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Physics-Informed Neural Networks in Aerospace: A Structured Taxonomy with Literature Review

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Purpose. This study aims to develop a structured four-tier taxonomy that systematically organizes aerospace engineering tasks suitable for the application of Physics-Informed Neural Networks (PINNs), while validating this classification through a literature review and identifying opportunities for future research. **Design / Method / Approach.** The methodology involves grouping tasks into four distinct tiers—Physical Modeling, Dynamic Analysis, Functional Assessment, and System-Level Assessment—based on their physical, operational, and systemic characteristics. This framework is subsequently populated with real-world examples derived from the analysis of 145 peer-reviewed studies. **Findings.** The reviewed literature confirms a balanced distribution of PINNs applications across all tiers. Contrary to initial assumptions, studies were identified even in areas previously presumed underrepresented, such as acoustic modeling, optical simulations, and environmental impact assessment. This outcome reveals the broader applicability of PINNs and calls for a reassessment of current assumptions regarding underexplored domains. **Theoretical Implications.** The proposed taxonomy offers a coherent framework for structuring interdisciplinary PINNs applications by integrating physics-based modeling with machine learning across aerospace engineering contexts. **Practical Implications.** It provides engineers and researchers with a practical roadmap for selecting PINNs methods tailored to specific problem types, potentially improving computational efficiency and enhancing predictive accuracy in aerospace design and analysis. **Originality / Value.** The study's originality lies in its empirically validated, four-tier taxonomy that synthesizes the fragmented body of literature on PINNs in aerospace, offering a unified perspective for researchers and practitioners. **Research Limitations / Future Research.** While the taxonomy covers a wide range of existing applications, future studies should consider extending it with new tiers—particularly related to manufacturing-aware modeling—and pursue methodological standardization to ensure reproducibility and scalability. **Article Type.** Review.

Keywords:

Physics-Informed Neural Networks (PINNs), aerospace engineering, machine learning, mathematical simulation, flight vehicles, aerospace design

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Мета. Це дослідження має на меті розробити структуровану чотирирівневу таксономію, яка систематично впорядковує задачі аерокосмічної інженерії, придатні для застосування Physics-Informed Neural Networks (PINNs), водночас забезпечуючи верифікацію такої класифікації через огляд літератури та виявлення потенціалу для подальшого розвитку. **Дизайн / Метод / Підхід.** Методологія ґрунтується на групуванні задач за чотирма рівнями — Фізичні, Динамічні, Функціональні та Системний аналіз — відповідно до їхніх фізичних, операційних і системних характеристик. Після цього здійснено аналіз 145 рецензованих джерел, що дозволило заповнити кожну категорію реальними прикладами застосування PINNs. **Результати.** Рецензована література демонструє рівномірну представленість усіх рівнів таксономії. Наявність підтверджених застосувань PINNs навіть у раніше недооцінених напрямах, зокрема акустиці, оптиці та екологічному моделюванні, свідчить про широку сферу охоплення методу та вимагає переосмислення поточних уявлень про межі його застосування. **Теоретичне значення.** Запропонована таксономія надає інструмент систематизації міждисциплінарних застосувань PINNs, інтегруючи фізичне моделювання з машинним навчанням у контексті складних інженерних задач. **Практичне значення.** Таксономія забезпечує дослідників практичним орієнтиром для вибору PINNs залежно від типу задачі, підтримуючи ефективність обчислень та підвищуючи якість прогнозування у процесах аналізу та проєктування в аерокосмічній галузі. **Оригінальність / Цінність.** Унікальність роботи полягає в побудові та емпіричній перевірці цілісної чотирирівневої таксономії застосування PINNs, що дозволяє системно охопити актуальні дослідження у галузі, замість фрагментарного представлення, притаманного попереднім оглядам. **Обмеження дослідження / Майбутні дослідження.** Незважаючи на повноту охоплення, подальші дослідження мають бути спрямовані на інтеграцію нових рівнів, зокрема пов'язаних із виробничими параметрами, а також на стандартизацію методологій для забезпечення відтворюваності та масштабованості PINNs. **Тип статті.** Огляд.

Ключові слова:

фізично-інформовані нейронні мережі (PINNs), аерокосмічна інженерія, машинне навчання, математичне моделювання, літальні апарати, аерокосмічне проєктування

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Aerospace engineering faces complex modeling challenges, from turbulent flows around hypersonic wings to thermal loads on satellite structures. Conventional methods, such as finite elements or computational fluid dynamics, provide accuracy but demand significant computational resources and time, slowing down design phases. Physics-Informed Neural Networks (PINNs) offer an alternative, embedding physical equations, like Navier–Stokes or conservation laws, directly into the loss function of neural networks, enabling faster results while maintaining physical fidelity.

Physics-Informed Neural Networks (PINNs) occupy a distinct position within the framework of Scientific Machine Learning (SciML), falling under the category of Physics-Informed Methods. They are distinguished by their integration of differential equations into the loss function of a neural network, ensuring a rigorous incorporation of physical laws compared to other approaches, such as Physics-Guided Neural Networks (PGNNs), which utilize physics in a less formal manner. In contrast to Physics-Constrained Neural Networks (PCNNs), PINNs focus specifically on differential equations rather than broader physical constraints, such as energy conservation. As a subset of Neural ODE/PDE Solvers, PINNs specialize in solving differential equations, though not all solvers qualify as PINNs, as some may rely entirely on data-driven techniques.

In the broader context of SciML, PINNs constitute a formalized segment of Physics-Augmented Machine Learning, explicitly leveraging physical equations. They can serve as Surrogate Models, approximating complex simulations, but not all surrogate models are PINNs, as many do not incorporate physics. Similarly, PINNs may form components of Hybrid Physics-AI Models or Digital Twins, yet these categories are more expansive, encompassing methods that do not necessarily rely on neural networks or differential equations. Thus, PINNs represent a specialized tool that combines the rigor of physical principles with the flexibility of machine learning, carving out a niche within the SciML classification.

Therefore, Physics-Informed Neural Networks (PINNs) represent an innovative approach that integrates physical laws, expressed as differential equations, into the training of neural networks by incorporating these equations into the loss function, ensuring physically consistent predictions even with limited data (Karniadakis et al., 2021; Farea et al., 2024; Meng & Karniadakis, 2020;). This method enables PINNs to model complex phenomena, such as turbulence or thermal loads, with high accuracy, making them valuable for resource-intensive fields like aerospace engineering (Raissi et al., 2019; Cai et al., 2021; Faroughi et al., 2024; Zhao et al., 2024). By embedding physics directly, PINNs offer a powerful alternative to traditional computational methods, yet their broad application requires a systematic framework to identify optimal use cases. In the methodology section, we detail our approach to developing a taxonomy that organizes aerospace tasks suitable for PINNs, leveraging literature to validate and refine this classification.

To provide a more comprehensive explanation of the capabilities of Physics-Informed Neural Networks (PINNs), attention will be given to the content of the referenced sources. In a review article by Karniadakis et al. (2021), a systematic analysis of approaches to integrating fundamental physical laws into artificial intelligence models is presented. Particular emphasis is placed on the application of these integrated models to address complex engineering problems. The article primarily focuses on PINNs, a class of neural networks that incorporate physical laws, such as differential equations, directly into their training process. This approach enables models to adhere to fundamental physical constraints even in the presence of incomplete or inaccurate data. Specifically, PINNs can be effectively utilized for modeling complex aerodynamic processes, heat transfer phenomena, structural mechanics problems, and other physical phenomena. The authors conclude that physics-informed machine learning, particularly PINNs, represents a highly promising direction for addressing a wide range of complex scientific and engineering challenges.

In a review study by Farea et al. (2024), a group of researchers conducted an in-depth analysis of PINNs as an interdisciplinary approach that integrates machine learning techniques with fundamental physical laws to tackle pressing scientific and technical problems. The authors focused on elucidating the essence of PINNs, thoroughly examining their foundational concepts and diverse architectures. Particular attention was devoted to the methodology of integrating physical principles into the neural network training process and identifying key challenges hindering the further development and broader adoption of this promising technology. Summarizing their findings, the authors concluded that PINNs serve as a powerful tool, effectively combining the advantages of data-driven machine learning with a deep understanding of physical processes. This enables the resolution of complex problems even under conditions of limited experimental data. However, several existing challenges were identified, including the high computational cost of training, the scarcity of high-quality data for certain applications, and the complexity of integrating sophisticated physical models. The authors emphasized the need for further research to overcome these obstacles and expand the scope of PINNs' applications across various scientific and engineering disciplines.

In an article by Meng & Karniadakis (2020), the authors extended the PINNs framework by proposing Multi-fidelity PINNs (MPINNs). The primary objective of the study was to develop a composite neural network capable of leveraging a combination of low- and high-fidelity data to approximate complex functions and solve inverse problems associated with partial differential equations. The enhanced architecture integrates the strengths of physical modeling with the capabilities of machine learning on data of varying quality. The proposed methods hold significant potential for applications in aerospace engineering, where high-fidelity experimental data are often limited, yet there is a critical need to account for fundamental physical laws in modeling complex aerospace systems and processes. The authors demonstrated that the developed composite neural network and MPINNs can effectively learn from a limited volume of high-fidelity data supplemented by a larger amount of low-fidelity data. This enables high accuracy in function approximation and the resolution of inverse problems related to partial differential equations. The proposed approach opens prospects for reducing reliance on costly experimental studies and enhancing the efficiency of modeling complex physical phenomena across various scientific and technical domains.

The primary objective of the study by Raissi et al. (2019) was to explore the feasibility of directly incorporating physical principles into the neural network training process to effectively solve problems governed by nonlinear differential equations. The key element of the presented research is the concept of Physics-Informed Neural Networks (PINNs). In their conclusions, the authors underscored that PINNs are a highly effective tool for addressing both forward (predicting system behavior given known parameters) and inverse (determining unknown system parameters based on observations) problems described by nonlinear differential equations.

In an article by Cai et al. (2021), the authors investigated the potential of PINNs for solving heat transfer problems, which are traditionally considered challenging for numerical methods. These problems include cases with incomplete boundary conditions, limited experimental data, or complex physical behavior. Specifically, in the context of forced and mixed convection problems, PINNs demonstrated a significant ability to reproduce temperature and flow velocity distributions, even under conditions of incomplete boundary information. Notably, the developed models maintained stability and exhibited high predictive accuracy while relying on a limited amount of input data. Furthermore, the effectiveness of PINNs was validated for solving classical two-phase Stefan problems related to phase transition processes, such as melting or solidification. In these scenarios, the models accurately predicted not only the position of the moving phase boundary but also the temperature profiles in each phase. This capability is highly valuable, as traditional numerical methods often encounter significant difficulties in modeling such problems. Additionally, successful applications in analyzing thermal processes in power electronics were presented, highlighting the growing maturity of the methodology and its readiness for practical implementation in addressing pressing engineering challenges.

In a scientific paper by Faroughi et al. (2024), a group of researchers reviewed four primary approaches to integrating fundamental physical knowledge into artificial neural networks: Physics-Guided Neural Networks (PgNNs), Physics-Informed Neural Networks (PiNNs), Physics-Encoded Neural Networks (PeNNs), and Neural Operators (NOs). The authors analyzed the application of these methods in the context of scientific computing, particularly in critical domains such as fluid and solid mechanics. Although the article's primary focus was not exclusively on the aerospace sector, the authors highlighted the significant relevance of the discussed methods for aerospace engineering. Specifically, they noted their potential for modeling fluid and solid mechanics, which is critically important in the design and analysis of various aerospace systems and components. Summarizing their findings, the authors concluded that integrating physical knowledge into neural networks significantly enhances the accuracy and reliability of developed models, particularly in scenarios with limited experimental data.

The study by Zhao et al. (2024) focused on analyzing advancements in PINNs, with an emphasis on their application to modeling complex hydrodynamic processes. The authors concluded that PINNs demonstrate significant potential for addressing complex hydrodynamic problems. However, several challenges were identified, including ensuring model accuracy, computational efficiency, and the ability to generalize results to new, previously unseen scenarios. The authors underscored the need for further intensive research to overcome these barriers and develop standardized benchmark problems specifically designed to evaluate the effectiveness of PINNs in complex hydrodynamic scenarios.

However, the practical application of PINNs in flight vehicle design remains fragmented — researchers demonstrate successes in specific tasks like aerodynamics, structural integrity, or control systems, but lack a consistent classification of effective application domains. This absence of systematic organization raises questions: which physical, dynamic, functional, or system-level tasks in aerospace design are best suited for PINNs, and where do the greatest research gaps lie?

This article addresses these challenges by proposing a comprehensive four-tier taxonomy of PINNs applications in aerospace engineering. We group tasks into categories—Physical (aerodynamics, mechanics, thermodynamics), Dynamic (trajectories, ballistics, motion dynamics), Functional (control, optimization, identification, prediction), and System Analysis (validation, safety analysis, environmental impact). Each category is illustrated with examples from peer-reviewed publications, showing where PINNs have been successfully applied and where they remain underutilized, particularly in acoustic, optical, and environmental modeling. This first-of-its-kind taxonomy provides a clear roadmap for engineers and researchers, aids in optimizing method selection for specific tasks, and outlines directions for future research.

Aim and Objectives

The primary aim of this study is to conduct a comprehensive and systematically structured literature review on the applications of Physics-Informed Neural Networks (PINNs) within aerospace engineering. This review employs a four-tier taxonomy – categorizing aerospace engineering tasks into Physical Modeling, Dynamic Analysis, Functional Evaluation, and System-Level Assessment – as a framework to classify and analyze existing research. By identifying key research directions, reported implementations, and recurring methodological challenges, this study aims to delineate the current state of research on PINNs in aerospace contexts and to outline substantiated directions for further investigation. To achieve this aim, the study pursues the following specific objectives.

1. To develop a four-tier taxonomy that classifies aerospace engineering tasks into four categories—Physical Modeling, Dynamic Analysis, Functional Evaluation, and System-Level Assessment—based on physical, operational, and systemic characteristics, thereby establishing a structured framework for analyzing the applicability of Physics-Informed Neural Networks (PINNs).

2. To perform a structured literature review of peer-reviewed studies by assigning real-world examples to each taxonomic category, in order to validate the taxonomy and to assess the extent and maturity of PINNs applications in aerospace engineering.

3. To identify research gaps by determining underrepresented or unexplored application domains, including but not limited to acoustic modeling, optical simulations, and environmental impact assessment.

4. To derive methodological and application-oriented insights that support the selection and implementation of PINNs for specific aerospace tasks, with emphasis on the integration of physics-based modeling and machine learning.

5. To synthesize the findings into a unified analytical framework that consolidates fragmented research on PINNs applications in aerospace engineering, enabling comparative assessment and promoting further optimization of computational and predictive performance. This structured approach ensures that the taxonomy not only serves as a theoretical contribution but also as a practical tool for advancing the application of PINNs in aerospace engineering, guiding both current practices and future investigations.

Methodology

This study implements a reproducible procedure for constructing a **four-tier taxonomy** of Physics-Informed Neural Networks (PINNs) applications in aerospace engineering. The methodology comprises three sequential stages.

1. Taxonomy Development

Based on a comprehensive review of aerospace engineering problems, four hierarchical categories were defined for the potential application of PINNs (see Figure 1):

– *Physical Modeling* (e.g., aerodynamics, heat transfer, structural strength),

– *Dynamic Analysis* (e.g., trajectory computation, ballistics, flight dynamics),

– *Functional Assessment* (e.g., control systems, operating-mode optimization, parameter identification),

– *System-Level Analysis* (e.g., model validation, reliability and safety assessment, environmental impact).

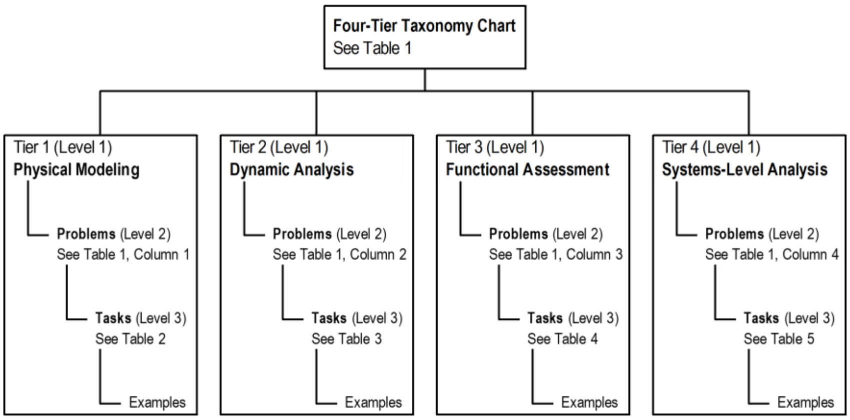

Figure 1 – Chart of the Four-Tier Taxonomy of PINNs Applications in Aerospace Engineering (Source: authors)

Classification criteria for each category took into account the governing physical conditions, the level of integration into complex technical systems, and the nature of PINNs-solvable problems. Tasks not matching any of these categories were excluded. The proposed four-tier taxonomy is presented in Table 1. Each tier in the taxonomy is further subdivided into task-specific layers, forming a structured three-layer hierarchy within each of the four tiers. A detailed breakdown of tasks classified under each Tier is presented in Tables 2–5.

2. Compilation of the Literature Corpus

Primary sources were selected via keyword queries derived from the developed taxonomy — using English terms (“Physics-Informed Neural Networks”, “PINNs”, “aerospace engineering”) — in the Scopus, Web of Science and other databases. Priority was given to articles published in peer-reviewed journals during 2019–2025 that provided detailed implementations of PINNs for aerospace or contextually analogous problems. Conference abstracts, review papers without original results, and publications lacking technical specificity were excluded.

3. Systematic Content Analysis

Each selected publication underwent a structured content analysis along four dimensions:

– *Nature of the problem studied* — identification of the specific physical or engineering challenge addressed, emphasizing mathematical formulation and application context.

– *PINNs implementation characteristics* — examination of the network configuration, including the governing equations incorporated, network architecture, and training strategy.

– *Relevance assessment for aerospace engineering* — evaluation of how the addressed problem, irrespective of its original domain, aligns with aerospace-specific requirements.

– *Authors' conclusions* — extraction of key findings, stated limitations, and proposed directions for future research.

This approach ensures a consistent evaluation of each research case, reveals prevailing application scenarios for PINNs, and highlights opportunities for their further integration into aerospace engineering.

Table 1 - Overview of the Four-Tier Taxonomy of PINNs Applications in Aerospace Engineering (Source: authors)

Tier 1. Physical Modeling	Tier 2. Dynamic Analysis	Tier 3. Functional Assessment	Tier 4. Systems-Level Analysis
Aerodynamic Problems	Ballistic and Trajectory Problems	Control and Navigation Tasks	Model testing and validation
Structural Problems	Motion-Dynamics Problems	Optimization Tasks	Safety-oriented physical condition modeling
Thermal Problems	Rigid-Body Motion Dynamics	Identification Tasks	Subsystem interaction modeling
Acoustic Problems		Prediction Tasks	Environmental variable prediction
Electromagnetic Problems			
Optical Problems			
Chemical and Thermochemical Problems			
Material–Environment Interaction Problems			
Multicomponent-System Problems			

Table 2 — Tasks (Level 3) within Tier 1: "Physical Modeling" by Category (Level 2) with Examples (Source: authors)

Task (Level 3)	Examples
Aerodynamic Problems (Level 2)	
Air-drag computation	estimation of aerodynamic drag forces acting on bodies in flow
Lift-force calculation	prediction of lift generated by wings or airfoils under given flow conditions
Turbulence modeling	simulation of turbulent flow structures and eddy viscosity distributions
Shock-wave calculation	resolution of discontinuities and pressure jumps in high-speed flows
Flow around a wing	detailed modelling of pressure and velocity fields adjacent to lifting surfaces
Flow-separation modelling	analysis of boundary-layer detachment from surfaces, prediction of stall onset and reattachment
Aerodynamic-moment computation	roll, pitch, yaw moments, determination of moments induced by pressure distributions
Interaction with control surfaces	flaps or ailerons, simulation of flow changes due to movable elements
Supersonic and hypersonic flow analysis	high-speed vehicles, capture of compressibility and high-enthalpy effects for
Structural Problems (Level 2)	
Stress–strain analysis in structures	prediction of internal stresses and deformations under load
Vibration and resonance modeling	identification of natural frequencies and mode shapes
Strength and stiffness calculation	assessment of load-bearing capacity and rigidity
Material failure simulation	modelling of crack initiation and propagation
Fatigue analysis	evaluation of structural durability under cyclic loading, lifetime prediction under repeated stresses
Contact mechanics between components	joint interfaces, analysis of stress transfer in connections
Elastic and plastic deformation computation	for non-linear materials, capture of permanent deformations
Stability assessment	buckling under compression, determination of critical loads for loss of equilibrium

Table 2 (continued)

Task (Level 3)	Examples
Thermal Problems (Level 2)	
Engine heat-transfer calculation	simulation of convective and conductive heat fluxes in propulsion systems
Thermal expansion modeling	prediction of deformation due to temperature changes
Cabin thermal-environment analysis	evaluation of temperature distribution for crew comfort and equipment safety
Acoustic Problems (Level 2)	
Engine noise prediction	simulation of sound-pressure levels generated by propulsion systems
Cabin acoustic field modeling	analysis of sound-wave propagation and attenuation inside compartments
Electromagnetic Problems (Level 2)	
Antenna-radiation calculation	prediction of far-field electromagnetic emissions
Engine electromagnetic-field modeling	simulation of fields in electric or hybrid propulsion units
Optical Problems (Level 2)	
Material optical-property computation	evaluation of refractive index, absorption, and scattering coefficients
Navigation-optics simulation	modelling of lens systems and imaging performance
Chemical and Thermochemical Problems (Level 2)	
Combustion-reaction modeling	fuel burn in jet engines, resolution of reaction kinetics and heat release
High-temperature thermochemical process calculation	atmospheric re-entry, prediction of gas-phase chemistry and energy exchange
Material–Environment Interaction Problems (Level 2)	
Corrosion-process modeling under atmospheric conditions	simulation of oxide-layer growth and material degradation
Radiation-damage analysis	for space applications, evaluation of material property changes under ionizing radiation
Multicomponent-System Problems (Level 2)	
Fluid–gas interaction in fuel systems	modelling of two-phase flows and mixing phenomena
Multicomponent-flow dynamics	fuel–oxidizer mixtures, prediction of mixture behavior under varying thermodynamic states

Table 3 — Tasks (Level 3) within Tier 2: "Dynamic Analysis" by Category (Level 2) with Examples (Source: authors)

Task (Level 3)	Examples
Ballistic and Trajectory Problems (Level 2)	
Flight-path simulation	computation of rocket, projectile, or UAV trajectories under gravity, drag, and other forces
Ballistic-coefficient analysis	determination of shape and atmospheric-condition effects on trajectory
Space-flight trajectory modeling	simulation of satellite or spacecraft motion in gravitational fields
Motion-Dynamics Problems (Level 2)	
Fluid-body interaction in motion	parachute descent or vehicle, prediction of drag-induced dynamics
Particle-dynamics analysis	study of particle motion in force fields, electromagnetic or gravitational
Rigid-Body Motion Dynamics (Level 2)	
Drag-induced trajectory simulation	descent paths of parachutes under varying drag coefficients
Hydrodynamic-load modeling	force distributions on vehicles in unsteady currents
Attitude-dynamics prediction	rotational response of bodies subjected to fluid-induced moments

Table 4 — Tasks (Level 3) within Tier 3: "Functional Assessment" by Category (Level 2) with Examples (Source: authors)

Task (Level 3)	Examples
Control and Navigation Tasks (Level 2)	
Flight-control algorithm development	design of control laws for stability and maneuvering
Flight-dynamics modeling	simulation of closed-loop aircraft response
Trajectory-optimization algorithms	course-correction strategies for aerial vehicles, minimization of fuel or time via optimal control
In-flight behavior modeling for navigation enhancement	prediction of vehicle states for guidance systems
Optimization Tasks (Level 2)	
Wing-shape optimization	for drag reduction, identification of aerodynamic geometries using driven solvers
Flight-path optimization	for fuel efficiency, optimal trajectory generation under mission constraints

Table 4 (continued)

Task (Level 3)	Examples
Identification Tasks (Level 2)	
Parameter estimation from experimental data	inverse problem solving to infer model parameters
Fault diagnostics in systems	detection and localization of anomalies via data-driven models
Prediction Tasks (Level 2)	
Material-degradation forecasting	remaining-useful-life estimation under operational loads
System-behavior prediction in extreme conditions	extrapolation of performance beyond tested regimes
Structural-lifetime prediction	time to failure or maintenance need, cycle-based durability assessment
Aerodynamic-characteristic prediction under variable conditions	altitude or speed changes
Thermal-load forecasting	during atmospheric re-entry, prediction of heat-flux time-histories

Table 5 — Tasks (Level 3) within Tier 4: "Systems-Level Analysis" by Category (Level 2) with Examples (Source: authors)

Task (Level 3)	Examples
Model testing and validation (Level 2)	
Physical-field reconstruction	pressure and stress fields from wind-tunnel or structural tests
Benchmark consistency verification	comparison of PINNs outputs with CFD/FEA (Computational Fluid Dynamics / Finite Element Analysis) results
Error and sensitivity quantification	approximation errors and sensitivity to boundary/initial conditions
Safety-oriented physical condition modeling (Level 2)	
Critical-state simulation	stress concentrations or thermal overload preceding failure
Operational-regime identification	PINNs-based detection of high-risk conditions within safe limits
Parametric safety modeling	variation of safety margins under uncertain loads or temperatures
Subsystem interaction modeling (Level 2)	
Coupled multi-domain simulation	joint aerodynamic–structural PINNs models
Thermo-mechanical interaction modeling	simultaneous loading and heating effects in components
Subsystem integration	unified PINNs framework for interacting sub-models
Environmental variable prediction (Level 2)	
Pollutant-field approximation	transport-equation-driven concentration in flow environments
Acoustic-field prediction	near-field engine noise distributions
Environmental-impact simulation	prediction of variables under modified boundary or operational conditions

Despite the structured approach adopted in this study, several limitations must be acknowledged. First, the taxonomy itself, while developed to comprehensively cover the principal categories of aerospace-related PINNs applications, cannot claim to be exhaustive. The domain of flight systems is inherently open-ended, with continually evolving configurations, mission profiles, and interdisciplinary problem formulations that may give rise to new application classes beyond the current classification.

Second, the literature review was necessarily constrained by practical considerations. Although the time window of 2019–2025 was selected to reflect the most active and relevant phase of PINNs development, it excludes earlier conceptual works and any recent studies that may not yet be indexed. Moreover, the taxonomy-driven search strategy, while systematic, may fail to capture publications whose titles and abstracts do not explicitly reflect the underlying physical or methodological relevance. As such, some relevant contributions may have been unintentionally omitted due to limitations in metadata exposure or terminological inconsistency.

These limitations do not diminish the validity of the taxonomy, or the findings derived from the literature analysis but should be considered when interpreting the scope and generalizability of the results.

Publications Related to Tier 1: Physical Modeling

This section reviews studies where Physics-Informed Neural Networks (PINNs) have been applied to model fundamental physical processes relevant to aerospace engineering. These tasks involve the solution of differential equations that govern fields such as pressure, temperature, stress, or electromagnetic intensity, typically under complex boundary and initial conditions.

The focus is on how PINNs are used to capture these phenomena with physical fidelity—without reliance on mesh-based discretization—and how they incorporate domain knowledge directly into the learning process. By examining representative works, the review highlights both established practices and unresolved challenges in applying PINNs to core physical modeling tasks.

Aerodynamic Problems

Muralidhar et al. (2019) proposed a methodology based on Physics- guided Deep Neural Networks (PhyDNNs), a subclass of Physics-Informed Neural Networks (PINNs), for modeling drag force on particles in moving fluids. By integrating physical priors into the network structure and utilizing aggregated supervision during the training process, their approach enhanced drag force prediction accuracy by 8.46% compared to traditional models, while maintaining physical consistency of the results. The findings demonstrate the effectiveness of PhyDNNs for accurate and interpretable modeling of complex hydrodynamic systems under limited data conditions, which holds significance for aerospace flow modeling tasks.

Mao at al. (2020) developed a PINN-based method for modeling supersonic flows governed by the Euler equations. Their research focused on both forward and inverse problems, including flows with shock waves and expansions. The PINNs accurately reproduced velocity and pressure fields in two-dimensional supersonic flows, specifically when modeling oblique shock waves and expansion waves, demonstrating high accuracy and physical fidelity even with limited data. This method confirms the effectiveness of PINNs for modeling complex high-speed flows in aerospace applications.

Ang and Ng (2022) developed a PINN model for predicting pressure and velocity fields during airfoil flow. This model integrates the Navier-Stokes equations and boundary conditions directly into the neural network's loss function. The model demonstrates accuracy comparable to that of traditional Computational Fluid Dynamics (CFD) methods, yet performs computations up to five times faster without requiring prior simulation or experimental data. This work underscores the potential of PINNs as an efficient surrogate model for accelerating aerodynamic design in aerospace engineering.

In their study, Jagtap et al. (2022) explored the application of PINNs and their extended version, XPINNs, for solving inverse problems in supersonic flows. The primary objective was to reconstruct density, pressure, and velocity fields using limited experimental data, such as density gradients obtained from Schlieren images, along with inlet and partial wall data. To achieve this, the authors integrated physical laws, specifically the Euler equations, entropy conditions, and positivity constraints for density and pressure, directly into the neural network's loss function.

In their study, Arzani et al. (2023) developed a novel architecture called BL-PINN (Boundary Layer Physics-Informed Neural Network). This architecture integrates perturbation theory and asymptotic expansions to effectively model thin boundary layers characterized by sharp gradients. BL-PINN demonstrates high accuracy in solving both forward and inverse problems, outperforming traditional PINNs and XPINN (eXtreme Physics-Informed Neural Network). Furthermore, it enables the generation of parametric solutions without the need for retraining. This approach effectively models boundary layer separation, thereby opening new possibilities for aerodynamic design.

Hanrahan et al. (2023) applied PINNs to model turbulent boundary layer flows with an adverse pressure gradient (APG) and over periodic hills. Their approach utilized the Reynolds-Averaged Navier–Stokes (RANS) equations, crucially without relying on traditional turbulence models. The PINNs accurately reproduced mean flow characteristics, such as shear stress and pressure, and were capable of inferring Reynolds stress fields directly, even with limited experimental data. While computational costs did not increase with rising Reynolds numbers, a reduction in accuracy was observed in separation zones due to data scarcity. This methodology demonstrates the potential of PINNs for efficient modeling of turbulent flows in aerodynamic analysis.

Sun et al. (2023) implemented an approach where PINNs simultaneously perform hydrodynamic modeling and geometric airfoil optimization, directly incorporating the Navier–Stokes equations. Instead of employing traditional adjoint analysis, the authors included shape parameters directly within the PINN's input space. This enabled the identification of optimal configurations without the need for separate optimization codes. The methodology demonstrated high accuracy in reproducing pressure and velocity fields and successfully scaled from single- to multi-parameter cases. Despite a higher computational cost, this work highlights the significant potential of PINNs for integrated aerodynamic shape optimization.

The model proposed by Yan et al. (2023) implements an innovative approach for reconstructing aerodynamic fields around bridge structures by integrating the Navier–Stokes equations and passive scalar transport into a PINN framework. Input data, derived from flow visualizations, consists of concentration fields, which are then used to reconstruct velocity and pressure fields, and to compute lift and drag coefficients. The method's efficacy was confirmed through case studies of flow around a bridge deck at Reynolds numbers Re=1250 and Re=5000 — the results demonstrate accuracy comparable to classical Computational Fluid Dynamics methods. A key advantage of this approach is its ability to operate with indirect, visualization-based data, significantly reducing experimental requirements and opening possibilities for analyzing objects with difficult access or high costs associated with direct modeling. Despite its orientation toward bridge structures, the methodology shows promise for application in assessing the aerodynamics of ground-based aerospace systems, particularly launch vehicles, which are characterized by similar hydrodynamic and geometric conditions.

Harmening et al. (2024) developed a PINN model for simulating turbulent flow around a DU99W350 airfoil at angles of attack ranging from 10° to 17.5°. This model integrated the RANS equations and boundary conditions into its loss function, with the angle of attack serving as an input parameter. The PINN accurately predicted pressure and velocity fields, including separation zones, outperforming the traditional k-ω turbulence model in terms of accuracy, particularly during interpolation and extrapolation of angles of attack. Analysis revealed that accuracy was contingent on the distribution of training data in high-gradient regions, such as the boundary layer and stagnation point. This finding underscores the necessity for labeled data to ensure generalizability in complex flow conditions.

In their study, Michek et al. (2024) proposed a methodology that combines PINNs with ensemble uncertainty quantification methods for modeling aircraft flight dynamics. This approach accounts for the variability of aerodynamic parameters and environmental conditions. The methodology provides accurate predictions of aerodynamic lift and drag coefficients, as well as flight trajectories under uncertainty, demonstrating high precision and reliability compared to standard methods. The results underscore the potential of integrating PINNs with ensemble techniques to create adaptive models that enhance the safety and efficiency of aerospace systems.

In their work, Ren et al. (2024) proposed two modifications to PINNs for modeling steady transonic flows around a cylinder at high Reynolds numbers: PINN–RANS, which utilizes the Reynolds-Averaged Navier–Stokes equations, and PINN–Euler, based on the Euler equations. To accurately reproduce boundary layers and shock waves without mesh-based methods, the authors incorporated a signed distance function, hard boundary conditions, and a gradient-based weighting coefficient into the loss function. The results demonstrated that PINN–RANS accurately reproduced the boundary layer and wake region using only local velocity data. Conversely, PINN–Euler proved effective in inviscid regions but was less suitable for boundary layer modeling, despite requiring three times less training time.

The application of PINNs for optimizing the parameters of the k–ω turbulence model is presented in the study (Yazdani & Tahani, 2024). The developed methodology integrates the physical equations of the model and experimental data, which enables the refinement of turbulence model constants to enhance the accuracy of describing turbulent flow characteristics. Experimental validation demonstrated that the optimized parameters provide a superior reproduction of velocity profiles and turbulent kinetic energy, and also reduce discrepancies with experimental measurements compared to standard k–ω models. The proposed approach showcases the potential for developing more reliable turbulence models, which are critical for high-fidelity aerodynamic flow calculations in complex engineering problems.

Zhang et al. (2024) applied physics-informed neural networks (PINNs) for two-dimensional modeling of turbulent airflow in enclosed spaces. Their approach integrated the Reynolds-averaged Navier–Stokes equations and the k–ε turbulence model, along with high-quality experimental data. The inclusion of this data significantly enhanced the prediction accuracy of pressure, horizontal velocity, and vertical velocity parameters by 82.9%, 59.4%, and 70.5% respectively, compared to classical methods. The results demonstrate the effectiveness of combining physical equations and empirical data to improve the modeling of complex aerodynamic conditions within confined volumes. This has practical significance for aerospace engineering, particularly in tasks where turbulent flows are restricted by geometric obstacles, such as launch vehicles or launch pads.

Cao et al. (2024) developed a numerical solver for modeling subsonic flow around airfoils by integrating PINNs with grid transformation. This approach allows the problem to be mapped from physical space, where complex local velocity gradients exist near the leading edge, to a computational space with simplified geometry and more efficient implementation of boundary conditions. The results demonstrated accuracy comparable to a second-order finite volume method (FVM) scheme, with an almost order-of-magnitude reduction in error. The model also exhibited high efficiency in solving parametric problems, such as varying angles of attack, making it a flexible tool for inviscid, incompressible flows and showing

Wassing et al. (2024) investigated the application of PINNs for approximating parametric solutions to steady two-dimensional Euler equations under sub- and supersonic flow conditions. Their key achievement lies in the implementation of an adaptive artificial viscosity reduction procedure, which stabilizes network training and prevents non-physical solutions. This represents the first successful application of this concept within PINNs for complex conservation laws in a high-dimensional space. The proposed methodology provides accurate approximations of solutions at various Mach numbers without traditional discretization, effectively solving problems in a continuous parametric space and opening new avenues for optimization and sensitivity analysis in aerodynamic problems.

In their work, Lin et al. (2025) proposed a PINN-based method for identifying aircraft aerodynamic parameters. This approach integrates the six-degrees-of-freedom equations of motion as physical constraints directly into the network architecture. The method demonstrated high accuracy and robustness to data noise during the analysis of aircraft longitudinal motion, surpassing genetic algorithms and traditional neural networks in both precision and generalization capabilities. The proposed approach facilitates the creation of efficient surrogate models without requiring detailed physical models, thereby simplifying the modeling of aerodynamic characteristics under conditions of limited or noisy data.

In their study, Wassing et al. (2025) developed an approach for modeling transonic flows around a NACA0012 airfoil using PINNs. This approach was augmented with an analytical sensor function to locally introduce artificial viscosity in shock wave regions. This innovation stabilized the training process and ensured accurate reproduction of compressional effects without the need for mesh discretization. The proposed method demonstrated an error of less than 1% compared to classical Computational Fluid Dynamics algorithms based on the finite volume method. Furthermore, it enabled the construction of parametric models capable of approximating solutions across a wide range of angles of attack. This work confirms the potential of PINNs in the context of transonic aerodynamic problems and facilitates their further integration into industrial environments.

Structural Problems

Bastek and Kochmann (2023) successfully applied PINNs to model small deformations in arbitrarily curved thin-walled shell structures. They achieved this by employing Naghdi's shell theory and formulating the problem in curvilinear coordinates, thereby eliminating the need for mesh discretization. They demonstrated PINNs' ability to accurately reproduce stress and strain fields, particularly in classic benchmark problems such as the Scordelis-Lo roof. Notably, the weak form of the equilibrium equations proved more effective for solution convergence and stability. Despite challenges in training the network when using the strong form of the equations, especially for thin shells with numerical stiffness due to differing energy scales, this research highlights the significant potential of PINNs as a promising alternative to traditional finite element methods, avoiding issues like “locking” and complex mesh generation.

In their study, Keshavarz et al. (2025) presented an innovative approach for modeling the deformation of crystalline materials. This involved integrating PINNs with object-oriented crystal plasticity finite element (CPFE) methods. This synergy combined the physical fidelity of CPFE with the computational efficiency of PINNs, enabling rapid and accurate prediction of material mechanical response across a wide range of conditions, including large deformations. The object-oriented architecture of the CPFE code simplified the integration of complex constitutive models and numerical methods, enhancing the flexibility and scalability of simulations. This was confirmed by the successful reproduction of complex deformation mechanisms and anisotropic plasticity in crystalline structures, validated against experimental data.

Khalid et al. (2024) presented a comprehensive overview of the applications of PINNs for modeling laminated composites. In their work, they classified and analyzed the effectiveness of various PINN approaches (traditional, Theory-Constrained, k-space, optimal, and discrete) in addressing problems in composite mechanics. The study highlighted the high accuracy of PINNs in reproducing the mechanical behavior of composites, particularly noting k-space PINNs for their ability to leverage spectral representations for vibrational characteristics and discrete PINNs for efficiently decoupling multi-physics problems into modular sub-networks. This modularity significantly reduces computational costs without sacrificing accuracy. The research underscores the potential of PINNs to revolutionize the analysis of composite materials by integrating physical laws into neural network structures, while also pointing to the necessity for further research to overcome challenges related to data scarcity, high computational demands, and complex boundary conditions.

Niu et al. (2023) developed an innovative methodology for modeling large-deformation plasticity, based on PINNs. Their approach directly integrates a rate-independent elastoplastic model with isotropic hardening into the PINN structure, effectively addressing complex problems where traditional mesh-based methods have limitations. The study confirmed the model's ability to accurately predict stress and strain distributions under large plastic deformations without the need for mesh discretization, demonstrating its versatility and reliability in adapting to various loading conditions. This opens new possibilities for material analysis, as the integration of physical laws into neural networks reduces the reliance on extensive experimental data and enhances prediction accuracy.

In a multidisciplinary study (Ramezankani et al, 2025) presented an advanced Physics-Informed Deep Operator Network (PIDON) model, representing a significant advancement for optimizing highly nonlinear systems, particularly in aviation composite processing technologies. The authors' achievement lies in integrating nonlinear decoders, curriculum learning, and domain decomposition, which enabled PIDON to effectively handle numerous input functions and high nonlinearity, outperforming traditional DeepONets. This innovative architecture provides “zero-shot” prediction with accuracy two orders of magnitude higher and reduces the maximum temperature prediction error in nonlinear regions from 6.1°C to 2.3°C. By combining process modeling with material science characteristics, PIDON demonstrates high generalizability and predictive accuracy without retraining for new configurations, making it an exceptionally valuable tool for accelerating the design and optimization of composite processing.

Singh et al. (2024) investigated the application of PINNs to solve a one-dimensional solid mechanics problem, modeling the mechanical properties of a prismatic cantilever beam (helicopter blade) under triangular loading. The authors demonstrated that PINNs significantly outperform traditional artificial neural networks (ANNs) and fourth-order differential equation analytical solutions in terms of accuracy, stability, and computational efficiency. Integrating physical laws into the network's loss function allows PINNs to accurately predict deflections and internal stresses without complex numerical discretization. This makes them a promising tool for aerospace engineering, where reducing computational costs while maintaining high accuracy is essential.

Xu et al. (2023) developed an innovative approach for solving inverse problems in structural mechanics by employing PINNs with transfer learning. Their work aimed to reconstruct external loads on engineering structures from limited displacement data in linear elasticity and hyperelasticity problems. The use of multi-task learning with uncertainty weighting allowed for effective resolution of these inverse problems, even with noisy and incomplete data. Thanks to transfer learning, the model significantly reduces adaptation time to new loading conditions or geometries, making it a highly efficient and flexible tool for identifying loads and assessing stress-strain states in engineering applications.

Yan et al. (2022) introduced a novel computational framework that integrates PINNs with the Extreme Learning Machine (ELM) method for analyzing composite structures, specifically plates and shells. Their objective was to develop an efficient approach for solving forward linear elasticity problems that bypasses traditional mesh discretization. This was achieved by directly embedding the differential equilibrium equations and boundary conditions into the network's training process. Numerical experiments confirmed the model's high accuracy in predicting the stress-strain state of composites, including structures with variable stiffness, while the use of ELM significantly reduced training time. This approach shows promise for modeling complex geometries and inhomogeneous material properties, offering an effective alternative to conventional methods.

Yucesan and Viana (2023) introduced a hybrid PINN for predicting the fatigue life of wind turbine main bearings. Their model innovatively combines known physical laws, such as L10 life calculation criteria, with machine learning to account for complex factors difficult to describe analytically, such as lubricant degradation. The model's hybrid nature allows it to adapt to various operating conditions by effectively integrating physics-informed layers with data-driven layers. Although the study focuses on wind turbines, the proposed approach holds significant potential for application in the aerospace industry, where similar hybrid models could be adapted for accurate fatigue life prediction of components subjected to complex loads and environmental influences.

Thermal Problems

Aygun and Karakus (2022) investigated the application of PINNs for modeling two-dimensional incompressible thermal convection, described by the Navier–Stokes equations and the heat conduction equation, while bypassing traditional mesh discretization. They demonstrated the effectiveness of PINNs in solving both steady and unsteady thermal convection problems across various geometries, including channels and enclosed domains with temperature gradients. Results, compared with analytical and numerical solutions, confirmed the high accuracy of the model, specifically highlighting the importance of tuning weighting coefficients in the loss function to achieve optimal precision. The study underscores the potential of PINNs for efficient and accurate modeling of complex thermal phenomena, particularly in problems with intricate boundary conditions.

Bararnia and Esmaeilpour (2022) investigated the application of PINNs for solving problems involving thermal and hydrodynamic processes within boundary layers. Their objective was to model convective heat transfer and boundary layer flows, bypassing traditional mesh-based methods and accommodating complex boundary conditions. The authors successfully demonstrated that PINNs effectively reproduce temperature and velocity distributions, exhibiting good convergence with classical numerical methods and avoiding issues related to stability and discretization. The study confirms PINNs' potential for accurate and flexible modeling of heat and mass transfer in boundary layers, although it also indicates the need for further refinement for more complex multi-dimensional and turbulent problems.

In their article, Bararnia and Esmaeilpour (2022) investigated the application of PINNs for solving boundary layer thermohydrodynamic problems. They focused on modeling two-dimensional temperature and flow velocity distributions, described by the Navier–Stokes equations coupled with the heat conduction equation, taking into account Prandtl and Grashof numbers. The authors demonstrated that PINNs can accurately approximate these systems of differential equations, yielding convergent results for both the temperature field and velocity profile without the need for labeled data points. Network training was based on a loss function formulated from the residuals of the governing equations and boundary conditions, ensuring physically consistent behavior. This confirms the potential of PINNs for efficiently solving thermohydrodynamics problems without mesh discretization, offering flexibility for complex geometric domains and reducing computational costs.

Bowman et al. (2023) investigated the application of PINNs to solve the heat conduction equation with a heat source and various boundary conditions, focusing on the interaction of laser radiation with biological tissues. The study revealed that the optimal choice of network architecture and activation functions significantly impacts model accuracy: for problems with a heat source, the Tanh activation function yielded the best results, whereas for problems without a heat source, hybrid combinations were superior. This underscores the effectiveness of PINNs for modeling complex thermal processes, which has direct relevance for bioengineering and aerospace medicine.

In their article, Zhang et al. (2023) presented a parametric physics-informed deep learning (PIDL) methodology for the probabilistic design of thermal protection systems (TPS) in aerospace engineering. PIDL, similar to PINNs, is an approach that integrates physical laws into deep learning models; however, PIDL can encompass a broader range of deep learning architectures, not limited exclusively to neural networks that solve differential equations (as PINNs do). The authors' key achievement lies in incorporating parametric uncertainties (e.g., variations in thermal conductivity and heat capacity of TPS materials) to assess their impact on temperature distribution and system reliability. The proposed PIDL model demonstrated high speed and accuracy in predicting temperature fields under uncertainty, achieving results comparable to traditional finite element methods but with significantly lower computational costs. This makes PIDL a promising tool for rapid and reliable design and real-time evaluation of TPS, which is critically important for aerospace applications.

Zhao et al. (2023) proposed an innovative approach for predicting temperature fields based on heat source locations, utilizing a physics-informed convolutional neural network (PI-CNN). This method obviates the need for labeled data, a common challenge in engineering problems. PI-CNN, a variation of the broader PINNs concept, integrates physical laws directly into the network's convolutional architecture. It is trained based on the heat conduction equation and the finite difference method, employing a physical loss function that accounts for the divergence between the network's prediction and the analytical solution of the differential equations, along with padding for hard boundary conditions. The study demonstrated that PI-CNN yields results comparable to traditional numerical methods but significantly accelerates the optimization process. The application of online mining of important examples helps balance optimization across different pixels, rendering this approach exceptionally efficient for engineering applications such as thermoregulation in electronic devices or spacecraft.

Fowler et al. (2024) investigated the application of PINNs for modeling heat flow in a naturally convective cavity, utilizing a vortex-stream function formulation of the Navier–Stokes equations. They demonstrated PINNs' ability to autonomously generate solutions for two- and three-dimensional geometries at various Rayleigh numbers without relying on known data, confirming high accuracy through comparison with analytical solutions. The study revealed that for high Rayleigh numbers, the increasing nonlinear coupling between thermal and hydrodynamic processes necessitates more iterations. Furthermore, the three-dimensional simulations confirmed PINNs' potential for operation in high-dimensional spaces, which is crucial for thermal regime calculations in aerospace engines.

Gholampour et al. (2024) investigated the application of parameterized physics-informed neural networks (P-PINNs) for solving a transient thermal problem describing natural convection with a heat source. Their work focused on the efficacy of P-PINNs in multi-parameter problems, including Rayleigh and Prandtl numbers, without utilizing experimental data. The results demonstrated P-PINNs' ability to accurately reproduce solutions comparable to classical numerical methods; however, parameterizing one variable increased computational cost by 15%, and three variables by 46%. The authors emphasized the importance of employing specialized normalization techniques for large parameters, as training might not converge otherwise. This confirms the effectiveness of P-PINNs for calculating thermal regimes in aerospace engines.

In their study, Jalili et al. (2024) investigated the application of physics-informed neural networks (PINNs) for predicting heat transfer and hydrodynamics in two-phase flows, focusing on modeling gas bubble movement and heat transfer near heated surfaces. The authors demonstrated PINN's high accuracy: maximum interface tracking error was 5.2% at the phase boundary and 2.8% for the bubble's center of mass position. Even without input velocity data, the model remained accurate, showing a maximum root mean square error of 0.28 for unknown fluid properties. In the case of bubble movement near a hot wall, the maximum temperature error was 6.8%, and the bubble's positional error was 3.6%. The study also highlights PINN's versatility, evidenced by its independence from geometry and fluid properties in convection and buoyancy analysis, as well as significant computational cost savings compared to CFD modeling, especially for inverse and extrapolation problems. Furthermore, modifications such as Bayesian PPNN (BPINN) enhance robustness to noisy data.

In their study, Oddiraju et al. (2024) presented an innovative application of physics-informed machine learning (PIML) for developing a real-time thermal simulator for spacecraft. PIML is a broader paradigm that integrates physical laws directly into machine learning algorithms, whereas PINNs are a specific implementation focusing on using neural networks to solve physical problems described by differential equations. The authors' key achievement lies in creating a hybrid model that combines neural networks with simplified physical models. This approach enables efficient and accurate real-time prediction of thermal states, which is critically important for autonomous space missions. The proposed architecture employs a neural network to predict a reduced node distribution based on orbital thermal loads, followed by the application of a finite difference model. This model offers improved generalizability and reduces computational costs by up to 1.7 times compared to high-fidelity models, by integrating physical knowledge to enhance interpretability and robustness, which is crucial for optimizing thermal calculations and reducing spacecraft mass.

Yang et al. (2024) applied a PINNs to solve the problem of thermoelastic expansion of a cavity under plane stress conditions. Their work focused on modeling the interaction of thermal and mechanical processes in geotechnical structures, demonstrating PINN's effectiveness in solving complex problems without mesh discretization. Simulation results confirmed PINN's accuracy in reproducing temperature and stress distributions, accounting for nonlinear thermoelastic effects. This study highlights PINN's potential as a powerful tool for thermoelastic problems with complex geometries and boundary conditions. Its principles are directly applicable in aerospace engineering, for instance, in analyzing thermal and mechanical loads on rocket engine components or high-temperature heat exchangers.

Bobzin et al. (2025) applied PINNs to predict particle properties during plasma spraying, a crucial process for applying protective coatings in aviation. They developed a PINN model that directly integrates physical laws (equations of motion, heat exchange, viscous drag, turbulent fluctuations) into the network, avoiding the need for numerical grids or extensive experimental data. The study showed that the model accurately predicts particle trajectory, temperature, and velocity, ensuring stable convergence and low error. This confirms the effectiveness of PINNs for modeling microscale particle dynamics in plasma jet processes, offering a tool for the preliminary design of coatings with good generalizability.

Acoustic Problems

Pettit and Wilson (2020) presented a pioneering application of PINNs for modeling sound propagation in the atmospheric boundary layer. This work integrates the acoustic wave equation directly into deep neural networks, ensuring physical consistency of predictions even with limited data. The proposed PINN model demonstrates high accuracy in predicting sound exposure levels, surpassing traditional data-driven models due to its generalization capabilities. This research represents an important step in the development of physics-informed modeling for acoustic phenomena, particularly for the needs of aerospace acoustics, where accurate noise propagation prediction is critically important.

In their work, Borate et al. (2023) proposed an innovative approach for predicting laboratory earthquakes by integrating physical laws into the structure of neural networks. They developed a PINN that utilizes ultrasonic monitoring data from shear zones in conjunction with physical constraints describing the elastic coupling of the shear zone to the surrounding rock and the dependence of shear zone stiffness on the ultrasonic wave transmission coefficient. This hybrid approach significantly enhanced prediction accuracy (by 10–15% compared to purely data-driven models), especially under conditions of limited training data, and improved the models' ability to transfer learning to new experimental conditions. It is important to note that the application of PINNs for modeling acoustic phenomena, particularly aviation noise, demonstrates the potential of this methodology for scaling to aerospace acoustics tasks.

Mariappan et al. (2024) applied PINNs to study complex thermoacoustic interactions in combustion chambers that lead to combustion instability. Using acoustic pressure oscillations from three points and the total flame heat release rate as input data, the researchers demonstrated PINN's ability to effectively reconstruct the full spatio-temporal acoustic field (pressure and velocity oscillations) and identify key model parameters. This approach provides a powerful tool for optimizing existing and designing new thermoacoustically stable and structurally efficient combustion chambers, which is critically important for rocket engines and industrial burners, and also holds significant potential for application in aerospace acoustics.

In their study, Schmid et al. (2024) successfully applied PINNs to solve the inverse problem of estimating acoustic boundary admittance, even under conditions of limited and noisy data. The authors trained a neural network to approximate the solution of the Helmholtz equation in 2D without explicitly specifying boundary conditions. They then compared the estimated boundary admittance with reference data from the finite element method and experimental measurements in an acoustic impedance tube. This approach demonstrated high accuracy in reproducing the acoustic field and effectiveness in solving the inverse problem, including spatially varying boundary conditions. This opens up significant prospects for identifying material parameters and localizing noise sources in acoustics and other fields of computational physics.

Yokota et al. (2024) developed an innovative PINN named ResoNet for in-depth analysis of acoustic resonances in one-dimensional pipes. Their model combines standard PINN loss functions with a periodicity condition, enabling accurate modeling of resonance phenomena in the time domain, accounting for energy losses. The study encompasses both forward and inverse analyses of the wave equation, demonstrating ResoNet's accuracy compared to the finite difference method and its ability to successfully identify the energy loss coefficient and optimize acoustic tube design. This work opens new avenues for modeling and optimizing acoustic systems, which is crucial for aerospace acoustics.

In their study, Zhu et al. (2024) presented a PGNN for predicting aviation noise at airports. The authors integrated the European Civil Aviation Conference (ECAC) model, which is based on aerodynamic and acoustic principles, into a deep neural network. This hybrid approach significantly enhanced accuracy: the mean absolute error (MAE) for predicting sound exposure level (SEL) was only 0.98 dBA, outperforming traditional ECAC Doc. 29 models (MAE 1.5−2.2 dBA). The model's effectiveness, which utilized Aircraft Noise and Performance (ANP) and Automatic Dependent Surveillance-Broadcast (ADS-B) data from Frankfurt (EDDF) and Schiphol (EHAM) airports, persisted even with incomplete information: with 30% missing flight trajectory data, the error increased by only 12%, whereas in pure deep neural networks (DNNs), it rose by 45-60%. This research demonstrates the significant potential of PGNN for creating adaptive noise maps with updates every 15 minutes, marking an important step in the development of aerospace acoustics and aviation noise prediction.

Schoder (2025) presented an extended application of PINNs for predicting modal wave fields in three-dimensional room acoustics by solving the inhomogeneous Helmholtz equation. The research focuses on improving the network's generalization capability for realistic point excitation sources using methods such as hyperparameter optimization, adaptive refinement, feature engineering via Fourier transformation, and locally adaptive activation functions. The results indicate that the modified PINN architecture with feature engineering significantly enhances modeling accuracy, achieving a relative error of 0.086% for a point source. It also surpasses the finite element method in terms of training time and the number of tunable parameters, highlighting its potential for computationally efficient modeling of acoustic fields in complex geometries, which is crucial for aerospace acoustics.

Electromagnetic Problems

Baldan et al (2023) explored the application of PINNs for solving inverse electromagnetic problems, a crucial aspect for diagnosing and analyzing electromagnetic systems. The authors successfully demonstrated how PINNs can reconstruct unknown parameters, such as current distributions and magnetic permeability, by integrating Maxwell's equations directly into the neural network's loss function. The method exhibited high accuracy and stability in reconstruction, even with limited or noisy measurements, surpassing classical inverse methods due to the absence of a need for mesh discretization and its flexibility with complex boundary conditions. This approach holds promise for non-invasive diagnostics, material and design optimization, and has direct applications in the aerospace industry for analyzing and optimizing electromagnetic systems.

In their article, Qi and Sarry (2023) investigated the application of PINNs for complex multiphysics simulations, focusing on interconnected electromagnetic and thermal processes. The authors successfully integrated equations from both domains into a unified model, allowing for accurate modeling of phenomena where an electromagnetic field induces material heating, and temperature changes, in turn, affect electromagnetic properties. The results showed that PINNs reproduce field distributions and temperature profiles with high accuracy, comparable to classical numerical methods, demonstrating flexibility in working with limited data and complex boundary conditions. This approach is promising for reducing computation time and optimizing complex systems, particularly for analyzing electromagnetic fields in aerospace engine and antenna components, where multiphysics interactions are crucial.

In their work, Wang et al. (2024) presented the application of PINNs for modeling electromagnetic fields in the frequency domain, which is critically important for geophysical sounding and analyzing subsurface structures. The authors successfully solved Maxwell's equations in inhomogeneous media by integrating physical laws and boundary conditions directly into the PINN's loss function, thereby avoiding the need for mesh generation. The results demonstrate high accuracy in reproducing electromagnetic fields in multi-layered and complex configurations, robustness to noise in input data, and excellent generalization capability. This approach, which significantly simplifies modeling and reduces computational costs, can be extended to three-dimensional problems. Despite its geophysical focus, it has direct applications for modeling electromagnetic processes in complex aerospace environments.

Chen et al. (2024) successfully tackled the complex inverse problem of reconstructing surface profiles from measured electromagnetic fields using PINNs. Their model accurately reconstructs the topography of intricate surfaces by integrating physical laws directly into the training process, even with limited observations and noisy input data. The proposed approach demonstrated high accuracy and robustness, outperforming traditional inversion methods, and showed versatility when applied to various surface types. This methodology opens up significant prospects for remote sensing, particularly in the aerospace industry for analyzing structural integrity and planetary topography, as it allows for a reduction in the number of necessary measurements and an increase in reconstruction reliability.

In their article, Fieramosca et al. (2024) presented an innovative approach to predicting radio frequency (RF) signal propagation, specifically considering the impact of human body movements in indoor environments, using physics-informed generative neural networks (GNN). The authors developed a model based on a variational autoencoder (VAE) that integrates the physical principles of electromagnetic wave diffraction by the human body. This model is capable of quickly and accurately reproducing changes in the RF field caused by human movements, which is critical for real-time applications such as contactless localization and tracking. The results showed that GNN-VAE effectively reproduces the statistical properties of signal propagation and provides a significant reduction in computation time compared to traditional methods, opening new possibilities for RF sensing in complex environments.

Zucker et al. (2025) presented the application of PINNs for modeling atmospheric radiative transfer, focusing on solving radiation transfer equations. Their work demonstrates that PINNs can accurately and efficiently numerically solve these complex equations without traditional mesh discretization, reproducing radiation intensity distributions in various atmospheric layers with high precision, comparable to classical methods. The approach proved robust to variations in environmental parameters and effectively handles inhomogeneous absorption and scattering profiles, while also generalizing well to new conditions. This research opens new possibilities for reducing computational costs and increasing modeling flexibility in remote sensing, climate modeling, and aerospace engineering, which is key for analyzing the propagation of electromagnetic radiation in complex environments.

Optical Problems

Chen and Dal Negro (2022) presented an application of PINNs to solve the inverse problem of image reconstruction and parameter retrieval for photonic nanostructures from experimental near-field data. The researchers demonstrated how PINNs, by integrating Maxwell's equations, can accurately reconstruct the spatial distributions of the refractive index and geometric parameters of nanophotonic objects. The model exhibited high robustness to noise in the data and effectiveness in parameter retrieval, even in cases where traditional methods were less successful. This approach significantly enhances the accuracy and physical fidelity of reconstruction, opening new possibilities for the analysis of photonic systems.

In their study, Ghosh et al. (2022) presented the application of physics-informed machine learning for modeling electromagnetic modes in composite materials. They developed an approach based on PINNs, which integrates physical laws directly into the training process. This allows for more accurate and physically consistent solutions to describe wave propagation in complex, inhomogeneous media. The results demonstrated high accuracy and stability in reproducing electromagnetic modes in composites, effectively incorporating physical constraints and exhibiting generalization capabilities to new configurations. This approach strikes a balance between accuracy, efficiency, and physical interpretability, significantly improving the design and analysis of systems in high-tech fields like aerospace engineering.

In their 2022 study, Saba et al. presented the application of PINNs for solving diffraction tomography problems. The authors focused on reconstructing the three-dimensional refractive index distribution of objects from scattered light measurements, directly integrating the physical equations of wave optics into the neural network's training process. This approach significantly enhanced reconstruction accuracy and ensured the physical correctness of the results, even under conditions of limited quantity and quality of experimental data. The model demonstrated high robustness to noise and effectiveness, outperforming classical diffraction tomography methods in accuracy and generalization capability. The use of PINNs in this field opens new possibilities for high-precision reconstruction of the internal structure of materials, by combining experimental data with fundamental physical laws.

In their work, Gigli et al. (2023) applied physics-driven neural networks (PDNNs) to predict nonlinear optical scattering in complex materials. The authors successfully integrated the relevant physical equations directly into the neural network's structure, allowing the model to accurately reproduce complex nonlinear light scattering processes, considering both spatial and spectral characteristics. The proposed PINN approach demonstrated robustness to noise and the ability to generalize to new configurations, providing significant advantages in speed and accuracy compared to classical methods. This opens new possibilities for analyzing and optimizing optical systems with pronounced nonlinear phenomena, which is critically important for developing new materials and devices in photonics and optoelectronics.

Ünal and Durgun (2025) presented a physics-aware neural network — a variant of PINNs for rapid and accurate prediction of the effective refractive index of photonic waveguides. This approach, which integrates physical knowledge directly into the network's structure, eliminates the need for time-consuming numerical simulations, such as the finite difference or finite element methods. The developed model demonstrates high accuracy and significantly outperforms traditional methods in computational speed for a wide range of waveguide structures, including those with complex geometries and inhomogeneous materials. This innovation will considerably accelerate the design of photonic devices, providing a balance between accuracy, speed, and physical interpretability, which is crucial for the advancement of modern photonics and aerospace engineering.

Zucker et al. (2025) explored the application of PINNs for modeling atmospheric radiative transfer. They focused on solving radiation transfer equations, which are crucial for accurate predictions in climate modeling, satellite monitoring, and remote sensing. The authors successfully integrated physical laws, specifically the radiative transfer equations, directly into the neural network's structure. This allowed for highly accurate reproduction of radiation intensity distributions in the atmosphere across various spectral ranges and scattering conditions. The model demonstrated robustness to noise, generalization capabilities, and speed advantages compared to classical numerical methods. This opens new possibilities for modeling the optical properties of the atmosphere and radiation transfer in aerospace engineering and satellite technologies.

Chemical and Thermochemical Problems

In the study by Ghaderi et al. (2022), a PINN was developed to model the pyrolysis and ablation of polymers, a process critically important for thermal protection systems in aerospace engineering. The authors successfully integrated relevant physical laws—encompassing heat transfer, chemical reactions, and material degradation—directly into the network's architecture. This innovative approach enabled the PINN to effectively solve complex multiphysics differential equations. The model demonstrated remarkable accuracy in reproducing temperature profiles, pyrolysis rates, and ablation depths, even when relying on limited experimental data. This underscores its high precision and notable generalization capability to novel conditions. Consequently, this methodology not only provides reliable predictions but also ensures the physical interpretability of its results, a crucial aspect for its application in critical aerospace processes.

The research by Ihunde and Olorode (2022) zeroes in on PINNs for the comprehensive modeling of multicomponent systems that involve phase transitions and component transport. This approach, notably scalable to aerospace challenges, facilitates the modeling of critical processes such as fuel combustion in aircraft and rocket engines. In such scenarios, accurately accounting for phase transitions, mixture composition, and heat exchange is paramount. Similarly, PINNs hold significant promise for simulating thermochemical processes during spacecraft atmospheric re-entry and for optimizing thermal protection materials. By seamlessly integrating physical laws with neural network learning capabilities, PINNs effectively solve complex differential equations without grid discretization. This translates into a substantial reduction in computational costs and an enhancement in model generalizability. Ultimately, this paves the way for achieving greater accuracy and speed in simulations crucial for the design of advanced aerospace systems.

In their work, Shadram et al. (2022) introduced an innovative approach to modeling combustion instabilities within a single-injector combustor—a critical challenge in aerospace engine design. They developed a physics- aware neural network (a type of PINN) for flame closure modeling. This model seamlessly integrates experimental data with the underlying physical laws that govern the intricate interactions of chemical kinetics, turbulence, and acoustic phenomena. The model accurately reproduced the complex dynamics of combustion instabilities, including pressure oscillations and heat/reactivity distribution. It demonstrated significantly better agreement with experimental data and superior generalization capabilities compared to traditional models. This achievement highlights the immense potential of embedding physical constraints into neural networks to enhance the reliability of simulating complex thermochemical processes. Ultimately, this paves the way for optimizing the design and operational modes of aerospace engines, particularly in the context of effectively controlling combustion instabilities.

In their article, Wang et al. (2022) explored the potential of PINNs for solving differential equations that describe chemical combustion processes, particularly focusing on complex reaction kinetics. The authors demonstrated that PINNs can accurately reproduce the dynamics of reactant and product concentrations, as well as temperature profiles across various chemical systems, encompassing both simple and intricate reaction mechanisms. The model exhibited robustness with limited data and proved efficient in solving problems with nonlinear kinetics, where traditional methods typically demand significant computational resources. These findings confirm that PINNs offer a flexible and precise tool for modeling chemical combustion kinetics. This is particularly valuable for enabling rapid and reliable calculations in aerospace engineering.

The scientific paper by Song et al. (2024) details the development and application of PINNs, integrated with a flamelet/progress variable model, for the efficient and accurate modeling of combustion with a detailed chemical reaction mechanism. This hybrid approach successfully tackles the nonlinear differential equations that describe chemical reactions and heat transfer, precisely replicating temperature and concentration distributions, as well as the dynamics of reaction progress in multidimensional combustion scenarios. A key achievement of this work is the substantial reduction in computational costs compared to classical methods. This makes the methodology highly promising for complex aerospace applications, particularly for better incorporating the intricacies of reaction mechanisms and accurately predicting flame behavior.

In their work, Zhang et al. (2024) introduced an innovative CRK-PINN (Combustion Reaction Kinetics Physics-Informed Neural Network) designed to solve ordinary differential equations that describe the kinetics of chemical combustion reactions. The primary achievement here is a significant enhancement in the accuracy and efficiency of modeling complex reaction mechanisms, which are particularly characteristic of aerospace systems. This advancement stems from the seamless integration of physical laws directly into the neural network's architecture. The CRK-PINN demonstrated high fidelity in reproducing the dynamics of reactant and product concentrations, even with limited data. It also outperformed classical numerical methods in terms of convergence speed and noise resilience, while effectively scaling to accommodate large reaction mechanisms. This approach expands the capabilities of PINNs for modeling chemical combustion kinetics, providing both high accuracy and flexibility. This makes it an invaluable tool for the design and optimization of aerospace engines.

Material–Environment Interaction Problems

In the study by Dourado and Viana (2019), the application of PINNs for predicting corrosion-fatigue damage in materials is presented. The authors developed a model that combines the physical principles governing corrosion and fatigue with the capabilities of deep learning. This involved integrating both experimental data and differential equations that describe the evolution of damage. The PINNs accurately replicated the dynamics of crack growth under the combined influence of corrosion and cyclic loading. They demonstrated high consistency with experimental results regarding crack propagation rates and time to failure, even with a limited amount of training data. This highlights the significant potential of PINNs for predicting the remaining useful life of materials and gaining a deeper understanding of their degradation mechanisms, which is critically important for aerospace engineering.

In their research, Mishra and Molinaro (2021) successfully applied PINNs to model radiative transfer processes. They achieved this by integrating the Radiative Transfer Equation (RTE) as a physical constraint within the loss function. The developed PINN accurately reproduced RTE solutions for various configurations, including both one-dimensional and multi-dimensional problems with varying absorption and scattering coefficients. Even with limited training data, the model demonstrated its effectiveness in accounting for complex physical interdependencies, which are significantly more challenging to resolve using traditional numerical methods. The authors emphasize that PINNs serve as an efficient tool for modeling intricate radiative transfer processes, a capability critically important for analyzing thermal processes in the aerospace industry. Furthermore, they note that this approach can be expanded to solve a wider spectrum of multiphysics problems.

In a pioneering study, Zhang et al. (2022) showcased the application of PINNs for analyzing internal structures and defects within materials. The authors developed a model that integrates solid mechanics equations with neural networks, enabling the precise detection and characterization of defects (such as cracks and voids) without requiring direct internal access. The PINNs successfully reconstructed the distribution of stresses and strains around defects, accurately predicting their impact on mechanical properties. This was validated by high precision when compared to classical methods and experimental data. This work opens new avenues for non-invasive material quality control and is critically important for ensuring the reliability and longevity of structures in the aerospace industry.

In their work, Choi and Lee (2023) developed a Physics-Informed, Data-Driven model based on a Bayesian network for predicting the atmospheric corrosion of carbon steel. This approach is groundbreaking because it integrates the physical laws of corrosion processes with experimental data, allowing for more accurate modeling of oxide layer growth and material degradation. The model effectively forecasts corrosion rates by accounting for the influence of humidity, temperature, and other environmental factors, as well as the inherent uncertainty in input data. This ensures the adaptability and reliability of long-term predictions. The researchers emphasize the promising nature of such a combination of physical knowledge and statistical methods for a better understanding of material-environment interactions and for enhancing the efficiency of materials science research, especially within the aerospace sector.

In their work, Hu et al. (2024) investigated and systematized the application of PINNs within computational solid mechanics (CSM). They achieved this by developing numerical frameworks for modeling the mechanical behavior of materials and structures. Their advancements in PINN architecture enable accurate reproduction of stress-strain states, displacement and stress distributions, and even the modeling of defects and cracks in thin-walled structures. A key achievement is the integration of physical knowledge—such as equilibrium equations, compatibility conditions, and material laws—without the need for mesh discretization. This provides significant flexibility and scalability in modeling. The authors emphasize that PINNs open up new avenues for analyzing material degradation, crack propagation, and corrosion, all of which are exceedingly relevant for aerospace engineering.

In their article, Janssen et al. (2024) introduce the Physics-Informed General Convolutional Network (PIGCN)—a novel approach that extends the concept of PINNs by integrating physical laws directly into the architecture of convolutional neural networks (CNNs). This is achieved by utilizing convolutional operations to approximate differential operators. This innovation effectively accounts for local spatial dependencies and the geometric characteristics of damaged materials, significantly reducing computational costs. The PIGCN successfully models the distribution of stresses, strains, and displacements in materials with defects, demonstrating high accuracy and consistency with Finite Element Method (FEM) results. Remarkably, it achieves stable outcomes with only 2% of training data, indicating improved generalization capability and physical reliability. The authors emphasize the promising potential of PIGCN for modeling defective materials, which reduces data requirements and is critically important for both materials science and aerospace engineering.

In their comprehensive review, Malashin et al. (2025) provided an in-depth analysis of the current state and future prospects of applying PINNs for modeling polymeric materials. Their focus was on integrating physical laws into neural networks to describe the mechanics, thermal conductivity, diffusion, and degradation of these materials. The review highlights the high efficacy of PINNs in modeling multiphysics processes in polymers, especially in situations with limited or hard-to-obtain data. They offer examples of predicting mechanical behavior, aging, corrosion, and the influence of external factors. The authors emphasize that PINNs unlock new possibilities for creating versatile, physically grounded models of polymeric materials. These models can be adapted for diverse materials science tasks, including optimizing composition, predicting durability, and developing new materials with tailored properties—all of which are critically important for aerospace applications.

Multicomponent-System Problems

In their work, Almajid and Abu-Al-Saud (2022) successfully applied PINNs to predict fluid movement in porous media. The study demonstrated the high accuracy of PINNs in modeling flow dynamics, including pressure and velocity distribution, even with a limited amount of input data. This highlights PINNs' potential as an effective complement to traditional numerical methods, especially for complex systems with heterogeneous geometry or a scarcity of information. This capability is critically important for modeling multicomponent flows in the oil and gas and aerospace industries.

Zhu, Hu, and Sun (2023) developed an advanced PINN model for solving problems related to two-phase interface dynamics, encompassing the movement of the boundary between liquid and gaseous phases in both 2D and 3D configurations. Their approach integrates the Navier-Stokes equations, impermeability conditions, and surface tension laws without the need for traditional mesh discretization. This allowed them to achieve high accuracy in reproducing phase deformation, merging, and separation, while avoiding the numerical artifacts characteristic of classical methods and significantly reducing computational costs. The results confirm the effectiveness of PINNs for modeling complex dynamic processes of two-phase interaction, which is critically important for engineering applications in fuel and energy systems, as well as for understanding the behavior of mixtures under challenging physical conditions.

In their research, Zhang et al. (2024) successfully applied PINNs to model multiphase flows in porous media, with a particular focus on accounting for double shock waves and interphase solubility. The authors demonstrated that PINNs effectively reproduce the dynamics of multiphase flow, including accurate modeling of shock wave behavior and the mutual solubility of components, achieving high precision even with limited data. This approach stands as a powerful tool for analyzing complex multicomponent systems within porous media, ensuring the physical fidelity of results in scenarios involving nonlinear effects. This is critically important for advancements in energy and fuel technologies.

In their research, Jalili et al. (2024) successfully applied PINNs to predict heat transfer in two-phase flows, specifically emphasizing the complex thermal processes involved in fluid-gas interactions. The PINNs demonstrated high accuracy in forecasting temperature distributions and heat fluxes, effectively integrating physical laws and boundary conditions. This resulted in better agreement with experimental data compared to classical methods. The authors highlighted the promising potential of PINNs as a tool for modeling heat transfer in complex two-phase systems, especially when experimental data is limited. They also noted the potential to extend this approach to more intricate multicomponent systems.

Brumand-Poor et al. (2024) successfully demonstrated the application of PINNs for solving the Reynolds equation with transient cavitation modeling. Their models accurately reproduce the complex nonlinear effects and the dynamics of cavitation zones within lubrication layers, which is critically important for multicomponent hydrodynamic systems, particularly fuel systems in the aerospace sector. The research highlights the effectiveness of PINNs in predicting pressure dynamics and cavitation distribution over time, offering a powerful tool for analysis where traditional methods face limitations.

In their research, Parfenyev et al. (2024) successfully applied PINNs for the reconstruction of parameters and the retrieval of two-dimensional turbulent flows. Their approach allowed for the accurate identification of key parameters such as viscosity and turbulence intensity, as well as the reconstruction of spatiotemporal velocity fields and other physical quantities, even when using limited experimental data. This study demonstrates the significant potential of PINNs for analyzing complex dynamic systems, such as turbulent multicomponent flows, where traditional methods often face challenges due to data scarcity or lack of flexibility.

Phạm and Mai (2024) successfully applied PINNs to model two-phase flow in porous media, specifically focusing on the process of waterflooding oil fields using the Buckley-Leverett theory. Their models demonstrated high accuracy and reliability in prediction, even under conditions of sharp changes in physical quantities and with limited input data. This is critically important for understanding the behavior of fuel mixtures in complex environments and for effective field development planning, and it holds significant relevance for the aerospace industry.

Yan et al. (2024) applied PINNs to simulate two-phase flows in heterogeneous and fractured porous media. Their research demonstrated that PINNs effectively and accurately model the distribution of phases, pressure, and velocity, even with limited data. Remarkably, they either surpassed or matched the precision of classical numerical methods in complex structures. This confirms the significant potential of PINNs for modeling multicomponent flows in intricate systems, which is critically important for understanding the behavior of fuel-oxidizer mixtures in the aerospace industry.

Zhou et al. (2024) presented an innovative integrated approach to simulating two-phase flows. This method combines PINNs with leading interface tracking methods, such as Volume of Fluid (VOF) and Level Set. This hybrid model significantly enhances simulation quality by incorporating the Navier-Stokes equations and impermeability conditions, ensuring high accuracy in reproducing complex interface dynamics. This includes processes like capillary pressure, surface tension, and phase transitions. The proposed method effectively reduces numerical interface smearing and stabilizes the solution, which is critically important for accurately predicting the behavior of fuel mixtures and optimizing aerospace fuel systems.

Publications Related to Tier 2: Dynamic Analysis

This section examines publications in which Physics-Informed Neural Networks have been applied to dynamic systems governed by time-dependent or trajectory-based formulations. These include problems such as flight mechanics, ballistic motion, rigid-body dynamics, and particle trajectories in external fields — phenomena that are central to both atmospheric and spaceborne vehicle modeling. The review considers how PINNs are employed to approximate motion governed by ordinary or partial differential equations, often under complex, nonlinear conditions. Emphasis is placed on how temporal evolution, external forces, and dynamic constraints are embedded into the structure and training of PINNs, and how these models enable high-resolution prediction of trajectories and dynamic responses without discretization artifacts.

Ballistic and Trajectory Problems

In their research, D'Ambrosio et al. (2021) proposed the application of PINNs, combined with the Extreme Theory of Functional Connections (X-TFC), for optimizing spacecraft maneuvers near asteroids while ensuring collision avoidance. This approach effectively solves two-point boundary value problems, generating fuel-efficient trajectories amidst complex dynamics. Numerical experiments confirmed the model's high accuracy, comparable to traditional methods, while demonstrating reduced computational costs and enhanced flexibility in modeling. The authors emphasize the promising potential of combining PINNs with X-TFC for solving optimal control problems in space missions, particularly in scenarios with limited resources and intricate dynamics, thereby ensuring high precision in spacecraft trajectory modeling.

In their study, Schiassi et al. (2022) introduced a novel methodology for solving optimal planar orbit transfer problems using PINNs. They combined an indirect method, based on Pontryagin's Minimum Principle, with PINNs to learn optimal control actions. To achieve this, they utilized the Extreme Theory of Functional Connections (X-TFC). X-TFC, a synergy of classical PINN and the theory of functional connections, analytically satisfies the boundary conditions of the two-point boundary value problem (derived from Pontryagin's Principle), thereby avoiding unbalanced gradients during training. The results demonstrate high accuracy in reproducing optimal trajectories and control actions, surpassing traditional numerical methods in terms of computational cost and convergence. This opens new perspectives for optimizing space missions.

In their research, Stachiw et al. (2022) developed a novel neural network architecture called FlyNet for modeling aircraft flight dynamics. The authors created a global flight model capable of accurately reflecting an aircraft's behavior across its entire operational envelope by combining physical principles with the capabilities of neural networks. It is important to note that while FlyNet isn't a classical PINN, it still leverages physical knowledge, specifically second-order Taylor series expansions, to enhance modeling accuracy. Tested against flight test data from a Bell 412HP helicopter, gathered by the National Research Council of Canada, the model demonstrated high precision in predicting forces and moments under various flight conditions. The authors concluded that integrating physical knowledge into the neural network's structure enables the creation of a universal flight model. This model can be applied to different types of aircraft, reducing the need for numerous localized models and simplifying the modeling process for the development of control systems and pilot simulators.

Varey et al. (2024) developed an application of PINNs for assessing the orbital state of satellites with low-thrust electric propulsion. By integrating classical astrodynamics models with deep neural networks, the authors successfully overcame the limitations of traditional physical models that do not account for anomalous accelerations. The PINN model, trained to determine an unknown acceleration profile by minimizing the root mean square error between observations and predictions, demonstrated a significant reduction in observational error (from 123 to 1.00 arcseconds) and a substantial improvement in predicting satellite position (from 3860 km to 164 km after five days) compared to purely physical models. This approach is critically important for accurate space traffic management and maintaining space situational awareness.

In their research, D'Ambrosio and Furfaro (2024) proposed Pontryagin Neural Networks (PoNNs), a subclass of PINNs, for learning fuel-optimal spacecraft trajectories, specifically for interplanetary transfers and landing trajectories. PoNNs leverage Pontryagin's Minimum Principle (PMP) to formulate the problem as a two-point boundary value problem (TPBVP), which they solve using the Extreme Theory of Functional Connections (X-TFC). This approach allows for the approximation of the system's state and costate using constrained expressions that combine analytical satisfaction of boundary conditions with a free function modeled by a shallow neural network. To handle discontinuous control, a smoothing technique is applied, enabling PoNNs to learn effectively without prior information on control switching. The results demonstrate the high accuracy of PoNNs, comparable to state-of-the-art methods, as well as the ability to analytically compute optimal control. This makes the approach highly promising for the optimization of space trajectories.

Michek et al. (2023) developed a methodology for estimating the free-flight parameters of aircraft using PINNs, including a modified version for nondeterministic parameters. The goal was to identify aerodynamic parameters from flight data, thereby eliminating the need for controlled tests. The proposed methods effectively extract aerodynamic parameters even in the presence of noise and incomplete data. Furthermore, the modified PINN demonstrates high accuracy, outperforming the traditional least squares method. This underscores the potential of PINNs for identifying aerodynamic parameters under real-world flight conditions, which can reduce the costs associated with experimental research and be applied to modeling and analyzing flight trajectories.

In their work, Moschou et al. (2023) presented the use of PINNs for modeling astrophysical shock waves. Their approach directly integrates the magnetohydrodynamics (MHD) equations into the neural network's structure, allowing the model to incorporate physical constraints. This enabled them to accurately reproduce the structure of shock waves, including internal layers and transitional regions, with high precision and generalization capability to various configurations. The application of PINNs also led to reduced computational costs compared to traditional methods. The authors emphasize that integrating physical laws into neural network training creates highly accurate and physically consistent models, significantly reducing the need for expensive numerical simulations. This opens up new possibilities for applying PINNs in astrophysics and space research.

Motion-Dynamics Problems

In their study, Seyed-Ahmadi and Wachs (2022) proposed a physics-inspired neural network architecture for modeling the hydrodynamic forces and torques acting on particles in particle-laden flows. The goal was to predict these quantities in stationary random arrays of spheres (typical of dense suspensions), while accounting for limited training data and ensuring the physical consistency of predictions. The resulting PINN-oriented architecture, based on a superposition of pairwise hydrodynamic interactions and shared learning parameters between network blocks, accurately reproduced forces and torques across a range of Reynolds numbers from 2 to 150 and solid volume fractions from 0.1 to 0.4. This architectural solution significantly reduced the degrees of freedom and mitigated the risk of overfitting, all while maintaining accuracy at the level of benchmark simulations. The authors concluded that the physically motivated structure of the neural network ensures consistency with the governing physics even under sparse training, which is critical for generalization in real-world flows, and demonstrates suitability for further scaling.

In their research, Rosofsky et al. (2023) thoroughly analyzed the application of Physics-Informed Neural Operators (PINOs) for modeling dynamic systems described by partial differential equations (PDEs). They specifically focused on those involving temporal evolution, fluid-body interaction, and particle movement in force fields. The authors successfully demonstrated PINOs' ability to achieve a prediction error level of 10^{-3} when modeling fluid dynamics (crucial for assessing aerodynamic drag) and accurately reproducing particle trajectories in gravitational fields, even with limited data. The advantage of PINOs over classical methods lies in their computational efficiency and their capacity to avoid discretization artifacts. While the researchers acknowledge the need for further optimization for real-world engineering tasks, they emphasize that integrating physical laws into neural networks through PINOs is a promising tool for solving nonlinear PDEs, ensuring the stability and accuracy of predictions.

Shao et al. (2023) introduced an improved Neural Particle Method (INPM) for modeling complex free-surface flows. This method overcomes the limitations of the basic NPM by combining PINNs with an alpha-shape algorithm to accurately detect fluid boundaries and dynamically update boundary conditions. Numerical experiments confirmed that INPM precisely identifies the free surface and ensures stable computations even with non-uniform particle distribution, demonstrating higher accuracy and stability compared to traditional mesh-free methods. The authors emphasize that integrating a surface recognition algorithm into the PINN structure significantly enhances the accuracy and stability of free-surface flow simulations, expanding the scope of application in problems with complex geometry and boundary conditions.

In their systematic review, Sharma et al. (2023) provided a profound analysis of the application of Physics-Informed Machine Learning (PIML), including PINNs, within the realm of fluid mechanics. The core emphasis was on integrating physical knowledge into machine learning to bolster the efficiency and accuracy of modeling complex turbulent flows, which are governed by the Navier-Stokes equations. The review clearly demonstrates that PIML significantly reduces the required data volume and enhances the stability of predictions when compared to traditional numerical methods. The authors highlight successful instances of PIML being applied to model turbulent flows at high Reynolds numbers and to reconstruct Reynolds stress distributions from Direct Numerical Simulation (DNS) data. They underscore the immense potential of PIML and PINNs to either replace or augment high-fidelity numerical simulations, particularly in scenarios where data is limited. Furthermore, the authors point to the crucial need for continued research to develop novel neural network architectures that can seamlessly and effectively integrate physical laws.

In their article, Son et al. (2023) proposed a novel PINN architecture for modeling the electromagnetic characteristics of a permanent magnet synchronous motor (PMSM). The authors aimed to overcome the limitations of traditional methods, such as the Finite Element Method (FEM), by directly integrating physical laws into the neural network's structure. The proposed PINN architecture accurately reproduces the electromagnetic fields within the PMSM, significantly reducing computational costs while effectively accounting for the motor's complex geometric and material properties, ensuring high accuracy even with limited data. The results underscore the potential of this approach for precise modeling of PMSM electromagnetic characteristics, reducing reliance on large volumes of training data, and opening new avenues for efficient modeling of complex electromechanical systems.

In their article, Barmada et al. (2024) investigated the effectiveness of PINNs for solving direct electromagnetic problems, particularly Maxwell's equations, by minimizing the integral error to account for physical laws. The study proved that PINNs provide accurate solutions to Maxwell's equations without the need for detailed spatial discretization. This was confirmed by examples of one-dimensional and two-dimensional Poisson equations, with results aligning with analytical and FEM solutions. The authors emphasize the promising potential of PINNs for electromagnetic analysis, especially in aerospace modeling, due to significantly reduced computational costs and enhanced model accuracy.

Jiao et al. (2024) delve into the integration of artificial intelligence, specifically PINNs, with physical sciences for modeling dynamic systems described by differential equations. The authors analyze the application of physical principles (such as classical mechanics and electromagnetism) to enhance AI algorithms, focusing on problems related to fluid dynamics and particle motion. The review demonstrates that PINNs effectively model dynamic systems, capable of accurately reproducing phase transitions and predicting parameters (e.g., aerodynamic drag) without traditional discretization methods, which in turn reduces computational costs compared to Computational Fluid Dynamics (CFD). While challenges related to scaling for complex systems are acknowledged, the authors emphasize that PINNs ensure the reliability and interpretability of models, enabling the prediction of trajectories and dynamic responses in real-time.

Sedykh et al. (2024) introduced an innovative Hybrid Quantum Physics-Informed Neural Network (HQPINN) for modeling laminar flows in complex three-dimensional geometries, such as Y-shaped mixers. This development combines the expressive power of quantum models with the flexibility of PINNs to effectively solve computational fluid dynamics (CFD) problems described by the Navier-Stokes equations, without the need for remeshing when geometry or boundary conditions change. The HQPINN demonstrated 21% higher accuracy compared to classical PINNs in modeling velocity and pressure distributions. It also exhibited the ability for transfer learning, adapting to geometry changes without full retraining, significantly reducing computational costs. The authors emphasize HQPINN's promising potential for shape optimization and flow analysis in complex geometries, opening new avenues in computational fluid mechanics.

Sultan and Zhang (2024) conducted a comparative analysis of the Moving-Mesh Finite-Difference Method (MMFDM) and PINNs to solve the generalized Kolmogorov–Petrovsky–Piskunov (gKPP) equation, which describes nonlinear reaction-diffusion processes. MMFDM demonstrated high accuracy, particularly with adaptive meshes in regions of steep solution gradients. PINNs, on the other hand, showed effective learning capabilities even with limited data, thanks to the integration of physical laws. While PINNs necessitate careful hyperparameter tuning for stability, the research highlights the distinct advantages of both methods: MMFDM excels in scenarios with known geometries and boundary conditions, while PINNs offer flexibility when dealing with limited or noisy data. The authors propose that hybridizing these approaches could combine the precision of traditional methods with the adaptability of neural networks.

Sun et al. (2024) applied PINNs to predict velocity in electromagnetic launch processes during manufacturing. The authors focused on modeling the dynamics of objects (specifically, projectiles) accelerated by electromagnetic forces. Their aim was to create a model that accurately replicates the temporal evolution of velocity, accounting for complex physical interactions described by systems of ordinary differential equations (ODEs). The proposed PINN model demonstrated high accuracy in velocity prediction, effectively reproducing experimental data and outperforming traditional methods (like the finite element method) in terms of input data requirements. The authors highlight the advantages of PINNs in modeling electromagnetic launch due to the direct integration of physical laws into the network's structure, which helps avoid discretization artifacts and ensures high precision. They also point to the potential for real-time application of PINNs in controlling and optimizing manufacturing processes.

Rigid-Body Motion Dynamics

Roehrl et al. (2020) presented an approach to applying PINNs for modeling the dynamics of mechanical systems, based on Lagrangian mechanics. The authors directly integrated Lagrange's equations into the neural network's structure, which allowed the model to account for physical laws during training. This effectively combined the advantages of physical models with the flexibility of neural networks. Numerical experiments confirmed the high accuracy of modeling mechanical system dynamics, even with limited data. The model demonstrated an ability to reproduce complex movements while adhering to physical constraints. The authors concluded that integrating physical laws into neural network training creates models that merge the precision of physical models with the adaptability of neural networks, opening new possibilities for modeling and control of complex mechanical systems in the aerospace and robotics industries.

Sedykh et al. (2024) presented a Hybrid Quantum Physics-Informed Neural Network (HQPINN) that integrates classical and quantum computing approaches to model linear fluid flows in complex three-dimensional Y-shaped mixers. The researchers achieved 21% higher accuracy compared to classical neural networks by employing quantum deep layers alongside classical multilayer perceptrons. The results of this study confirm HQPINN's high effectiveness in predicting velocity and pressure distributions, underscoring the method's significant potential for optimizing complex geometries in computational fluid dynamics, a task that traditionally demands substantial resources.

Aygun et al. (2023) explored the application of PINNs for mesh deformation with precise adherence to boundary conditions. The authors utilized the PINN collocation method to determine new mesh node positions, applying the equations of linear elasticity to model the deformation. To ensure exact enforcement of Dirichlet conditions for moving boundaries, which is critical for accurate solutions, they employed a strict boundary condition imposition technique. Their two-stage approach first involved training a PINN with soft boundary conditions, followed by correcting the solution with a new PINN incorporating exact boundary positions. The study demonstrated that the accuracy of this approach is comparable to the finite element method. Furthermore, it successfully addressed problems with moving boundaries, simulating typical fluid-structure interaction challenges. The authors concluded that using PINNs for mesh deformation problems without a discretization scheme is promising for modeling complex systems with moving boundaries, such as aerospace vehicles.

Gu et al. (2024) presented the application of PINNs for modeling quadcopter dynamics. The authors integrated the law of conservation of momentum as a training priority within the network's loss function, ensuring physical consistency. They also employed the Covariance Confidence Ellipse (CCE) visualization method to enhance model interpretability. Furthermore, a visual and physical simulator was developed based on AirSim, with a custom implementation of the ground effect. The proposed PINN outperformed linear mathematical models and conventional deep neural networks (DNNs) in terms of both accuracy and physical consistency, demonstrating a superior ability to generalize to unseen data. The authors concluded that integrating physical laws significantly improves the accuracy and interpretability of quadcopter dynamics models, contributing to the development of more reliable and safer control algorithms for UAVs.

In their article, Li et al. (2024) introduced a groundbreaking approach to applying PINNs to problems involving friction dynamics, specifically for modeling friction-induced vibrations in multipoint contacts. The authors developed four PINN variants: a basic single PINN, a dual PINN, and their enhanced versions incorporating interpolation techniques. These variants allow for the integration of theoretical equations of non-classical multibody dynamics without the need for traditional time-stepping. Numerical experiments on a one-dimensional "stick-slip" problem and a two-dimensional problem with separation and re-engagement showed that the proposed PINN approaches deliver high modeling accuracy, surpassing traditional methods, especially in complex two-dimensional cases. The authors concluded that embedding physical laws into neural network training enhances accuracy and significantly reduces computational costs by eliminating the necessity for exceedingly small time steps. This opens new possibilities for effectively analyzing complex dynamic systems with friction.

In their article, Sahin et al. (2024) investigated the application of PINNs for solving both direct and inverse problems in contact mechanics under small deformations. The authors employed a mixed-variable formulation with output transformation to rigorously enforce Dirichlet and Neumann boundary conditions. Crucially, the inequality conditions inherent in contact problems, specifically Karush-Kuhn-Tucker (KKT) conditions, were incorporated as soft constraints by integrating them into the loss function, utilizing the Fisher-Burmeister function for optimization. Numerical experiments on a Hertz contact problem demonstrated that PINNs can function as a PDE solver, a data-driven model, an inverse solver, and a rapid approximation model, accurately simulating contact phenomena. The importance of hyperparameter selection and combining optimizers (Adam and L-BFGS-B) for achieving superior results was highlighted. The authors concluded that integrating physical laws into neural network training creates models that combine the precision of physical models with the flexibility and adaptability of neural networks, contributing to the development of reliable control algorithms, particularly for unmanned aerial vehicles.

Publications Related to Tier 3: Functional Assessment

This section focuses on the use of Physics-Informed Neural Networks to address tasks that involve performance evaluation, decision-related modeling, and inference within aerospace systems. These include applications such as trajectory optimization, flight control, parameter identification, and prediction of system behavior under variable or uncertain conditions. The literature is reviewed in terms of how PINNs are configured to solve inverse and constrained problems, learn latent system properties from observed data, or forecast future states. Special attention is given to the role of PINNs in integrating physical laws with task-specific objectives, enabling hybrid modeling strategies that go beyond traditional simulations.

Control and Navigation Tasks

Li et al. (2023) proposed an intelligent diagnostic system for detecting faults in aero-engine control system sensors during dynamic operation. The methodology is built upon a physics-guided neural network (PGNN), which integrates data from physical engine models with historical sensor measurements. The PGNN generates predicted values, and a comparison of these with actual measurements yields residual signals. These residuals are then analyzed by a convolutional neural network (CNN) for fault classification. Experimental validation demonstrated that the proposed system outperforms traditional approaches, reducing the root mean square error of prediction and achieving a diagnostic accuracy of 95.9%. The introduction of a novel loss function that incorporates physical knowledge enabled the elimination of physical inconsistencies and improved the overall model performance. The authors emphasize the effectiveness of integrating physical models with deep learning to enhance the accuracy of aero-engine sensor fault diagnosis, which is critically important for flight safety and aviation maintenance.

Mowlavi and Nabi (2023) proposed an extension of the PINNs concept for solving optimal control problems constrained by nonlinear partial differential equations (PDEs). The authors integrated a PINN into the optimal control structure, approximating the state variable and control input with separate neural networks that are trained simultaneously. This approach circumvents the need for PDE discretization and offers flexibility in selecting the cost functional. The research demonstrated that PINNs achieve comparable accuracy to the traditional Direct-Adjoint Looping (DAL) method for optimal control problems constrained by PDEs, especially for complex nonlinear dynamics (like the Kuramoto-Sivashinsky and Navier-Stokes equations). The PINN also showed advantages in flexibility and ease of implementation, particularly with limited data. The authors conclude that PINNs are a promising tool for solving PDE-constrained optimal control problems, combining accuracy with flexibility and straightforward implementation.

Antonelo et al. (2024) introduced a novel approach to modeling and controlling dynamic systems using PINNs. This approach, termed Physics-Informed Neural Nets for Control (PINC), directly integrates physical laws into the neural network's architecture. This integration reduces the need for labeled data and enables more accurate modeling of complex systems. The research demonstrated that PINC, as an extension of the PINNs concept, can effectively model and control nonlinear dynamic systems such as the Van der Pol oscillator, a four-tank system, and an electric submersible pump, even without relying on real-world measured data. This is achieved through PINC's ability to perform rapid predictions, which is crucial for real-time applications. The authors conclude that PINC is a promising tool for modeling and controlling complex dynamic systems, especially in data-limited scenarios. They emphasize that this approach can be beneficial across a wide range of applications, including automatic control, modeling, and optimization.

Bianchi et al. (2024) investigated the application of PINNs for estimating dynamic models of Unmanned Aerial Vehicles (UAVs). The authors proposed a method that directly integrates physical laws into the neural network's architecture. This approach enables effective estimation of system parameters even with limited data and under conditions of high uncertainty. The research showed that the proposed method provides a more accurate estimation of the UAV's state and higher computational speed compared to traditional methods like the Extended Kalman Filter (EKF), which is critically important for real-time applications. The authors concluded that integrating physical laws into neural network training significantly enhances the efficiency of UAV dynamic model estimation, ensuring high accuracy even with limited data. This is a vital advancement for autonomous control systems in the aerospace industry.

In their article, Gu et al. (2024) presented the application of a PINN for modeling quadcopter dynamics. The authors integrated physical laws directly into the neural network's structure, enabling effective system parameter estimation even with limited data and under high uncertainty. The research demonstrated that the proposed approach provides a more accurate estimation of the quadcopter's state and higher computational speed compared to traditional methods like the Extended Kalman Filter (EKF), which is critically important for real-time applications. The authors conclude that integrating physical laws into neural network training significantly enhances the efficiency of quadcopter dynamic model estimation, allowing for high accuracy even with limited data. This is a vital advancement for autonomous control systems in aerospace applications

In their study, Li and Liu (2024) introduced an innovative approach to controlling the trajectory of Automated Guided Vehicles (AGVs) using a PINN within a nonlinear Model Predictive Control (MPC) framework. The authors propose replacing traditional ordinary differential equation models with a PINN, allowing for the direct integration of physical laws into the neural network's training process. This ensures accurate modeling of AGV kinematics without the need for numerical integration. The study demonstrated that the proposed method significantly enhances computational efficiency and control accuracy compared to traditional approaches. The use of Theory of Functional Connections (TFC) and adaptive loss balancing effectively addresses challenges related to initial conditions and control actions, which is crucial for real-time applications. The authors conclude that integrating PINNs into MPC is a promising approach for improving the accuracy and speed of AGV control in complex dynamic environments, providing a high level of adaptability and robustness to changing conditions.

Abdulkadirov et al. (2025) introduced an innovative approach to modeling quadcopter dynamics using Physics-Aware Machine Learning (PAML). This method directly integrates the ordinary differential equations describing UAV motion into the learning process. A notable feature is the use of fractional derivative optimizers, including Riemann-Liouville, Caputo, and Grünwald-Letnikov, which helps reduce modeling errors and lower energy consumption during flight. The research showed that PAML with fractional optimizers provides a more accurate quadcopter flight trajectory compared to traditional PID controllers, demonstrating a 25–35% reduction in errors in spatial coordinates and a 30–44% reduction in Euler angles. The authors emphasize that employing physics-aware neural networks with fractional optimizers significantly boosts the efficiency of quadcopter dynamics modeling and control, leading to more precise results with less energy consumption. This is critically important for autonomous UAVs.

Optimization Tasks

In this section, we limited the selection of sources, as PINNs are generally implemented through optimization problems involving explicit or implicit minimization of a loss functional. This optimization-based formulation is universal and applies to a wide range of problems, including those where finding an optimum of a physical or functional characteristic is not the primary goal but is inherently performed during the model training process.

In their work, Gustafsson and Andersson (2024) investigated the influence of labeled data on the performance of PINNs, specifically Fully Connected Neural Network (FCNN) and Fourier Neural Network (FNN) architectures, in surrogate modeling and the optimization of designs for flow resistance reduction. They compared training approaches: physics-equation-only, data-only, and their combination. It was revealed that for FCNNs, the inclusion of labeled data significantly increased the prediction accuracy of velocity and pressure fields, especially in flow separation zones, with the best results obtained by reducing the weight of the data loss in the loss function. In contrast, for FNNs, the addition of labeled data led to unstable results, limiting their application. The authors concluded that for hydrodynamic design optimization tasks, an FCNN combining physical constraints and labeled data is optimal, ensuring high accuracy and model stability.

Liu et al. (2024) introduced a hybrid approach for airfoil shape optimization, integrating Convolutional Neural Networks (CNNs), PINNs, and Deep Reinforcement Learning (DRL). This method aims to enhance aerodynamic efficiency, specifically the lift-to-drag ratio, by minimizing the dimensionality of the design space. In their framework, CNNs are employed to compress airfoil shape parameters into six key values, effectively reducing the complexity of the search space. PINNs are then applied for a more stable and accurate evaluation of aerodynamic characteristics, circumventing the convergence issues often encountered with traditional methods. DRL, particularly based on Proximal Policy Optimization (PPO), integrates both dimensionality reduction and performance evaluation. This allows it to identify optimal solutions and enhance the algorithm's transferability. The reported results demonstrate a successful improvement in the lift-to-drag ratio, thereby affirming the effectiveness and stability of the proposed optimization strategy.

In their paper, Ma et al. (2025) presented a hybrid methodology for optimizing aviation route planning, combining Physics-Informed Neural Networks (PINNs) with the A algorithm*. The primary goal of this research was to enhance the accuracy of wind field prediction and to optimize routes within a dynamic atmospheric environment. The authors utilized PredRNN for predicting wind fields based on ERA5 data, notably integrating physical constraints, specifically the Navier-Stokes equations, directly into the neural network's loss function. This model was shown to outperform traditional approaches in prediction accuracy. Routes optimized using the A* algorithm, which accounted for these predicted wind conditions, enabled the avoidance of unfavorable zones and a reduction in fuel consumption. This outcome underscores the significant advantages of employing predicted data over historical data for flight planning. The integration of physical constraints into the neural network's training proved pivotal in enhancing prediction accuracy and, consequently, the effectiveness of route planning.

Identification Tasks

The concept of PINNs, which integrate deep learning with physical laws described by nonlinear partial differential equations (PDEs), was introduced in a seminal paper by Raissi et al. (2019). Their research delineates two key application areas for PINNs: solving PDEs based on data (where the network approximates the solution) and discovering unknown PDEs from data (where the network uncovers the equations themselves). For each, they proposed corresponding algorithms suitable for both continuous and discrete time. Experimental results on classical problems, such as flow around a right angle, shock waves, and reaction-diffusion equations, convincingly demonstrated PINNs' ability to accurately reproduce physical solutions even with limited or noisy data. This was further validated by comparisons with analytical and numerical solutions. This makes PINNs a powerful tool for solving both forward and inverse problems in science and engineering, ensuring high accuracy with minimal data requirements.

To address forward and inverse problems with noisy data, Yang et al. (2021) introduced an extended model of PINNs — B-PINNs, which combines them with a Bayesian approach. This innovative method integrates physical laws (via PINNs) with Bayesian Neural Networks (BNNs), where the BNN serves as a prior distribution. The estimation of the posterior distribution is performed using Hamiltonian Monte Carlo (HMC) or Variational Inference (VI), allowing B-PINNs not only to form predictions but also to quantify aleatoric uncertainty arising from noise in the data. Experiments demonstrated that B-PINNs provide more accurate predictions under significant noise compared to traditional PINNs by avoiding overfitting. Furthermore, the HMC method proved more effective for posterior distribution estimation, and the use of BNNs as a prior distribution improved accuracy. This makes B-PINNs a powerful tool for problems described by nonlinear PDEs with noisy data, ensuring accurate predictions and effective uncertainty quantification.

One of the key methods for solving inverse problems in supersonic compressible flows has been presented through the application of PINNs and their extended version, XPINNs. This approach is distinguished by its integration of computational domain decomposition into sub-regions, which significantly enhances the accuracy and expressiveness of the modeling, especially in areas with complex flow dynamics. To ensure the physical correctness of the solutions, the network's loss function integrates not only the basic Euler equations but also entropy conditions and conditions for the positivity of density and pressure. Parameter identification relies on density gradient data obtained from Schlieren photography, as well as information from inlet and partial wall boundaries. The results of numerical experiments, conducted on cases involving expansion waves, flow around a corner, and shock waves, convincingly demonstrate the advantages of XPINNs over PINNs in terms of generalization capability and accuracy in complex regions (Jagtap et al., 2022).

In their study, Hijazi et al. (2023) proposed a combination of model order reduction (ROM) methods, specifically POD-Galerkin, with PINNs to solve inverse problems related to the Navier-Stokes equations. The authors integrated physical equations into the PINN's loss function, which enabled the effective identification of unknown parameters, such as physical viscosity or boundary conditions. Numerical experiments across three test cases (steady flow around a backward-facing step, flow around a circular cylinder, and unsteady turbulent flow around a cubic obstacle) confirmed that the integrated PINN model with POD-Galerkin ROM accurately identified parameters even with limited or noisy data. Crucially, this approach significantly reduced computational costs compared to traditional methods. This makes it a powerful tool for identifying parameters and boundary conditions in fluid dynamics, which is critically important for real-time applications and optimization tasks.

An effective approach to solving inverse problems in engineering structures under various loading scenarios is presented in a paper by Xu et al. (2023). This approach is based on combining PINNs with transfer learning. A key development in their work is a multi-task learning method with uncertainty-weighted adjustment, which significantly enhances the efficiency and accuracy of PINNs in linear and hyperelastic mechanics. This allows, in particular, for the prediction of external loads on structures using limited displacement monitoring data. Numerical experiments confirmed that even with noisy and incomplete data, the model yields satisfactory results. This is attributed to the dual regularization (by physical laws and prior knowledge), providing better stability compared to traditional methods. This approach also successfully overcomes challenges related to geometric scaling and diverse loading scenarios, considerably accelerating learning convergence by inheriting weights from pre-trained models. This paves the way for its application as surrogate models in real-world engineering projects.

The research by Ma at al. (2024) presents an innovative approach to solving inverse problems for partial differential equations (PDEs) by integrating Lasso regression into the structure of PINNs. The developed Sequentially Threshold Least Squares-Lasso (STLasso) module, which combines Lasso regression with the Sequential Threshold Least Squares (STLS) algorithm, enables sparse regression of PDE coefficients. The integration of this module led to the creation of the PINN-STLasso model, capable of discovering underlying PDEs from data while demonstrating lower data volume requirements and improved interpretability. Experiments on classical inverse PDE problems showed that PINN-STLasso outperforms other methods, achieving lower error rates even with limited data. This underscores the approach's effectiveness in discovering underlying PDEs from real, potentially noisy, data.

The research by Sahinet al. (2024) showcases the effective utilization of PINNs for solving both forward and inverse problems within small deformation contact mechanics. The authors employed a mixed-variable PINN formulation with output transformation to strictly impose Dirichlet and Neumann boundary conditions. Notably, they focused on the "soft" incorporation of Karush–Kuhn–Tucker (KKT) type inequalities directly through the loss function, with optimization performed using the Fisher–Burmeister function. Experiments on a Hertzian contact problem demonstrated that PINNs successfully function as Partial Differential Equation (PDE) solvers, tools for enhanced data-driven modeling, inverse solvers for parameter identification, and fast surrogate models. The application of Adam and L-BFGS-B optimizers, along with the fine-tuning of loss weights, led to improved accuracy and reduced training time. The results underscore PINNs' potential as a powerful tool for contact mechanics problems, allowing the integration of physical laws and available data to achieve high accuracy even with limited or noisy measurements.

Lin, Chen, Yang, Jiang, and Liu (2025) introduced a PINN-based method for identifying aerodynamic parameters of aircraft. Their objective was to reduce reliance on resource-intensive traditional approaches. The authors integrated the six-degrees-of-freedom equations of motion as physical constraints into the neural network's loss function, treating aerodynamic parameters as variables for identification. A study on the longitudinal motion of an aircraft demonstrated that this method effectively mitigates the influence of systemic and measurement errors, exhibiting high identification accuracy even when data is noisy. Comparisons with genetic algorithms and traditional neural networks confirmed PINNs' advantages in terms of accuracy and robustness against disturbances. Furthermore, the approach significantly reduces the required volume of experimental data, making it a promising candidate for practical application in the aviation industry.

Prediction Tasks

Yan et al. (2022) presented a new methodology for solving forward problems in linear elasticity, particularly for plates and shells. This approach combines PINNs with the Extreme Learning Machine (ELM) method. The innovation lies in their sub-domain decomposition method, which allows for the effective analysis of structures composed of multiple elements, as well as an improved solution within individual elements. Experimental results demonstrated that the proposed methodology achieves accuracy comparable to exact analytical solutions and finite element method calculations, confirming its potential for wide application in structural mechanics. This combination of PINNs and ELM underscores the promise of integrating physical laws into the neural network training process to achieve high accuracy and computational efficiency.

The prediction of material fatigue life under conditions of limited experimental data became the focus of research by Chen et al. (2023). They proposed an innovative approach based on PINNs, developing a multi-level neural network architecture. A key feature lies in the integration of physical fatigue damage models directly into the activation functions of hidden layers, which allows for the effective combination of data with varying degrees of accuracy. Validation using experimental data for two metallic materials demonstrated that this PINN model provides physically consistent and accurate fatigue life predictions even with a minimal number of training samples. Particularly important is the model's ability to extrapolate beyond the available data, which is critical for practical application. Comparisons with traditional neural networks confirmed PINNs' superiority in terms of prediction accuracy and physical validity, underscoring the effectiveness of integrating physical knowledge to reduce reliance on large volumes of experimental data.

Yang et al. (2024) introduced an innovative physics-guided neural network (PGNN) for predicting material fatigue life. Unlike direct prediction methods, their approach initially estimates S-N curve parameters (specifically, the coefficients of Basquin's equation) based on loading environment characteristics, such as stress concentration factor and stress ratio. This methodology significantly reduces problem complexity and ensures high accuracy in fatigue life prediction, even with limited training data, demonstrating strong extrapolation capabilities. PGNN's advantages over traditional artificial neural networks (ANNs) and Support Vector Regression (SVR) lie not only in its enhanced accuracy but also in the improved interpretability of results due to the model's foundation in physical laws, which allows engineers to make more informed decisions regarding structural design.

The prediction of heat pump thermal load is the central theme of research by Chifu et al. (2024), where PINNs are applied. The essence of their approach lies in integrating thermodynamic principles directly into the neural network's loss function, effectively combining experimental data with theoretical knowledge about heat pumps. Thermal load modeling is performed as a function of input variables such as inlet and outlet temperatures, as well as water flow rate, leading to reduced model complexity and increased prediction accuracy compared to purely data-driven approaches. Experimental results demonstrated significant improvements in accuracy: a 7.49% reduction in RMSE, a 6.49% decrease in MAPE, and a 0.02 increase in R^2, even under unstable or extreme temperatures. This confirms that PINNs serve as an effective and less complex tool for thermal load prediction, without requiring detailed knowledge of system topology or refrigerant parameters.

The review by Li et al. (2024) presents an analysis of contemporary approaches to predicting the Remaining Useful Life (RUL) of engineering systems, combining physical models with deep learning methods. This work systematically categorizes existing methods into three key areas: condition monitoring, fault diagnosis, and RUL prediction, with a particular focus on integrating physical knowledge into deep learning models to enhance prediction accuracy and interpretability. The authors emphasize that traditional RUL prediction approaches often face challenges such as data limitations, the complexity of modeling degradation processes, and a lack of physical interpretation. To overcome these limitations, they propose the use of PINNs, which integrate physical equations directly into the neural network's structure, thereby providing improved generalization capability and more accurate RUL predictions. The review also discusses the challenges and opportunities in this field, pointing to the significant potential of such hybrid approaches for enhancing prediction accuracy and the reliability of technical system condition monitoring.

The innovative Physics-Informed Neural Network Classification (PINNC) model, proposed by Shi and Beer (2024), significantly enhances structural reliability analysis. This development combines physical knowledge with deep learning methods to classify the safety or failure states of structural elements. At its core, PINNC integrates two types of losses—classification loss and physical loss—allowing it to simultaneously account for both actual output values and their adherence to physical laws. This is achieved using a parametric sigmoid activation function that links output values to structural states, with the total loss calculated as a weighted sum of these components. Experiments demonstrated a significant advantage of PINNC over traditional neural networks that only consider classification loss, thanks to improved classification accuracy. The developed adaptive training strategy, which gradually incorporates new samples close to the failure boundary, further enhances the model's accuracy. This underscores the effectiveness of combining physical knowledge and deep learning for robust analysis of complex structures.

The importance of applying Digital Twins for the structural design and life-cycle assessment of aircraft structures is emphasized in the article by Tavares et al. (2024). This research highlights the necessity of integrating sensor data, operational inputs, and historical records to create virtual replicas of physical systems. Such an approach significantly improves the accuracy of predicting structural behavior and enhances their efficiency throughout their entire life cycle. The authors note that traditional numerical models are often unable to adequately reflect real-world behavior due to material variations and manufacturing deviations, proposing Digital Twins as a solution. Additionally, the paper discusses the use of PINNs for addressing various uncertainties in structural analysis. These hybrid approaches, combining experimental data with numerical models, contribute to a more adaptive strategy for ensuring the structural integrity and safety of aircraft throughout their operational life.

A new approach for predicting the remaining useful life (RUL) of fatigue crack growth has been proposed by Liao et al. (2025), leveraging PINNs. This work aimed to develop a method that combines experimental data with fundamental physical laws to accurately determine parameters for crack growth models and subsequently predict the RUL of structures. The key lies in the integration of physical knowledge directly into the neural network's structure to enhance the reliability of predictions. The proposed method effectively establishes the relationship between crack length and the number of loading cycles through automatic differentiation. A specially designed loss function, which incorporates physical constraints, allows for the simultaneous updating of physical model parameters during network training. The results demonstrated that the predicted RUL is significantly more accurate and reliable compared to traditional methods, with all predicted values falling within a 1.5-fold error margin. This approach is particularly valuable for scenarios with limited access to experimental data, reducing the reliance on large quantities of measurements.

Publications Related to Tier 4: Systems-Level Analysis

This section surveys research where PINNs are used to model complex, interconnected aerospace systems at a higher level of abstraction. The focus is on tasks involving system-level behavior, multi-domain interactions, and environmental implications—such as the simulation of coupled subsystems, assessment of operational limits, or prediction of external effects like noise and emissions.

The review highlights how PINNs are applied to represent physical processes within integrated architectures, where outputs from one model inform or constrain another. Also considered are studies where PINNs serve as lightweight surrogates for system-level evaluations, balancing model fidelity with computational tractability in simulations involving large or coupled physical domains.

Model testing and validation

An innovative approach to solving inverse problems in continuum mechanics is presented in a study by Xu et al. (2023). This approach is based on PINNs, integrating transfer learning and multi-task learning with uncertainty weighting. The goal was to enhance the efficiency and accuracy of identifying loads in structures with varying geometries and loading conditions, relying on limited displacement data. The essence of the approach lies in pre-training the model on simplified scenarios followed by re-training for specific cases. This allows the model to adapt to new conditions with minimal computational cost. The results showed that the proposed method can accurately predict external loads even with limited or noisy data. PINNs trained with transfer learning demonstrated high robustness to noise and fast convergence when adapting to new scenarios, outperforming traditional methods like finite element analysis in terms of generalizability and efficiency. This underscores that the integration of transfer learning with PINNs significantly expands the capabilities for solving engineering inverse problems, reducing the need for large volumes of data and computational resources, and opening avenues for real-time structural health monitoring and damage detection.

The assessment of PINNs efficacy in high-fidelity reconstruction of two-dimensional flow fields around a cylinder is a key aspect of research by Yang et al. (2023). This work aimed to determine PINNs' ability to reconstruct full velocity and pressure fields based on limited or noisy data, a common challenge in experimental fluid dynamics. Both numerical data obtained through Direct Numerical Simulation (DNS) and experimental measurements from Particle Image Velocimetry (PIV) were used to train the PINN. The results demonstrated that PINNs outperform traditional methods, such as cubic spline interpolation and classical neural networks, providing more accurate reconstruction of velocity and pressure distributions, even under noisy or sparse data conditions. This confirms PINNs' ability to effectively integrate physical laws, particularly the Navier-Stokes equations, into the training process, which significantly improves the accuracy of physical field reconstruction. The authors underscore the significant potential of PINNs for applications where traditional methods are limited by data quality or volume, as the integration of physical laws into the network structure ensures adherence to physical constraints.

A novel PINNs architecture, named WaveNets, was introduced for the full reconstruction of rotational flow fields under large, high-amplitude periodic water waves. This model, developed by Chen et al. (2024), comprises two distinct neural networks: one predicts the free surface profile, and the other predicts the velocity and pressure fields. Its loss function meticulously integrates Euler's equations and other physical knowledge about wave processes. It also utilizes a novel dynamic sampling point updating method for residual evaluation, which is critically important given that the free surface forms during training. Thanks to highly accurate datasets generated by the numerical continuation method, WaveNets is capable of reconstructing the wave surface and flow field using only a small amount of data, both on the surface and within the flow, for both single-layer and two-layer rotational flows. The accuracy of vorticity estimation can be significantly improved by adding a redundant physical constraint according to prior information about its distribution, underscoring the model's effectiveness under conditions of strong nonlinearity and complex free surface geometry.

The construction of a metamodel based on PINNs for predicting Reynolds-averaged separated turbulent flow around a DU99W350 airfoil at varying angles of attack is a central aspect of the research by Harmening et al. (2024). The model was trained on a limited set of simulation data for specific angles of attack, demonstrating the ability to predict velocity and pressure fields for arbitrary angles within the range of 10.0° to 17.5°, encompassing both interpolation and extrapolation. The results showed successful prediction of flow separation development on the airfoil's upper surface with changing angles of attack, achieving high accuracy, even near the wall. The sensitivity analysis conducted concerning the Reynolds number, the quantity and distribution of training data, and the choice of turbulence model, highlighted the advantages of the Reynolds pseudo-stress method and the importance of having labeled data within the domain. This research confirms the effectiveness of PINNs for creating accurate surrogate models of flow around airfoils with variable geometry, thereby reducing the need for extensive simulation

A highly efficient framework for PINNs to identify parameters of beam structural models is presented in a study by Teloli et al. (2025). The work aimed to solve inverse problems in structural analysis, specifically determining mechanical properties like stiffness and mass, based on limited displacement and strain data. A key feature is the integration of physical laws, particularly beam theory equations, directly into the neural network's training process. This ensures the physical consistency of results even with limited or noisy data. The research demonstrated that the proposed approach can accurately recover model parameters even under uncertain boundary conditions and with a limited volume of data. It also showed high accuracy in predicting the dynamic behavior of beam structures compared to experimental data. This underscores the model's ability to generalize and apply to various scenarios without needing extensive training data, opening possibilities for real-time condition monitoring and damage diagnosis.

The PINN framework developed by Zhu et al. (2025) offers a simultaneous approach for discovering hidden solid boundaries and reconstructing flow fields based on limited observations. The model's uniqueness lies in the integration of a fractional body parameter into the governing equations, which allows for adherence to no-penetration and no-slip conditions in solid regions while preserving hydrodynamic conservation laws. This enables the simultaneous reconstruction of an unknown flow field and the determination of the body's fractional distribution, thereby detecting hidden boundaries. Testing the framework across diverse scenarios, including incompressible Navier–Stokes flows and compressible Euler flows (e.g., steady flow around a fixed cylinder, oscillating cylinder, and subsonic flow over an airfoil), demonstrated accurate hidden boundary detection, reconstruction of missing flow data, and estimation of moving body trajectories and velocities. Further analysis confirmed the method's robustness to sparse data, velocity-only measurements, and noise, making it a promising tool for applications where only limited experimental or numerical data are available, particularly in aerodynamics, biomedical imaging, and marine engineering.

Safety-oriented physical condition modeling

For safety-oriented physical condition modeling, particularly in the context of analyzing temperature fields and thermal loads in critical systems, the research by Cai et al. (2021) demonstrates significant potential. This work explores the application of PINNs to solve inverse heat transfer problems in forced and mixed convection regimes, as well as the Stefan problem with a moving phase-change boundary. This is especially relevant in situations with limited or unknown boundary conditions where traditional methods prove ineffective. PINNs demonstrated the ability to accurately reconstruct temperature and velocity fields, and successfully recover the position of the moving boundary and corresponding fields using only a limited number of internal temperature measurements. This included the successful modeling of thermal processes in complex power electronics thermal design. Thus, PINNs are a powerful tool for solving ill-posed heat transfer problems, unifying computational and experimental approaches, which is critically important for predicting potentially unsafe system operating modes in the interest of safety.

A method for identifying parameters of structural systems with multiphysics damping, based on PINNs, is presented in a study by Liu and Meidani (2023). Their development, named PIDynNet, aims to accurately determine the parameters of nonlinear structural systems, accounting for the complex interaction between mechanical and thermal processes. The essence of this approach lies in integrating physical laws describing structural dynamics and heat transfer directly into the neural network's architecture. This allows the model to learn from limited data while maintaining high physical fidelity in its results. The research showed that PIDynNet can accurately identify parameters even with limited or noisy data, successfully predicting the system's nonlinear response to unknown excitations. For effective training, subsampling and early stopping strategies were employed, which helped prevent overfitting and improved accuracy. This capability for accurate parameter identification in complex systems is critically important for structural integrity monitoring and assessing stability after, for instance, natural disasters, providing a basis for making safety-related decisions.

The modeling of finite deformation plasticity is the primary focus of research by Niu et al. (2023), which employs PINNs. The work aimed to develop an approach that accurately reproduces the behavior of materials during large deformations, including multi-step loading and unloading scenarios. The proposed PINN model directly integrates the physical laws describing the plastic behavior of materials into the neural network's structure, ensuring the physical consistency of results even when trained on limited data. The results demonstrated that the PINN model can accurately reproduce material behavior under finite deformations, successfully predicting the system's nonlinear response to multi-step loading and unloading, and exhibiting significant generalization capability. Furthermore, the performance of the PINN was evaluated in terms of accuracy and stability with mesh refinement and changes in network architecture. This ability to accurately model material behavior in critical pre-failure states is extremely important for ensuring the reliability and safety of engineering structures, allowing for the prediction of potential problems even with limited experimental data.

In the study by Chen et al. (2024), significant advancements have been made in modeling crack propagation and predicting the fatigue life of structures using PINNs. This research focuses on developing a methodology capable of accurately modeling crack behavior in materials under overload conditions. A key aspect of their work is the integration of asymptotic displacement functions near the crack tip into the PINN structure, which ensures highly accurate computation of stress intensity factors without the need for local mesh refinement. An automated crack propagation modeling method was proposed that does not require changes to the network architecture or node distribution during the process, only modifications to the loss functions. Additionally, an algorithm for fatigue life prediction under overloads was developed, which accurately predicts crack propagation delay and the overall life of structures under cyclic loading with periodic overloads. Such a capability for precisely predicting crack behavior, especially under overload conditions, is critically important for maintaining the safety and reliability of complex engineering systems, where monitoring critical states and predicting remaining useful life play a crucial role.

For the purposes of Safety-oriented physical condition modeling, particularly in the context of preventing failures due to stress concentration, Imran Azeem and Pinho (2024) developed a physics-informed machine learning model for predicting stresses in composite structures with open holes, accounting for finite-size effects. The goal of this work was to create a fast and accurate method for stress prediction within a global-local modeling context, which is crucial for aircraft design. Traditional analytical solutions often fail to consider finite-size effects, and semi-analytical methods have limited accuracy. The proposed model, which combines analytical solutions with machine learning methods, demonstrated accuracy comparable to analytical solutions for infinite width, and surpassed them in cases of finite dimensions. It provides highly accurate stress predictions under uniaxial and biaxial loading, utilizing significantly less training data due to the integration of analytical solutions. This allows for reduced computational costs and increased prediction accuracy, both of which are critically important for ensuring structural integrity and safety in aerospace engineering.

Modeling the behavior of materials under simultaneous thermal and mechanical loads, which is critically important for safety-oriented physical condition modeling in geotechnical and other applications, is the central theme of research by Yang et al. (2024). They proposed the application of PINNs to solve the problem of thermoelastic cavity expansion under plane strain conditions. The authors formulated the relevant partial differential equations, normalized them into dimensionless form, and integrated them into the PINN structure. This allowed the model to learn based on physical laws without the need for extensive experimental data. The study's results showed that the proposed PINN model can accurately predict temperature, stress, and strain distributions, which is confirmed by comparison with analytical solutions. Furthermore, the model demonstrated stability and efficiency in solving problems with various material parameters and loading conditions, indicating its versatility and potential for accurate prediction of critical states in complex thermoelastic processes.

The method of PINNs developed by Liao at al. (2025) is designed for identifying parameters and predicting the remaining useful life (RUL) of fatigue crack growth. This research aimed to create a model that accurately determines crack growth parameters and forecasts their future development, which is crucial for assessing the durability of structures. A key feature of the proposed approach lies in the integration of physical laws describing the crack growth process directly into the neural network's structure. This allows the model to learn from limited data while maintaining high physical fidelity and accuracy of results. Experimental data confirmed that PINNs can accurately reproduce fatigue crack growth behavior and predict the RUL of structures, even under limited or noisy data conditions. The model successfully identified key parameters influencing crack growth and demonstrated its ability to generalize. This methodology, which provides reliable predictions even with restricted data, is particularly valuable for ensuring the reliability and structural health monitoring of engineering structures, where accurate prediction of critical damage is essential for safe operation.

Subsystem interaction modeling

An innovative approach to solving complex multi-physical problems was presented by Nguyen et al. (2022) in their work. They developed a new methodology called PINNs-DDM, which effectively integrated PINNs with the Domain Decomposition Method (DDM). This synergy allowed for accurate modeling of interactions between various physical processes, such as fluid dynamics and scalar transport in confined spaces. Practical application of the method to Poisson and Burgers' equations, as well as in aerosol dispersion modeling, confirmed its high accuracy even with a limited amount of training data, which is critically important for real-world applications. The authors emphasized that PINNs-DDM is a flexible and efficient tool, capable of adapting to different types of differential equations and conditions, thus opening new possibilities for systemic analysis.

A significant contribution to the field of identifying nonlinear structural systems with multi-physical damping properties, particularly interactions with a thermal environment, was made by Liu and Meidani (2023). They presented an innovative method called PIDynNet, which effectively combined PINNs with additional loss functions. This allowed for increased accuracy in estimating system parameters, considering both structural dynamics and heat transfer. The research demonstrated that PIDynNet surpassed traditional methods, such as the Extended Kalman Filter, providing more precise identification and the ability to generalize nonlinear responses to new excitations, even with limited data. The authors emphasized that integrating physical knowledge into the neural network's structure significantly improved the efficiency of identifying nonlinear parameters in limited and noisy data environments.

The application of PINNs for predicting the separated turbulent Reynolds flow field around a DU99W350 airfoil at varying angles of attack became a central achievement in the study by Harmening et al. (2024). They successfully created a data-driven metamodel that effectively predicted the spanwise-averaged velocity and pressure in the flow, utilizing a limited set of numerical simulations. This model was trained by incorporating boundary conditions and the Navier-Stokes equations, which guaranteed the physical correctness of the results. The research showed that the developed PINN accurately predicted the evolution of flow separation on the airfoil's suction surface across an angle of attack range from 10° to 17.5°, maintaining high accuracy even near the wall. This confirmed the potential of PINNs as a powerful tool for creating surrogate flow models under data-limited conditions.

A recent study by Beitalmal (2025) presented a ground-breaking hybrid methodology for addressing complex multiscale fluid-structure interaction (FSI) challenges. This novel approach masterfully combined PINNs and the finite element method (FEM). A key aspect of their work involved utilizing PINNs to meticulously model microscopic phenomena, such as turbulence, specifically at the fluid-structure boundaries. This setup facilitated a dynamic, two-way data exchange with the FEM component. The results were quite impressive: their proposed model delivered a fivefold improvement in computational speed when benchmarked against conventional LES-FEM methods. Furthermore, it exhibited a 20% gain in accuracy for tasks like simulating wind turbine blade vibrations and precisely identifying arterial stiffness, outperforming purely FEM-driven solutions. This research compellingly illustrated the power of merging the physically-informed capabilities of neural networks with the well-established accuracy of FEM, ultimately leading to substantial reductions in computational burden.

In a study, Bianchi et al. (2025) introduced an innovative approach to evaluating the dynamic model of unmanned aerial vehicles (UAVs) using PINNs. Their methodology integrated physical laws directly into the neural network's architecture, which allowed for efficient resolution of UAV system identification problems even with limited, nonlinear, and noisy data. The research demonstrated that the proposed PINN method surpassed the traditional Extended Kalman Filter (EKF) in both accuracy and computational speed, providing enhanced adaptability and reduced computational costs, critically important for real-time applications. This approach highlighted the potential of PINNs as a robust tool for modeling and evaluating complex dynamic systems while minimizing the need for continuous network retraining.

Environmental variable prediction

A novel approach to predicting troposphere temperature was presented by Chen et al. (2021), who developed a Physics-informed Generative neural network (PGnet). This innovative model combined fundamental physical constraints, describing heat transfer and diffusion processes, with the powerful capabilities of deep learning to achieve significantly more accurate forecasts of 500 hPa temperature fields. PGnet functioned in two stages: first, physically-constrained prediction, followed by result correction using a generative neural network that employed a mask to identify and improve low-quality predictions. Experiments with ERA5 data confirmed the superiority of PGnet-Momentum over traditional methods (CDNN, ConvLSTM, DeepRNN), demonstrating the lowest Mean Squared Error (MSE = 8.877), the highest correlation coefficient (CORR = 0.9860), and improved SSIM and PSNR metrics. This underscored the effectiveness of integrating physical laws and deep learning for accurate prediction of complex atmospheric phenomena.

An approach to reconstructing acoustic fields in pipes, particularly under conditions of limited and noisy measurements, was proposed by Luan et al. (2025a). Their research demonstrated how PINNs can effectively recover acoustic fields, even when radiation parameters remain unknown. A key achievement was the model's ability to accurately reconstruct acoustic fields using only pressure data from the pipe's outlet end. Importantly, their Fine-Tuning PINN (PINN-FTM) method showed higher accuracy and noise robustness compared to traditional optimization methods. Thus, the authors proved that PINNs are a highly promising tool for solving inverse problems in acoustic analysis under data-insufficient conditions, which is critically important for evaluating the acoustic characteristics of systems where classical approaches cannot be applied.

In the realm of near-field acoustic field reconstruction, Luan et al. (2025b) introduced the Physics-Informed Neural Network-Driven Sparse Field Discretization (PINN-SFD) methodology. This approach innovatively combined physics-informed neural networks with sparse field discretization, integrating the Kirchhoff-Helmholtz integral as a wave propagation model. Importantly, the method did not require a large training dataset and operated in a self-learning mode. Experimental data confirmed that PINN-SFD ensured high accuracy in reconstructing acoustic fields across various vibrational modes, surpassing the traditional Compressive-Equivalent Source Method (C-ESM). An additional advantage was its reduced sensitivity to regularization parameters, making it particularly valuable for practical application in conditions of limited data and complex vibrational modes.

Focusing on the "gradient pathology" issue in traditional PINNs, which leads to inaccurate predictions, Chatterjee et al. (2024) developed and implemented a modified loss function in MATLAB. This modification substantially increased approximation accuracy without additional computational cost. Their research demonstrated how the updated PINNs effectively solved both direct and inverse problems in structural vibrations, specifically for single and two-degree-of-freedom systems. The choice of MATLAB for implementation made this tool accessible and convenient for a wider scientific audience, including those not working with Python. The authors indicated the promise of this approach for aerospace engineering, especially in tasks related to vibrations and the dynamic behavior of structures.

A new model for predicting aviation noise in airports was developed by Zhu et al. (2024), who successfully integrated the physical principles of the ECAC model with deep learning capabilities. This approach ensured a combination of the stability of physically-oriented methods with the high data accuracy characteristic of deep learning approaches. Their model achieved a mean absolute error of just 0.98 dBA when predicting sound exposure levels, indicating its exceptional effectiveness. The research showed that this hybrid model surpassed both purely physically-oriented and exclusively data-driven models in prediction accuracy and generalization ability, underscoring that the integration of physical knowledge significantly increased the stability and reliability of predictions, even in data-limited conditions.

The following collection of studies showcases the broad spectrum of applications for PINNs in modeling environmental and hydrodynamic processes. While not directly focused on the aerospace industry, these investigations offer valuable methodological approaches. For instance, Chuprov et al. (2025) developed a PINN for the inverse solution of the advection-diffusion problem aimed at localizing atmospheric pollution sources, revealing the model's high accuracy and stability. Gomes et al. (2022) demonstrated that incorporating parametric coefficients into PINNs significantly improved the prediction of boundary layers in reaction-advection-diffusion problems. In their work, Hu and Kabala (2023) applied PINNs to model aerosol-cloud-precipitation interactions based on the conceptual Koren–Feingold scheme, ensuring accurate reconstruction of spatiotemporal changes with limited data. Another important area of research involves analyzing pollutant transport in soils and water. Ke et al. (2025) showed that pre-trained PINNs successfully solved both direct and inverse transport problems in porous media even with noisy observations, while Omarova et al. (2023) employed a PINN to simulate river silting, reproducing velocity and pressure distributions with high fidelity. Qi et al. (2024) developed PINN models for 2D shallow water equations that did not require labeled data and demonstrated competitive accuracy compared to finite volume methods. Finally, Ranjith (2023) proved that PINNs can model pollutant propagation in obstructed environments with extremely fast computation speeds and high accuracy. All these studies confirm the flexibility and effectiveness of PINNs in approximating pollution fields, forecasting hydrodynamic or atmospheric variables, and reconstructing complex physical processes. Despite lacking a direct connection to aerospace systems, the methodological advancements from this research can be adapted for modeling the environmental impacts of aerospace activities, specifically in predicting noise fields, emissions, and atmospheric interactions.

Discussion

The idea to undertake this review was inspired by the study of Ghalambaz et al. (2024), which documented a sharp surge in research activity related to Physics-Informed Neural Networks (PINNs). In 2019, only 37 papers were published on the topic, whereas by the end of 2022, the number had increased to 527, with a cumulative corpus of 996 reviewed publications. Such dynamics suggest a transition of PINNs from a niche approach to a mainstream tool within the domain of scientific machine learning. This rapid development motivated the present work. Initially, we anticipated the emergence of underrepresented domains in the application landscape of PINNs and thus designed a deliberately comprehensive and even somewhat redundantly detailed taxonomy to capture such gaps.

The proposed four-tier taxonomy served not only as a conceptual framework but also as a methodological instrument for structuring the literature review. Grounded in physical, operational, and systemic characteristics of aerospace engineering tasks, it encompasses Physical Modeling, Dynamic Analysis, Functional Evaluation, and System-Level Assessment. All selected sources were categorized in accordance with this framework, and each tier was populated with relevant examples, confirming the comprehensiveness of the classification.

As the literature review progressed, the suitability of the taxonomy became increasingly evident. Although the availability and accessibility of studies varied across tiers, representative applications of PINNs were identified in all categories. In some instances, locating pertinent sources required a broader disciplinary search, but their relevance to the defined categories was consistently substantiated. The resulting structure emerged not as a theoretical abstraction, but as a practically validated scheme for organizing existing research.

Early assumptions concerning the lack of studies in areas such as acoustics, optics, or environmental impact assessment did not hold. While these domains are indeed less frequently addressed compared to more established fields like aerodynamics or structural mechanics, publications were nonetheless found that demonstrate the feasibility of applying PINNs to such problems. This suggests that these areas are not entirely unexplored but are still in the early stages of methodological development, requiring further scholarly attention to mature into fully fledged subfields.

One recurring observation in the literature is the absence of standardized approaches to PINN implementation. Most studies feature bespoke neural network architectures and problem formulations tailored to specific tasks. As a result, generalizations regarding methodological limitations remain elusive. The diversity of approaches reflects both the flexibility of the framework, and the challenges associated with its formal consolidation. The lack of convergence toward canonical practices highlights the need for future efforts aimed at formalizing design strategies and training procedures.

Although we initially intended to synthesize the reviewed studies into a unified analytical model, this proved impractical due to the broad and even coverage of all tiers of the taxonomy. The presence of relevant research across the entire framework precluded the identification of structural voids that could serve as anchor points for comparative or meta-analytic synthesis. Nevertheless, the taxonomy itself serves as a valuable outcome of this study, offering a coherent system for classifying PINNs applications in aerospace contexts and guiding subsequent research trajectories.

In summary, the review confirmed the validity of the proposed classification and revealed a wide distribution of PINNs applications across the aerospace domain. While the current research landscape is characterized by methodological diversity and the absence of uniform implementation strategies, the breadth of existing applications underscores the adaptability and relevance of PINNs for complex engineering tasks. Moving forward, the focus may shift from discovering novel application areas to the consolidation of methodological standards and the refinement of theoretical underpinnings that will support broader and more robust integration of PINNs into aerospace system design and analysis.

Limitations and Future Directions of the Taxonomy

The proposed four-tier taxonomy, while methodologically grounded and sufficiently comprehensive for the scope of this review, was intentionally designed with a degree of redundancy. This is evident in the observation that certain studies could reasonably be assigned to more than one tier, a feature that reflects the inherent interdisciplinarity of aerospace tasks and was anticipated during the taxonomy's development.

Despite this flexibility, a notable limitation of the current framework lies in its initial omission of a category that addresses the relationship between design parameters and manufacturing outcomes. Specifically, we now identify a prospective fifth tier, which we propose to name **Tier 5. Applied Manufacturing Performance**. This category encompasses research focused on predicting the realized properties of manufactured components—such as composite structures—based on process-sensitive parameters originating from the design phase. It bridges a critical methodological gap between abstract physical modeling and the empirical realities of production, where fabrication methods and tolerances substantially affect structural performance and reliability.

The absence of this tier in the original formulation was due to the assumption that the volume of relevant studies would be insufficient for meaningful analysis. However, subsequent literature mapping has revealed a growing interest in this direction, and we therefore recognize the value of integrating this domain into future iterations of the taxonomy.

Conclusions

This review introduced and validated a four-tier taxonomy for classifying applications of Physics-Informed Neural Networks (PINNs) in aerospace engineering. The taxonomy—comprising Physical Modeling, Dynamic Analysis, Functional Evaluation, and System-Level Assessment—proved adequate for organizing a broad and diverse body of literature. Each tier was supported by representative implementations, confirming the taxonomy's practical relevance.

The distribution of sources across all levels revealed a wider-than-expected application landscape. Areas initially presumed underrepresented, such as acoustics or environmental impact analysis, were found to be present, albeit less developed. This outcome demonstrates that PINNs have already been applied across the full spectrum of aerospace tasks and confirms the flexibility of the proposed classification.

While methodological diversity across studies precluded generalization or meta-analysis, the taxonomy itself offers a foundation for further systematization. Its utility lies in guiding the mapping, comparison, and future refinement of PINNs applications.

As the field progresses, there is a growing need for methodological consolidation. Future research should aim to establish benchmark tasks, standardize evaluation protocols, and expand the taxonomy to include domains such as manufacturing-aware modeling, thus supporting reproducibility and scalability in aerospace system design.

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