more reliable estimates of the states of the system than the individual ones. Integrating measurements over time can be supported by numerical and probabilistic computation, and AI can be used to find complex relations between the output from the different sensors and enhance the predictability. The significance of AI-integrated sensors for advanced analytical and monitoring systems is growing as these systems integrate various types of data and incorporate predictive models to enhance the detection and estimation of patterns and trends (sai et al., 2026). Similarly, multisensor systems coupled with AI-driven analytical, and chemometric computation reveal the promise of intelligent algorithms to derive valuable insights from the intricate responses of sensor arrays.

5.5 Autonomous Navigation and Decision-Making

Continuous integration of perception, state estimation, trajectory planning and control is needed for autonomous systems. Examples include systems where AI algorithms interface with numerical models to aid in navigation and real-time decision making include unmanned aerial vehicles (UAVs), autonomous transportation systems, and mobile robots. With the development of UAVs, AI techniques have been playing a more and more crucial role in perception, navigation, control, communication, and autonomous operation of UAV systems (Sai et al., 2023). This change is also happening in ITS (intelligent transportation infrastructure). Intelligent motorways with AI capabilities integrate a variety of information and automated decision-making mechanisms to enhance transportation efficiency and operational intelligence (Anthi et al., 2025). Thus, hybrid AI–numerical methods can be used to help support autonomous systems, where models of physical systems are paired with adaptive and data-driven decision-making logic.

5.6 Complex-Valued Numerical Computation in Signal Processing

Signal processing is an important application of real and complex numerical computation because many signals are processed naturally in terms of amplitude, phase, frequency and complex valued transformations. Numerical integration can be useful for spectral analysis, filtering, signal reconstruction and extraction of the cumulative or frequency dependent information. The use of complex values is of special interest in the areas of communication, vibration monitoring, sensing, and frequency domain engineering. A shift from classical analytical methods towards chemometric and AI-based computational methods is an example of how intelligent algorithms can be used in addition to established mathematical methods when analysing multicomponent and overlapping signals (Elagamy & Elattar, 2026). Numerical and AI approaches can thus be combined to enhance the interpretation of complex signals, while at the same time allowing for the handling of nonlinearities as well as multidimensional relationships.

5.7 AI-Assisted Signal Analysis and Feature Extraction

AI-powered signal processing can go further than traditional numerical analysis, allowing for the automatic identification of informative features and patterns in large and complex datasets. Machine-learning and deep-learning models can process the signal from the sensor for classification, anomaly detection, fault diagnosis and prediction, whereas numerical methods can preprocess and transform, filter and provide physically interpretable quantities needed for the models. The common computational framework of numerical computation, multisensor information, and AI thus sets a platform for SHM, robotics, autonomous systems and signal processing. These systems can be used to convert continuously received signals to estimates of physical states and ultimately to predictions and/or control decisions. Such integration is crucial for real-time engineering applications where reliable sensing, fast computation, uncertainty handling and intelligent decision making are all required to work in concert. The applications of AI-assisted numerical computation in structural health monitoring, robotics, autonomous systems, and signal processing are summarized in Table 3. The major engineering application domains of AI-integrated numerical computation are presented in Figure 2.

Table 3. AI-Integrated Numerical Applications in SHM, Robotics, Autonomous Systems, and Signal Processing

Application	Data/Numerical Function	AI Role	Expected Engineering Outcome	Reference
Predictive failure analysis	Integration of real-time sensor measurements	Failure prediction and sensor fusion	Improved industrial safety and reliability	(Fazle et al., 2023)
Structural/prognostic health management	Degradation and lifecycle modelling	AI-based prognostics	Earlier fault identification and maintenance planning	(Zhuang et al., 2026)
Power-system fault detection	Processing multidimensional operational information	Fault classification and optimization	Improved system reliability	(Liu et al., 2025)

Power-system stability	Dynamic data analysis and state assessment	Intelligent prediction and control	Enhanced operational stability	(Zhang et al., 2025)
UAV/autonomous systems	Navigation, state estimation and dynamic computation	Autonomous perception and control	Improved autonomous operation	(Sai et al., 2023)
Intelligent transportation	Continuous traffic and infrastructure data processing	Intelligent monitoring and decision-making	Safer and more efficient transport	(Anthi et al., 2025)
Multisensor analysis	Integration of multiple sensor responses	Pattern recognition and predictive modelling	Improved detection accuracy	(Chen, 2026)
Advanced sensing	Processing sensor-generated analytical information	AI-assisted prediction	More reliable sensor interpretation	(Kumar et al., 2026)
Signal and multicomponent analysis	Mathematical separation and interpretation of signals	Chemometric and AI-based analysis	Improved extraction of complex signal information	(Elagamy & Elattar, 2026)

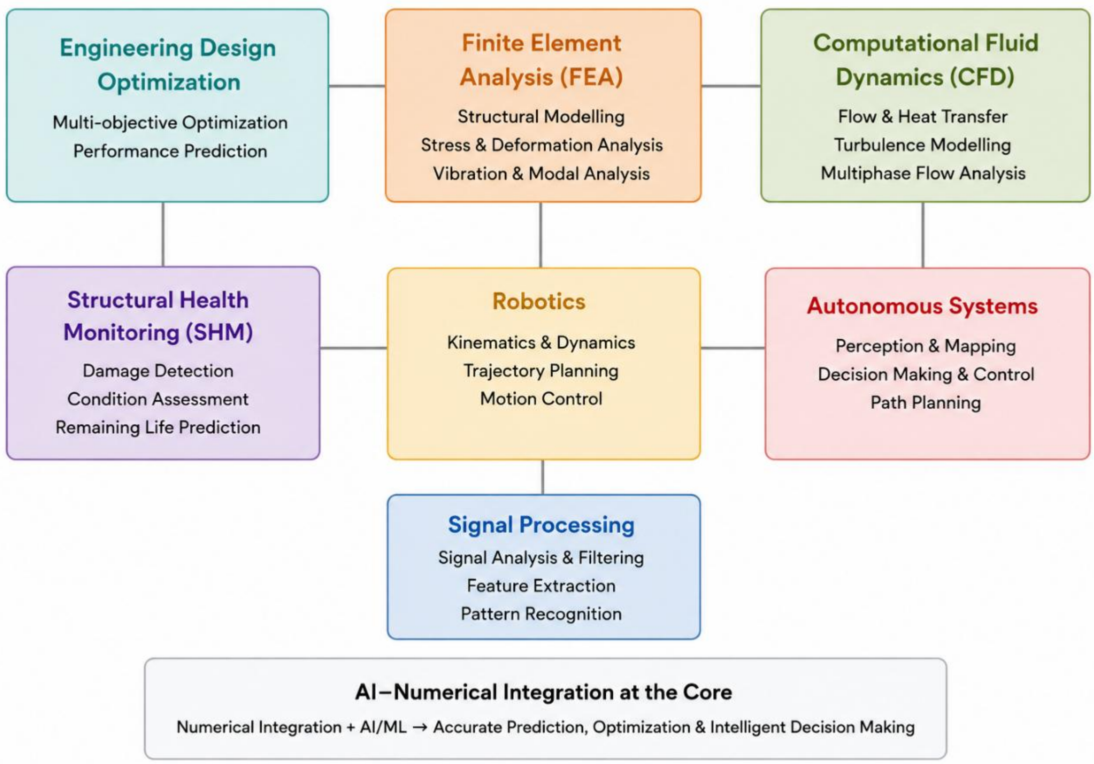

Figure 2: AI–Numerical Integration Framework for Modern Engineering Applications

6. IoT-Enabled Systems and High-Performance Computational Frameworks

6.1 IoT Sensor-Data Acquisition and Numerical Processing

Distributed systems that use sensors, communication networks and computation platforms to continuously monitor physical processes by using the Internet of Things (IoT) are called IoT-enabled engineering systems. Sensors can make more than one measurement in the same dimension like temperature, pressure, vibration, strain, flow, motion and other operating variables. Numerical integration is a vital approach to helping to convert these continuous or discrete measurements into useful estimates of cumulative or dynamic system behaviour. Another trend is the evolution of intelligent nano and microscale sensors with edge AI to realize autonomous sensing and real-time intelligent computing (Guo et al., 2025). AI-enabled sensor platforms can handle vast amounts of data to detect anomalies, make predictions, and make automatic decisions. AI-integrated optical biosensing is another example of an intelligent sensing architecture that integrates state-of-the-art sensors with computational analysis to quickly interpret complex measurements (Subburaj et al., 2025).

6.2 AI–IoT Integration for Real-Time Engineering Decisions

AI and IoT together can transform the way engineering systems are monitored, making it possible to make predictions and make intelligent decisions in real-time. The variables arising from the sensors can be processed by means of numerical methods, and the AI algorithms can recognize patterns, predict future states, recommend or initiate corresponding actions. These types of frameworks are highly beneficial in smart manufacturing, infrastructure monitoring, energy management, environmental systems and autonomous industrial operations. In complex environmental engineering applications, for instance, AI-based smart treatment systems can intertwine the sensing, data processing, prediction, and intelligent operational strategies. In parallel, the architectures of computational and cybersecurity systems must be strong, especially when engineering decisions are based on data that is continuously transmitted, in the case of interconnected intelligent systems (Ashfaq et al., 2023).

6.3 Edge and Cloud Computing

Volumes of data can accumulate in real time IoT applications, making it impractical to continually push that data to centralized computing facilities. To overcome this limitation, edge computing can be used to process the selected information near the sensor or physical system thus reducing the latency and communication requirements. Cloud computing on the other hand, offers higher amounts of computing resources for large scale modelling, historical data analysis, optimization and model training. Hybrid edge–cloud architectures are especially useful for numerical systems that are integrated with AI. Intelligent battery-management systems showcase this with a combination of artificial intelligence (AI), digital twins, state estimation, lifecycle optimization, and edge-cloud integration, which enhances battery monitoring and operational management (Madani et al., 2025). They can split the various numerical integration and AI tasks based on their computation complexity and real-time requirement in such architectures.

6.4 IoT-Enabled Predictive Monitoring and Maintenance

Predictive maintenance is the incorporation of data collected regularly during the operation of the system to provide information on the condition of the system and its deterioration before it stops working. Measurements needed can be obtained from IoT sensors and numerical processing can be used to obtain dynamic or cumulative indicators based on these measurements. These indicators are then used to detect degradation trends and forecast maintenance needs, which AI models can identify. Such systems require effective data engineering that can combine all the data together in a reliable way and ensure computational consistency. While being specific to a different application domain, risk-aware AI/data engineering frameworks highlight the overall need for incorporating intelligent prediction together with structured data-processing architectures whenever they have to make decisions based on large, ever-changing datasets (Paleti, 2022). These principles can be applied in engineering applications to condition based maintenance and life cycle management of connected assets.

6.5 Digital Twins and Smart Engineering Systems

Digital Twins are dynamic virtual models of physical systems which are continuously updated with operational data. In the digital twin, numerical simulation is a key element as the virtual representation needs to capture the relevant physical phenomena, and AI can be used to optimise and predict physical phenomena and to automate interpretation. Digital-twin technologies are thus increasingly gaining significance for complex engineering systems, which have to be monitored and simulated constantly. One example of the increasing use of digital twins is in the field of fusion research, where computational modelling is integrated with cutting-edge scientific and engineering activities (Schissel et al., 2025). In more recent works, the concept of digital twins is used in conjunction with conversational AI agents to assist with the management of complex infrastructures for prediction and decision-making (Vicente-Martínez et al., 2026). It can also be integrated with IoT sensing to allow for ongoing synchronization of physical assets and their computational assets. The integration of AI, IoT, digital twins, real-time analytics, and physical systems within an Industry 4.0 framework is illustrated in Figure 3.

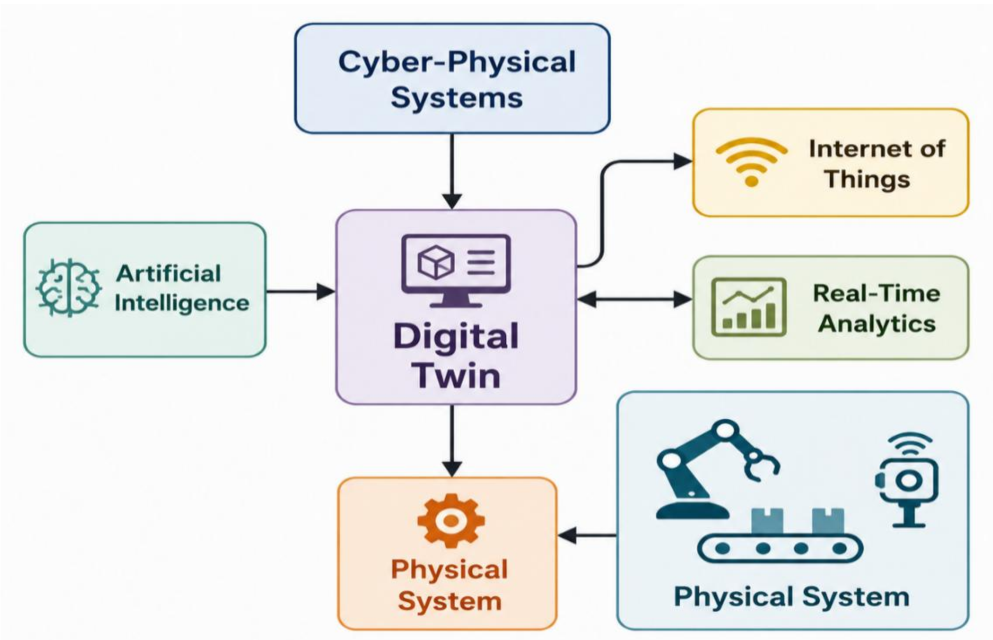

Figure 3: IoT-Enabled Digital Twin Architecture for Real-Time AI–Numerical Engineering Systems

6.6 High-Performance, Parallel, and GPU Computing

In high dimensional numerical integration or AI-assisted engineering simulations, many function evaluations and/or repeated simulations may be required, which can be a significant challenge in terms of computation. The use of high-performance computing (HPC) and parallel processing may be used to parallelise numerical operations and shorten execution times, which will allow bigger engineering models to be analysed. GPU processing works well for calculations with many parallel and/or repetitive mathematical steps. Thus, parallel and GPU architectures can be effectively used to advantage for Monte Carlo sampling, multidimensional integration, AI model inference and even for some FEA/CFD operations. The computational technologies are even more critical when AI and numerical integration are required to work in unison for large-scale engineering datasets or complex and compute-intensive digital-twin models.

6.7 Real-Time Simulation and Intelligent Control

In real-time engineering applications, the computation time must be short to influence the operation of the system in real time. This is especially critical for robotics, autonomous systems, smart infrastructure, energy management and process control in the industry. This can save unnecessary calculations using adaptive numerical integration and prioritize computational resources and predict the system response using AI. In this way, IoT sensing, edge–cloud computing and digital twins, AI, and high-performance computation converge to provide a solid basis for intelligent closed-loop engineering systems. The numerical models can be continuously updated with the sensor measurements, AI algorithms can be used to assess the predicted states, and control mechanisms can be used to react to variable operating conditions. This integration is an important step towards real-time, adaptive and more autonomous engineering computation from traditional offline simulation. The integration of IoT, digital twins, edge–cloud computing, and advanced computational frameworks is summarized in Table 4.

Table 4. IoT, Digital Twin, Edge–Cloud, and Advanced Computational Frameworks

Technology/Framework	Primary Function	Integration with AI/Numerical Methods	Engineering Benefit	Reference
Edge AI sensors and actuators	Local sensing and processing	Intelligent computation close to physical assets	Low-latency real-time analysis	(Guo et al., 2025)
AI-integrated intelligent sensors	Acquisition and interpretation of complex sensor information	AI-assisted sensing and prediction	Improved real-time detection	(Subburaj et al., 2025)
AI–digital twin battery systems	State estimation and lifecycle monitoring	Digital twins, AI and edge-cloud integration	Improved asset management and optimization	(Madani et al., 2025)
Resilient advanced computing	Secure processing of interconnected information	AI-supported computational defence	Greater reliability of connected systems	(Ashfaq et al., 2023)
Digital twins for scientific systems	Virtual representation of physical systems	Continuous computational modelling	Enhanced simulation and operational understanding	(Schissel et al., 2025)
AI-enabled infrastructure digital twins	Continuous virtual–physical system integration	AI agents and predictive computation	Predictive infrastructure decision-making	(Vicente-Martínez et al., 2026)
Smart environmental systems	Sensor-informed computational analysis	AI prediction and intelligent operation	Automated process optimization	(Wang et al., 2026)
AI-oriented data engineering	Processing and integration of heterogeneous data	Risk-aware intelligent analytics	Improved data-driven decisions	(Paleti, 2022)

7. Comparative Analysis, Challenges, and Emerging Research Directions

7.1 Comparative Performance of Numerical Integration Methods

There are several different types of numerical integration methods, such as deterministic, stochastic, adaptive, and hybrid approaches, each with its own set of advantages and disadvantages, depending on the dimensionality, complexity, and uncertainty of an engineering problem. Usually, the deterministic methods are more accurate, and convergence is predictable when applied to smooth, low to moderate dimensional functions, while the stochastic methods are more suitable for high dimensional and uncertainty-rich problems. Adaptive techniques focus computational effort in areas where numerical error is largest, thus increasing efficiency, and hybrid techniques mix several techniques to strike a balance between accuracy, robustness, and computational requirements. Additionally, the growing integration of AI in engineering education and practice suggests that AI is moving beyond standalone solutions to become a supporting tool that integrates with traditional engineering practices, thereby signalling a shift toward a more computational approach to engineering (Amarasinghege, 2025).

7.2 Accuracy, Computational Cost, and Scalability

One of the biggest problems in numerical integration is obtaining a high level of accuracy for a relatively low computational expense. High fidelity FEA, CFD, optimization and Multiphysics simulation can involve multiple evaluations of multidimensional integrals, significantly adding to simulation times. As the dimension increases, the deterministic methods can be rather costly, and stochastic ones may need large samples to attain low estimation error. This burden can be reduced using adaptive and AI-assisted strategies that selectively allocate computational resources. This is especially relevant in process modelling and intelligent control, where computational results must be produced within strict time constraints. In complex engineering scenarios, AI-driven modelling and optimization have shown promise in enhancing prediction and process control, but it is essential to select the right models and ensure accurate computational information is available (Fernando, 2025).

7.3 High-Dimensional Scalability, Numerical Stability, and Uncertainty

Computational scalability, convergence and numerical stability are issues with high-dimensional engineering models. Numerical errors can arise from the approximation from discretization, integration, sampling variability or finite precision computations. With the combination of numerical methods and AI, uncertainties might also stem from training data, model parameters, generalization errors, and prediction variability. For this reason, it is important to bear in mind the numerical uncertainty of the computational model in relation to AI-driven outputs. Thus, the systematic validation of the numerical and AI part of hybrid frameworks is required. This is especially relevant for safety-critical scenarios, like structural monitoring and control, autonomous systems, energy and water infrastructure, and industrial control, where mispredictions have impact on physical-system decisions.

7.4 Explainability, Reliability, and Engineering Implementation

As AI is added to computational systems, there is growing concern about their explainability and reliability. In engineering applications, it is not only essential to make accurate predictions, but also to understand how the computational results are obtained. If used in a numerical simulation, optimization, or automated control, opaque AI models may decrease the level of trust. Quality-focused AI systems highlight the significance of data integrity, performance evaluation, and structured implementation of AI in engineering and management procedures (Huang et al., 2026). Likewise, the importance of tying intelligent prediction to quantifiable measures of process performance and reliability (Sabry et al., 2026) is evident in data-driven and AI-enabled solutions for engineering process-capability assessment. In future AI/numerical frameworks, it is therefore imperative to integrate validation, uncertainty assessment and explainability along with computational efficiency. The major challenges, limitations, and emerging research directions associated with AI-integrated numerical engineering are presented in Table 5. The evolution from conventional numerical methods toward AI-integrated and autonomous intelligent engineering systems is illustrated in Figure 4.

Table 5. Key Challenges and Future Directions of AI-Integrated Numerical Engineering

Challenge	Current Limitation	Emerging Approach	Future Engineering Direction	Reference
Integration of AI into engineering practice	Need for appropriate computational and engineering competencies	AI-integrated engineering education and methodology	Engineers capable of combining physical and intelligent models	(Amarasinghege, 2025)
Computationally intensive process modelling	High cost of repeated modelling and optimization	AI-based modelling and intelligent control	Faster adaptive process optimization	(Fernando, 2025)
Reliability and quality of AI systems	Dependence on data quality and model performance	Systematic AI quality-management frameworks	More reliable and accountable AI systems	(Huang et al., 2026)
Engineering process variability	Difficulty integrating conventional process measures with intelligent models	Data-driven and AI-integrated assessment	Intelligent process monitoring and optimization	(Sabry et al., 2026)
High-dimensional computation	Rapid growth in computational cost	Adaptive, stochastic and surrogate methods	Scalable numerical computation	Liu et al., 2024; Llorente et al., 2020
Numerical and AI uncertainty	Combined errors from numerical approximation and	Probabilistic and uncertainty-aware AI	Trustworthy engineering predictions	Yaseen, 2023; Zhuang et al., 2026

	learned models			
Lack of explainability	Limited transparency of complex AI models	Explainable and physics-informed AI	Trustworthy AI-assisted engineering decisions	Liu et al., 2024; Mogra et al., 2025
Real-time computational constraints	High latency of complex simulations	Edge AI, GPU computing and reduced-order models	Autonomous real-time engineering systems	Guo et al., 2025; Brinda, 2025

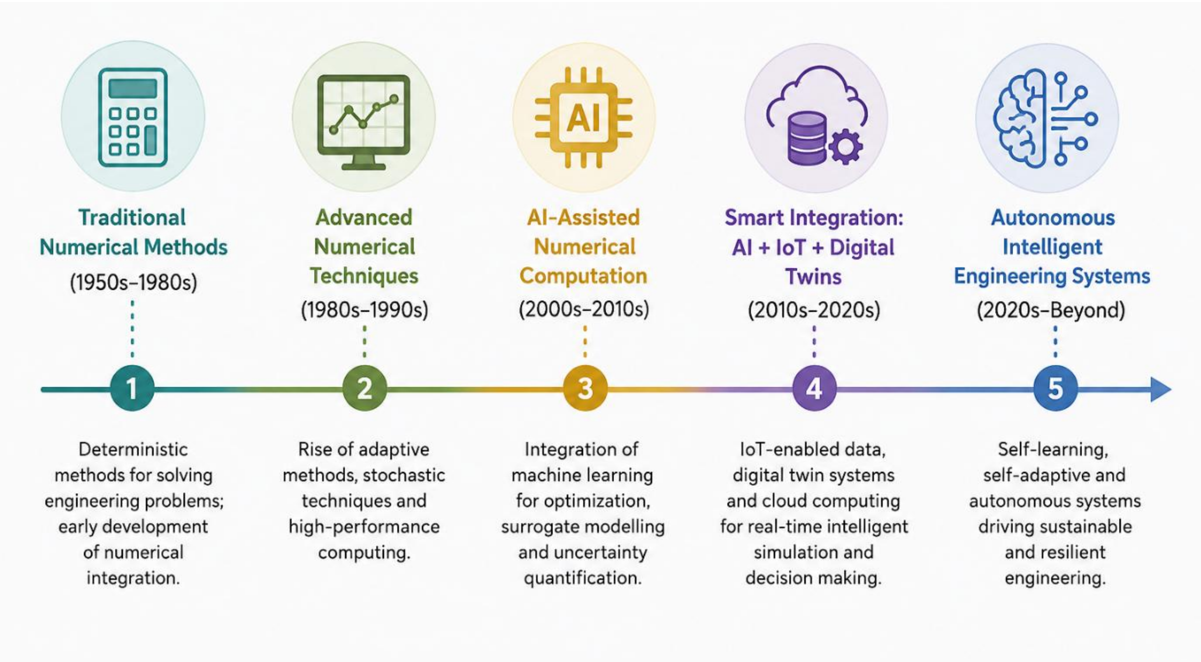

Figure 4: Evolution Toward Intelligent and Autonomous AI–Numerical Engineering Systems

7.5 AI-Driven Adaptive Integration and Self-Learning Computation

The adaptive integration based on AI is a significant way of solving the drawbacks of the fixed numerical schemes. Machine-learning algorithms may have the ability to learn where integration errors are liable to occur, decide on appropriate levels of refinement, optimise sampling locations and choose numerical methods based on problem characteristics. These would enable numerical integration to become a dynamically evolving process instead of a fixed computational procedure. Self-learning computational frameworks can also enhance their numerical strategies with knowledge gained from past simulations. For instance, in engineering optimization, a system might gradually discover areas of the design space which need high-fidelity integration and use surrogate approximations in other areas. The same method could be used to facilitate adaptive FEA, CFD, robotic control, and structural monitoring and reduce the computational cost without sacrificing the numerical accuracy of the solutions.

7.6 Autonomous Computational Methods and Intelligent Engineering Systems

Numerical integration, AI and real-time computing are bringing opportunities for ever more autonomous computational systems. Future frameworks could switch between deterministic, stochastic, adaptive and hybrid approaches, depending on the dimensionality, uncertainty, error tolerance, and available resources. AI could also handle the convergence assessment, allocation of computational resources and model updating with minimal human effort. But if more autonomy is to be granted in computations, there need to be robust systems in place to identify when the number of calculations becomes unstable, when the AI prediction is unreliable and when conditions fall outside of the validated domain of operation. Human supervision and physically meaningful restrictions will therefore continue to play a significant role, especially concerning the decision-making of autonomous engineering systems that are based on computational results.

7.7 Future IoT, Digital-Twin, and Intelligent Engineering Ecosystems

In the future, engineering environments will more and more feature computational ecosystems integrating IoT sensors, digital twins, AI algorithms, numerical simulation and edge–cloud computing. Continuous streams of data from sensors can be used to update the virtual representation of physical assets, and numerical models can be used to estimate the dynamic response, while AI algorithms can be used to facilitate prediction, optimization, and anomaly detection. The computational resolution might be able to be adapted based on the real-time operating situation, enabling the efficiency of continuously updated digital twins. The long term direction therefore is towards engineering systems that are intelligent and where physical sensing, numerical computing, AI-assisted learning, and automated decision making are interdependent. To attain this integration, scalable numerical algorithms, dependable AI models, explainable decisions, efficient computing architectures and strict uncertainty management will be crucial. The potential impact of these advances on more accurate and responsive applications spans engineering design to FEA, CFD, structural health monitoring, robotics, autonomous systems, signal processing, and infrastructure with IoT capabilities.

8. CONCLUSION

Numerical integration of real and complex multivariable functions is still fundamental in the solution of more and more complex problems in the modern engineering. This review illustrates that deterministic, stochastic, adaptive and hybrid integration approaches offer complementary capabilities for dealing with the dimensionality, uncertainty, numerical accuracy and complexity of the problem. A set of deterministic methods are well suited to smooth and relatively low dimensional problems whilst stochastic techniques are more flexible for high dimensional and uncertainty rich applications. Adaptive and hybrid strategies are additional ones that enhance the computational efficiency by allocating resources based on the complexity of the problem and by synergistically using the strengths of different numerical strategies. The combination of these methods with AI offers a tremendous potential for intelligent sampling, surrogate modelling, prediction of error, optimization and adaptive computation. These AI–numerical frameworks are very relevant to engineering design optimization, finite element analysis, computational fluid dynamics, structural health monitoring, robotics, autonomous systems and signal processing. Moreover, the synergy between sensing data and information in IoT, digital twins, edge–cloud computing, high-performance computing, and GPU acceleration are pushing numerical computation towards real-time engineering applications. However, there are still issues with high dimensional scalability, numerical stability, computational costs, uncertainty, explainability and AI reliability that need attention. Future research efforts should thus focus on reliable, self-learning and efficient hybrid approaches that can merge physical models, numerical algorithms, and data-driven intelligence. These advancements will aid the design of scalable, reliable, and more autonomous engineering decision systems.

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