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Editorial: Physics-informed machine learning for modeling and design optimization

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Editorial on the Special Issue
Physics-informed machine learning for modeling and design optimization

This Special Issue of Aerospace Research Communications showcases recent research and developments in Physics-Informed Machine Learning (PIML) for modeling and design optimization in aerospace engineering. Modern aerospace systems increasingly require a balance between physical fidelity and computational efficiency. Traditional numerical solvers remain essential for high-accuracy analysis, but their computational cost can limit their use in iterative design and real-time decision-making. Purely data-driven models, by contrast, may provide rapid predictions but often lack robustness when extrapolated to complex or safety-critical regimes. PIML addresses this gap by embedding governing equations, boundary conditions, conservation laws, and other domain knowledge into machine learning frameworks. In this way, it offers a promising route toward reliable, efficient, and interpretable modeling tools for aerospace applications.

For aerothermal prediction, Wang et al. explored a machine-learning-assisted framework for estimating high-speed flow heating around a two-dimensional cylinder. Chemical non-equilibrium numerical simulations were first used to generate aerothermal datasets under different freestream conditions. Based on these data, multilayer perceptron (MLP) and convolutional neural network (CNN) models were trained to predict wall heat flux and flow-field quantities. The results show that MLP is effective for surface and one-dimensional profile predictions, while CNN is more suitable for reconstructing full temperature and pressure fields, offering a rapid surrogate for thermal protection system design.

For rapid aerodynamic evaluation of supercritical airfoils, Liu et al. proposed a framework combining Deep Operator Network (DeepONet), multilayer perceptron, and variational autoencoder (VAE) for transonic flow-field prediction. The VAE extracts compact representations of flow fields, while the DeepONet-MLP model maps airfoil geometry and lift coefficient into the latent space for efficient reconstruction. By incorporating physical constraints related to mass conservation and pressure coefficient, the model improves both prediction accuracy and generalization. This work provides an efficient surrogate for CFD-based airfoil analysis and aerodynamic optimization.

As a representative advance in scalable PIML algorithms, Ye et al. developed overlapping physics-informed neural networks (PINNs) for solving forward and inverse partial differential equation (PDE) problems with spatial-temporal parallelism. By decomposing the computational domain into overlapping subdomains and training local PINNs in parallel, the method reduces the burden of global training while maintaining interface consistency. A subdomain-wise input rescaling strategy is further introduced to alleviate spectral bias in high-frequency solutions. Numerical tests on Helmholtz, Burgers, and heat-transfer problems demonstrate good accuracy and strong scalability on multiple graphics processing units (GPUs).

For optimal control problems, Schiassi et al. introduced Pontryagin Neural Networks (PoNNs) to learn open-loop control actions for systems with integral quadratic cost. By embedding the Pontryagin Minimum Principle (PMP) into a physics-informed learning framework, the method converts optimal control problems into two-point boundary value problems and approximates the associated state and costate variables with neural networks. Benchmark linear and nonlinear examples show that PoNNs can achieve accurate solutions with reduced computational time, indicating potential for real-time aerospace guidance and control.

For structural vibration analysis, Chatterjee et al. presented a MATLAB implementation of PINNs for both forward simulation and inverse parameter identification. The study considers representative vibration problems, including spring-mass systems, multi-degree-of-freedom systems, and membrane vibration. To improve the accuracy of conventional PINNs, the authors modify the neural network output so that initial and boundary conditions are embedded directly, reducing loss-scaling difficulties without additional computational cost. The release of executable MATLAB codes also improves the accessibility of PINN-based structural dynamics modeling for engineering users.

Beyond aerodynamics, control, and structural mechanics, Shen extends physics-informed learning concepts to high-mobility satellite communications. The study develops a deep learning-based channel estimation framework for orthogonal time-frequency space (OTFS)-enabled low-Earth-orbit (LEO) satellite systems under severe Doppler effects. By combining delay-Doppler feature extraction, temporal coherence modeling, and physics-informed regularization, the method improves estimation accuracy, reduces pilot overhead, and maintains robustness across different signal-to-noise ratios (SNRs) and orbital altitudes. This work highlights the broader relevance of PIML-inspired methods for future 6G non-terrestrial networks.

Together, these six articles illustrate the breadth of current PIML research in aerospace engineering. They cover fast surrogate modeling, scalable PINN algorithms, optimal control, structural dynamics, and satellite communications, while sharing a common objective: to combine physical knowledge with data-driven learning for more reliable and efficient prediction, simulation, and design optimization. Collectively, the contributions point toward a future in which physics-informed learning becomes an important computational foundation for next-generation aerospace systems.

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