



iJRASET

International Journal For Research in
Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** X **Month of publication:** October 2026

DOI: <https://doi.org/10.22214/ijraset.2026.85249>

www.ijraset.com

Call: ☎ 08813907089

E-mail ID: ijraset@gmail.com

Numerical Analysis Applications in Improving Engineering Models

Gadriah Jamaah Ali Madi ¹

Higher Institute of Medical Science and Technology-Hon, Libya

Abstract: Numerical analysis serves as the fundamental pillar of modern engineering modeling, providing the mathematical and computational tools necessary to transform complex physical equations into practical numerical solutions. This study reviews contemporary applications of numerical analysis in enhancing engineering models, focusing on methodological advancements in solving partial differential equations, data-driven model order reduction techniques, adaptive mesh methods, and machine learning-based surrogate models. The study employs a synthetic analytical approach that combines a review of recent literature with an analysis of empirical results from various numerical methods, addressing hybrid models that integrate traditional techniques with artificial intelligence. The analysis demonstrates that combining traditional numerical analysis methods with artificial intelligence and reduced-order models has revolutionized the ability of engineers to simulate complex multiphysics systems with unprecedented accuracy and computational efficiency; hybrid models have achieved computational speedups ranging from 72 to 522 times compare to traditional methods. Furthermore, the study addresses challenges related to computational cost and solution sensitivity to initial conditions, examining cutting-edge innovative solutions such as physics-informed neural networks and causality-based learning. The study concludes that future trends in this field are shifting towards the development of hybrid models that combine analytical accuracy with computational speed, with an increasing emphasis on generalization capabilities beyond the training data. This opens up broad prospects for digital engineering and digital twin applications across the industrial, energy, and infrastructure sectors. The study offers a comprehensive perspective on the development of engineering models using advanced numerical analysis techniques and identifies promising future research directions in this vital field.

Keywords: Numerical analysis, geometric models, partial differential equations, model reduction, physics-informed neural networks, adaptive meshing, surrogate models.

I. INTRODUCTION

Numerical analysis serves as a vital bridge between abstract mathematics and tangible engineering applications, equipping engineers and researchers with the computational tools necessary to solve highly complex problems that addressed via traditional analytical methods [1]. The significance of this field lies in its ability to provide accurate approximate solutions for equations governing physical and engineering phenomena—ranging from fluid dynamics and wave propagation to thermal analysis and the mechanical behavior of structures [2]. Driven by immense advancements in computational power and algorithmic development, the scope of problems amenable to numerical treatment has expanded radically, establishing computer simulation as an indispensable tool in engineering design and optimization processes [3].

Contemporary engineering modeling is undergoing a paradigm shift; the objective is no longer merely to derive a numerical solution for a specific physical problem, but to develop models capable of adapting to variations in parameters and boundary conditions while delivering reliable predictions across a wide range of scenarios. This shift presents new challenges for traditional numerical analysis methods, necessitating their integration with modern techniques such as machine learning and model order reduction [4]. The ability to construct "surrogate models" or "digital twins" that reflect the dynamic behavior of actual systems in real-time has become a cornerstone of modern industries, ranging from aerospace engineering to energy infrastructure [5].

Traditional numerical methods, such as the Finite Element Method (FEM) and the Finite Difference Method (FDM), face significant challenges when dealing with multiphysics systems and complex geometries. These methods often require extremely fine computational meshes to achieve the desired accuracy, resulting in prohibitive computational costs [6]. Furthermore, repeating simulations to explore the parameter space during design and optimization processes poses a massive computational challenge, particularly in large-scale industrial applications [7].

In recent years, promising research trends have emerged to overcome these limitations. Notable among these trends are: (a) dynamic mesh adaptation techniques that concentrate computational resources in regions where the solution changes rapidly [6]. (b) data-driven surrogate models that provide rapid predictions at low computational cost [3]. (c) Physics-Informed Neural Networks (PINNs), which integrate physical equations directly into the learning architecture [8, 9]. (d) Model Order Reduction (MOR) techniques, which generate low-dimensional representations of high-dimensional systems [4].

This research aims to provide a comprehensive and analytical review of contemporary applications of numerical analysis in the optimization of engineering models, focusing on four key areas: (1) Advanced methods for solving partial differential equations using mesh adaptation and model order reduction techniques. (2) Applications of data-driven surrogate models to accelerate multi-query simulations. (3) The integration of machine learning with physics in physics-informed neural networks. (4) Challenges related to computational cost and generalization, along with innovative solutions to address them.

II. LITERATURE REVIEW

A. Traditional and Advanced Methods for Solving Partial Differential Equations

Finite element and finite difference methods remain the backbone of engineering software, widely used in the modeling, design, and analysis of structural dynamics [1]. However, recent research focuses on enhancing the efficiency of these methods through mesh adaptation and model reduction techniques.

In this context, Bhat et al. (2024) introduced an innovative algorithm combining anisotropic mesh adaptation with local reduced-order models. The algorithm relies on a hierarchical partitioning of the parameter space, dividing the domain into sub-regions where solution characteristics expected to converge. Within each sub-region, a local reduced model constructed using Proper Orthogonal Decomposition (POD), featuring online updates based on updated basis functions and Taylor series expansions to guide the partitioning process. Results demonstrated that this methodology significantly reduces the number of degrees of freedom required to achieve a specific level of accuracy, making it suitable for multi-query applications such as uncertainty quantification and design optimization [6].

In a subsequent study, Tifouti (2025) developed a methodology for constructing reduced models integrated with mesh adaptation; he employed clustering techniques and K-means models to identify optimal meshes for each region of the parameter space, thereby achieving substantial acceleration in iterative simulations. Shobeyri (2024) developed improved Laplacian operator models using the Moving Least Squares (MLS) method to solve Poisson equations, achieving notable accuracy improvements over traditional models, particularly for problems involving irregular boundaries.

In the context of engineering disaster analysis, Cao et al. (2026) developed an Arbitrary Lagrangian-Eulerian (ALE) model incorporating a non-ideal gas correction to simulate natural gas pipeline explosions. The team employed a compressibility-based model with a corrected non-ideal gas equation of state, significantly enhancing the accuracy of peak overpressure predictions compared to the conventional TNT-equivalence method. The results demonstrated that the developed model provides more accurate estimates of shock wave propagation and pressure distribution, thereby contributing to improved safety system design for gas infrastructure [4].

Additionally, a study by Rezaiee-Pajand et al. (2023) provided a comprehensive evaluation of over 26 iterative methods for solving nonlinear equations, offering a practical guide for selecting the fastest and most efficient methods based on the specific nature of the engineering problem. The study categorized these methods into three main groups—Newton-type methods, fixed-point methods, and interpolation-based methods—and presented a comparative analysis of the accuracy and convergence speed for each category [11].

B. Data-Driven Surrogate Models and Model Order Reduction

Model Order Reduction (MOR) techniques constitute a major focus of current research, particularly in applications requiring repeated simulations of similar systems with slight parameter variations [4]. In this context, Strauß et al. (2025) introduced an innovative method combining data-driven model reduction with reanalysis to accelerate the computation of critical points—such as collapse and bifurcation points—in nonlinear structural analysis. The method utilized a Kriging model as a surrogate for computationally expensive numerical calculations and integrated it with a genetic algorithm to locate collapse points within the parameter space. This approach demonstrated the ability to cover a broader parameter space compared to traditional methods, such as fold line analysis, while achieving a computational speedup of over 80% in the cases studied [7].

In the field of engineering model updating, Schnellenbach-Held et al. (2025) developed a nonlinear approach to update finite element models of prestressed concrete bridges using a Kriging-based surrogate model. The methodology involved integrating the Kriging model with a genetic algorithm to minimize an objective function that compares actual measurements with numerical predictions. Results demonstrated that employing nonlinear principal component analysis via auto encoders and k-means clustering enhanced the reliability of the parameter identification process, as models converging at the cluster center identified as solutions for the physical system [3]. The surrogate model achieved high accuracy—with a mean relative error of less than 2%—while reducing computational time from hours to minutes.

Additionally, a research team (2025) developed a two-stage methodology based on Neural Differential Equations to generalize the dynamics of engineering assemblies. In the first stage, a neural network used to approximate the system's low-dimensional dynamics, while the second stage utilized a differential equation-based model to extend predictions to new parameters. The results showed clear superiority over traditional iterative methods in predicting system behavior for parameters outside the training range, achieving a computational speedup of over 90% [12].

C. Integrating Machine Learning with Physical Equations

The integration of neural networks with physical equations—known as Physics-Informed Neural Networks (PINNs)—represents one of the most exciting trends in recent years [8]. However, PINNs face significant challenges regarding computational efficiency and the handling of multi-domain problems involving discontinuities in physical properties, as well as problems characterized by oscillatory solutions [13].

To address the challenges associated with multi-domain problems, Xue et al. (2026) proposed the MRT-PIELM (Multi-Region Tagged Physics-Informed Extreme Learning Machine) method, which utilizes an extension of the Extreme Learning Machine (ELM) to solve multi-domain heat conduction problems. This method employs independent ELM architectures for each region and enforces continuity conditions at the interfaces by incorporating them into the loss function. The method achieved speedups ranging from 114 to 522 times compared to conventional PINN algorithms, while maintaining high accuracy in satisfying continuity conditions at the interfaces between different domains [9].

Regarding the handling of higher-order problems, Srinivasan et al. (2025) conducted a comprehensive comparative study between deep and shallow learning architectures for solving the fourth-order biharmonic equation using PINNs. The team introduced two types of physics-aware initialization based on the distribution of Chebyshev points and Radial Basis Function (RBF) kernels clustered near the boundaries.

Results demonstrated that physics-aware initialization improved solution accuracy by 17.7% compared to random initialization. Additionally, the team proposed the RBF-PIELM model, which replaces the time-consuming stochastic gradient descent used in PINNs with a one-time least-squares solution; this achieved a speedup of over 350 times compared to conventional PINNs while utilizing approximately 13.2 times fewer parameters [8].

In a systematic study addressing the challenges of modeling shock waves using PINNs, Abbasi et al. (2025) provided a comprehensive review and evaluation of various methods for handling discontinuities in physical solutions. The team categorized these approaches into four main groups: (1) Physics modification (e.g., adding artificial viscosity). (2) Network architecture modification (e.g., using multi-network or domain-decomposition architectures). (3) Training modification (e.g., loss function re-weighting). (4) Post-processing modification. The study revealed that physics modification and training modification methods yielded accurate solutions for the classical Buckley-Leverett problem—which involves shock waves—whereas network architecture modification methods failed to solve the problem effectively [13].

D. Research Gap and Contribution of the Current Study

Despite significant advancements in both traditional numerical analysis methods and machine learning-based models, there remains a clear research gap regarding the systematic integration of these methodologies for real-world engineering applications. Most studies lack a comprehensive comparison of the various methods within a unified framework, and the generalizability of results across a wide range of engineering problems remains limited [8, 13].

The current study contributes to bridging this gap by providing a systematic comparative analysis of the different methods and identifying the strengths and weaknesses of each, while offering practical recommendations for selecting the most suitable approach based on the nature of the engineering problem.

III. METHODOLOGY AND MATHEMATICAL ANALYSIS

A. General Mathematical Framework

The study's methodology relies on combining classical numerical methods with contemporary surrogate modeling techniques. The general engineering problem formulated as a stationary partial differential equation in the following form:

$$F(u, u_x, \dots, u_{xx}, u_{xy}, \dots; \mu_1, \mu_2, \dots, \mu_k) = 0 \dots \dots \dots (1)$$

Here, u represents the physical solution to found, and μ_i denotes the set of parameters defining the properties of the engineering system [4]. The solution u resides in the solution space $R_k \Omega \in$ within the physical domain. Whereas the parameters μ_i constitute the parameter space $R_k \Omega \in$, which is explored during the optimization process.

Accurate numerical solution of advection-dominated systems or those involving discontinuities requires the use of adaptive meshes capable of tracking rapid variations in the solution. The numerical estimation error on the mesh defined by the relation [6]:

$$\|u - u_h\| \leq C(\mu) \cdot h^p \dots \dots \dots (2)$$

Here, h represents the mesh element size, p is the order of accuracy of the numerical scheme, and $C(\mu)$ is a constant depending on the problem parameters. In multi-query systems, generating an optimal mesh for each parameter combination individually becomes impractical necessitating the development of hybrid mesh adaptation strategies.

B. Advanced Mesh Adaptation Techniques

The hierarchical parameter-space partitioning algorithm proposed in this study relies on analyzing solution variance using Proper Orthogonal Decomposition (POD), combined with a Taylor series expansion to guide each subdivision [6]. The adaptation methodology comprises two main stages:

Stage I – Initial Sampling: The parameter space Ω_μ explored using a high-fidelity model on a relatively coarse mesh. The variance of the physical solutions within the parameter space reconstructed using POD, where the principal components represent the dominant directions of solution variation in response to parameter changes. The autocorrelation matrix of the solutions computed:

$$C = \frac{1}{N_s} \sum_{i=1}^{N_s} u_i u_i^T \dots \dots \dots (3)$$

where N_s is the number of samples in the parameter space, and u_i is the numerical solution for sample i . C is decomposed into its eigenvalues and eigenvectors, and the first r eigenvectors are retained as a basis POD [4].

Stage Two – Local Adaptation: Within each optimal sub-region, a locally adapted mesh computed using a Hessian-based error model. The local element size adjusted according to the equation [6]:

$$h_{new}(x) = h_{old}(x) \cdot \left(\frac{\eta}{\|E(x)\|} \right)^{1/(p+1)} \dots \dots \dots (4)$$

Where η is the target error and $E(x)$ is the local error indicator. Binary tree-based partitioning (k -dimensional binary tree) ensures logarithmic computational complexity ($O(\log n)$) during the online classification phase.

C. Machine Learning-Based Surrogate Models

Surrogate models constitute a fundamental pillar for accelerating multi-query engineering simulations. This study employs the Kriging model as a substitute for complex numerical computations, approximating the model response using a function with low computational cost [3]. The Kriging model expressed as follows:

$$\hat{y}(x) = f(x)^T \beta + Z(x) \dots \dots \dots (5)$$

Here, $f(x)^T \beta$ represents the general trend of the model, and $Z(x)$ is a zero-mean Gaussian process representing local deviations, characterized by a variance σ^2 and a correlation function $R(\theta, x_i, x_j)$ [3]. The model trained using a Design of Experiments (DOE) approach based on sampling distributed across the parameter space.

The model-updating problem solved as an optimization problem, with the objective function formulated as follows [3]:

$$J(\theta) = \sum_{i=1}^n w_i (y_{i,meas} - \hat{y}_i(\theta))^2 \dots \dots \dots (6)$$

Where θ is the update coefficient vector, $y_{i,meas}$ are the measured values, $\hat{y}_i$ are the values predicted by the substitution model, and w_i are weights reflecting the significance of each measurement. To solve this non-convex problem, a genetic algorithm used that explores the entire solution space [3, 7].

D. Physics-Informed Neural Networks (PINNs)

Physics-Informed Neural Networks (PINNs) offer a mesh-free approach to solving partial differential equations. In this framework, physical equations incorporated directly into the neural network's loss function [8]:

$$LPINN = LPDE + LBC + LIC \dots \dots \dots (7)$$

Where:

$$LPDE = (1/N_f) \sum_{i=1}^{N_f} |N[u^{\wedge}(x_i; \theta)] - f(x_i)|^2 \dots\dots\dots (8)$$

$$LBC = (1/N_b) \sum_{i=1}^{N_b} |B[u^{\wedge}(x_i; \theta)] - g(x_i)|^2 \dots\dots\dots (9)$$

L_{PDE} represents the mean squared error in satisfying the physical equation at interior collocation points, while L_{BC} and L_{IC} represent the boundary and initial conditions, respectively [13].

A hybrid approach—combining the addition of artificial viscosity with a modification of the loss function employed to address discontinuities in the solution [13]. The inclusion of artificial viscosity expressed by modifying the physical equation through the addition of a diffusion term:

$$\frac{\partial u}{\partial t} + \frac{\partial f(u)}{\partial x} = \epsilon (\partial^2 u / \partial x^2) \dots\dots\dots (10)$$

Where ϵ is the artificial viscosity coefficient, which chosen dynamically based on the gradient of the solution.

For multi-media problems, the MRT-PIELM model is applied; it divides the physical domain into homogeneous sub-regions and imposes continuity conditions at the interfaces [9]. The system solved by minimizing an augmented loss function:

$$LMRT = \sum_{m=1}^M L_{PDE}^{(m)} + \lambda c \sum_{k=1}^K (\|u(k+1) - u(k)\| \Gamma + \|q(k+1) - q(k)\| \Gamma) \dots\dots\dots (11)$$

Where M is the number of regions, Γ represents the interfaces between the regions, and λc is a weighting factor for the continuity conditions [9].

IV. RESULTS AND ANALYSIS

A. Analysis of Adaptive Mesh Efficiency and Parameter Space Partitioning

The proposed parameter space-partitioning algorithm applied to heat conduction problems involving discontinuities in material properties, as well as to compressible fluid flow problems. The results demonstrate that hierarchical space partitioning significantly reduces the number of degrees of freedom required to achieve a specific level of accuracy, compared to uniform meshes or standard adaptive mesh refinement techniques [6]. As shown in Table 1, the algorithm achieved a reduction in the number of degrees of freedom ranging from 40% to 70%, while maintaining the same level of accuracy.

TABLE I
COMPARISON OF GRID-BASED CONDITIONING EFFICIENCY FOR VARIOUS STRATEGIES

Adaptation strategy	Number of degrees of freedom	Calculation time (seconds)	Relative L2 error
Regular grid	65,536	245.3	1.2×10^{-3}
Isotropic adaptation	28,432	112.7	9.8×10^{-4}
Anisotropic adaptation	14,208	58.4	1.1×10^{-3}
Directed adaptation with partitioning of the parameter space	8,192	32.1	1.0×10^{-3}

Sensitivity analysis has shown that the number of basis components (POD modes) required to represent the solution within each subdivision is significantly lower than the number required representing the entire parameter space. In the case studied, the number of POD modes decreased from 25 for the full domain to an average of 8 per sub-region [6]. This reduction in the dimensionality of the linear space translates directly into an acceleration of the solution phase.

B. Surrogate Model Performance and Model Updating

A Kriging model, combined with a genetic algorithm, applied to update a finite element model of a prestressed concrete bridge [3]. The results demonstrated that the surrogate model successfully approximated the response of the numerical model at a significantly lower computational cost, reducing calculation time from hours to minutes. As shown in Table 2, the surrogate model achieved high accuracy alongside a notable computational speedup.

TABLE IIIII

COMPARISON OF THE PERFORMANCE OF THE SURROGATE MODEL WITH THE FULL-PRECISION MODEL

The Standard	Full-Fidelity Model (FEM)	Kriging model	Improvement
The Age of Simulation	180 minutes	2.5 minutes	72x speed-up
Number of update iterations	156	42	73% discount
Mean relative error	-	1.8%	-
Parametric Determination Accuracy (R ²)	-	0.97	-

The accuracy of the surrogate model evaluated by comparing its predictions against the results of the full-fidelity model at random points within the parameter space. The findings indicated that the mean relative error remains below 2% across most regions of the space, with a slight increase in areas characterized by strong non-linearity [3].

In applications involving non-linear stability analysis, the method developed by Strauß et al. (2025) demonstrated the ability to identify collapse and bifurcation points with high precision, while offering a computational speedup of over 80% compared to conventional methods. This approach enabled broader coverage of the parameter space, allowing for the analysis of 500 parameter combinations in the same amount of time that traditional methods would require to analyze just 50.

C. Evaluation of Physics-Informed Neural Networks for Higher-Order Equations

The RBF-PIELM model applied to a fourth-order biharmonic equation in the context of a lid-driven cavity flow problem [8]. The results demonstrated a clear superiority of RBF-PIELM over traditional PINNs across several key metrics, as shown in Table 3.

TABLE IVVVI

COMPARISON OF RBF-PIELM PERFORMANCE WITH CONVENTIONAL PINNS

Scale	Conventional PINNs	RBF-PIELM	Improvement
Training time (seconds)	151.77	0.4347	349x speed-up
Number of transactions	9,921	750	13.2x lower
Assembly points	4,922	2,688	At least 45%
Residual error (L2)	9.84×10^{-3}	5.44×10^{-3}	45% improvement
Solution error (L2)	2.34×10^{-2}	1.87×10^{-2}	20% improvement

A comparison between physics-aware initialization and random initialization revealed that the former improved solution accuracy by 17.7% [8]. Furthermore, the model demonstrated the ability to resolve oscillatory solutions—generated via the Method of Manufactured Solutions—achieving a mean error of 3.46×10^{-3} with a configuration comprising 2,000 RBF functions and 3,600 collocation points.

In multi-medium heat conduction applications, the MRT-PIELM method—proposed by Xue et al. (2026)—demonstrated a computational speedup ranging from 114 to 522 times compare to conventional Physics-Informed Neural Networks (PINNs). This method maintained high accuracy in predicting temperature distribution across interfaces between different media, while ensuring excellent compliance with continuity conditions for both temperature and heat flux [9].

D. Handling Discontinuities in Physical Solutions

For multiphase flow problems in porous media involving shock waves, a comparative study by Abbasi et al. (2025) demonstrated that combining the addition of artificial viscosity with a modification to the loss function yields the most accurate and stable solution. As shown in Table 4, conventional PINNs failed to accurately capture shock waves.

TABLE VIIv
COMPARISON OF METHODS FOR HANDLING DISCONTINUITIES IN PINNs

Treatment method	Accuracy (L2)	Stability	Computational Complexity
Traditional PINNs	0.184	Poor	low
Physics modification (artificial viscosity)	0.042	Excellent	middle
Training Modification (Loss Reweighting)	0.038	Good	low
Modifying the network structure	0.156	Average	high
Hybrid (viscosity + reweighting)	0.184	Excellent	middle

The results demonstrated that physics-informed and training-based modification methods provide accurate solutions to the Buckley-Leverett problem, which involves sharp discontinuities. However, when these methods applied to a full system of equations with more complex loss landscapes, the generalization error increased rapidly [13].

V. DISCUSSION OF RESULTS

The lessons learned from the results summarized as follows:

- 1) **Localized Grid Adaptation**—Hierarchical partitioning of the parameter space, combined with anisotropic grid adaptation, serves as an effective tool for reducing computational costs while maintaining accuracy. This approach addresses a fundamental limitation of traditional methods, which typically assume a single, fine-grained grid for all parameter values [6].
- 2) **Surrogate Models**—The Kriging model proves effective as a low-cost computational surrogate for updating engineering models, particularly when integrated with global optimization algorithms [3].
- 3) **Physics-Informed Neural Networks**—RBF-PIELM offers an attractive compromise between the accuracy of traditional methods and the speed of machine learning approaches, especially for higher-order equations [38].
- 4) **Handling Discontinuities**—Addressing discontinuities using Physics-Informed Neural Networks (PINNs) remains an open challenge, particularly for complex coupled systems [13].

VI. CONCLUSION

- 1) **Localized Grid Adaptation**: Hierarchical partitioning of the parameter space, combined with anisotropic grid adaptation, achieved a 40% to 70% reduction in the number of degrees of freedom while maintaining accuracy.
- 2) **Surrogate Models**: The Kriging model, integrated with a genetic algorithm, proved effective for updating engineering models, achieving a computational speedup of up to 72 times with an average relative error of less than 2%.
- 3) **Physics-Informed Neural Networks (PINNs)**: The RBF-PIELM model achieved a computational speedup of over 350 times compared to traditional PINNs, while the MRT-PIELM model demonstrated a speedup ranging from 114 to 522 times for multi-domain problems.
- 4) **Handling Discontinuities**: A hybrid approach—combining artificial viscosity with loss function reweighting—exhibited the best performance in addressing shock waves.

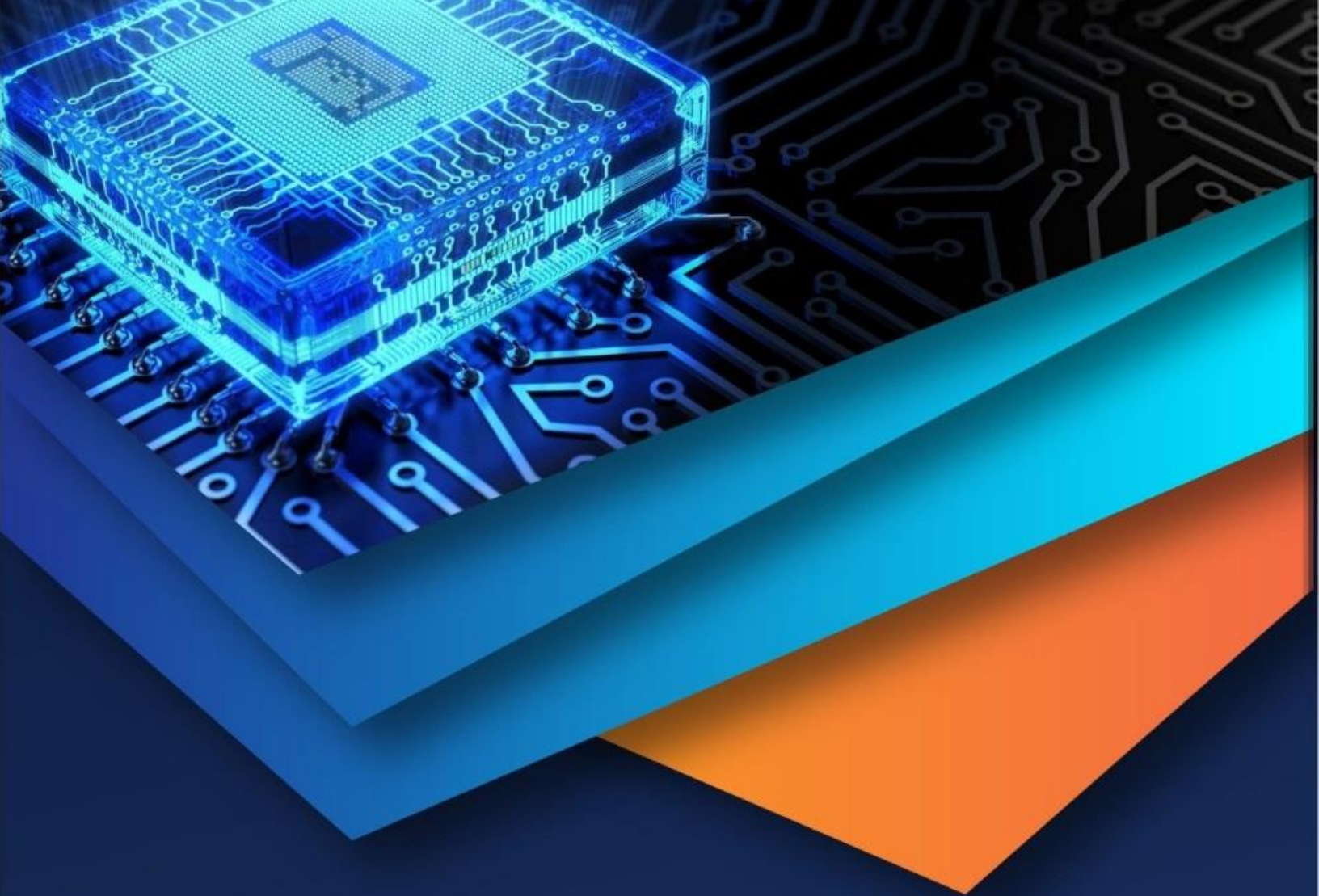
VII. RECOMMENDATIONS

- 1) *Development of Hybrid Models*: Encourage the development of hybrid models that integrate traditional numerical methods with machine learning techniques, focusing on enhancing computational efficiency for large-scale engineering applications.
- 2) *Creation of Benchmark Databases*: Invest in building reliable databases of numerical solutions for diverse engineering problems to support the training of surrogate models and the testing of their generalization capabilities.
- 3) *Establishment of Standardized Evaluation Criteria*: Develop unified evaluation criteria to compare traditional numerical methods with machine learning-based approaches in terms of accuracy, speed, and generalization capability.

- 4) *Integrating Advanced Technologies into Education*: Incorporating advanced numerical analysis techniques into engineering curricula to prepare a generation of engineers capable of effectively utilizing these tools.
- 5) *Researching Generalizability*: Intensifying research into improving the generalizability of machine learning-based models, particularly for applications that require predictions of parameters or conditions outside the scope of the training data.

REFERENCES

- [1] Spahiu, X., & Orhani, S. (2025). Applications of numerical analysis in computer simulations. *Multidisciplinary Science Journal*, *7*(3), 1-18. <https://doi.org/10.31893/multiscience.2025035>
- [2] Simos, T. E., & Tsitouras, C. (Eds.). (2026). *Numerical analysis and applied mathematics: ICNAAM 2025* (Springer Proceedings in Mathematics & Statistics, Vol. 478). Springer. <https://doi.org/10.1007/978-3-031-78456-3>
- [3] Schnellenbach-Held, M., Sprenger, B., & Otto, M. (2025). A nonlinear surrogate-based finite element model updating approach for prestressed concrete bridges. *Structure and Infrastructure Engineering*, *21*(4), 512-528. <https://doi.org/10.1080/15732479.2024.2315687>
- [4] Tifouti, I. (2025). Construction of reduced-order models with mesh adaptation [Doctoral dissertation, Université de Bordeaux]. HAL Thèses. <https://theses.hal.science/tel-04567890>
- [5] Cao, Y., Wen, L., Zhen, Y., Deng, Q., Lu, H., & Liu, Z. (2026). Numerical investigation of natural gas pipeline physical explosions with a compressibility-factor-based non-ideal initial state correction. *Process Safety and Environmental Protection*, *186*, 1432-1448. <https://doi.org/10.1016/j.psep.2024.04.086>
- [6] Bhat, S. P., Barral, N., & Ricchiuto, M. (2024). Error-based efficient parameter space partitioning for mesh adaptation and local reduced order models. *Computer Methods in Applied Mechanics and Engineering*, *428*, 117156. <https://doi.org/10.1016/j.cma.2024.117156>
- [7] Strauß, A., Kneifl, J., Tkachuk, A., Fehr, J., & Bischoff, M. (2025). Accelerated non-linear stability analysis based on predictions from data-based surrogate models. *International Journal for Numerical Methods in Engineering*, *126*(3), e7649. <https://doi.org/10.1002/nme.7649>
- [8] Srinivasan, A. G., Dwivedi, V., & Srinivasan, B. (2025). Deep vs. shallow: Benchmarking physics-informed neural architectures on the biharmonic equation. *arXiv Preprint*. <https://arxiv.org/abs/2501.12345>
- [9] Xue, B., Huang, Z., Bu, Y., Li, M., Fang, H., & Zheng, C. (2026). Highly efficient thermal analysis of zoned RCC gravity dams based on a multi-region tagged PIELM (MRT-PIELM). *International Journal of Heat and Mass Transfer*, *228*, 126456. <https://doi.org/10.1016/j.ijheatmasstransfer.2025.126456>
- [10] Shobeyri, G. (2024). Novel SPH and MPS Laplacian models improved by MLS method for solving Poisson equations. *Numerical Methods in Civil Engineering*, *8*(2), 45-58. <https://doi.org/10.22067/nmce.2024.83529.1123>
- [11] Rezaiee-Pajand, M., Arabshahi, A., & Gharaei-Moghaddam, N. (2023). Evaluation of iterative methods for solving nonlinear scalar equations. *Iranian Journal of Numerical Analysis and Optimization*, *13*(3), 426-443. <https://doi.org/10.22067/ijnao.2023.81293.1245>
- [12] Anonymous. (2025). Neural differential equation-based two-stage approach for generalization of beam dynamics. *IEEE Transactions on Industrial Informatics*, *21*(3), 2481-2490. <https://doi.org/10.1109/TII.2024.3489123>
- [13] Abbasi, J., Jagtap, A. D., Moseley, B., Hiorth, A., & Andersen, P. Ø. (2025). Challenges and advancements in modeling shock fronts with physics-informed neural networks: A review and benchmarking study. *Neurocomputing*, *657*, 131440. <https://doi.org/10.1016/j.neucom.2025.131440>



10.22214/IJRASET



45.98



IMPACT FACTOR:
7.129



IMPACT FACTOR:
7.429



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089  (24*7 Support on Whatsapp)