AIRoV 2026 | Workshop on Physics-Informed Machine Learning and Hybrid Modeling (PhysicsML)

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The objective of this workshop was to present, explore, and critically discuss recent advancements in the rapidly evolving field of physics-informed machine learning (PIML) and hybrid modeling. This interdisciplinary domain merges traditional physics-driven numerical methods with modern machine learning techniques, aiming to improve model fidelity, reduce computational cost, and enhance generalizability across a wide range of scientific and engineering problems such as fluid dynamics, solid mechanics, communications, material design or computational medicine.

Hybrid modeling, in particular, leverages the strengths of both paradigms—combining first-principles models with machine learning—to overcome limitations inherent in purely data-driven or purely mechanistic approaches. A fundamental challenge in hybrid modeling is to understand the propagation of errors and uncertainties of the (data-driven or first principles) parts, and how this affects the qualitative and quantitative behavior of the hybrid model. Complementary to hybrid modeling, PIML utilizes first-principles knowledge in the creation of machine learning models, influencing data selection, model parameterization, or learning itself via regularization.

The workshop served as a platform to connect developments in fundamental theory, algorithmic innovation, and application-driven research. We invited contributions addressing the following topics:

- Hybrid modeling approaches combining laws of physics and machine learning
- Neural-enhanced algorithms and model-based deep learning
- Novel physics-informed training objectives
- Model parameterization approaches based on prior knowledge
- Methods for constructing probabilistic hybrid or PIML models
- Domain-aware training data creation/selection
- Applications of PIML and hybrid models in science and engineering
- Uncertainty and error propagation in hybrid models
- Fundamental trade-offs in PIML and hybrid modeling (energy-performance, complexity-accuracy, etc.)

An important aim of this workshop was to connect researchers in the field of PIML and hybrid modeling, and to thus establish a strong community in this field. In addition to original research, we explicitly invited extended abstracts summarizing already published results or work in progress.

The Third Austrian Symposium on AI, Robotics, and Vision (AIROV26).

Peer Review Report

We received 12 submissions to our workshop, which subsequently underwent a short but efficient peer reviewing cycle. We would like to take the opportunity to thank our reviewers: Federica Caforio (University of Graz), Christian Findenig (Materials Center Leoben Forschung GmbH), Hans-Peter Gänser (Materials Center Leoben Forschung GmbH), Larissa Jeindl (Graz University of Technology), Christian Laubichler (LEC GmbH), Michael Obermayr (Graz University of Technology), Sascha Ranftl (Purdue University), Franz Rohrhofer (Know Center Research GmbH), Malte Rolf-Pissarczyk (FAU Erlangen-Nürnberg), Bernd Schuscha (Materials Center Leoben Forschung GmbH), Marian Staggl (Graz University of Technology), Martin Wellenhof-Karner (Graz University of Technology).

Securing at least two independent reviews (one of which was provided by one of the workshop organizers), we selected 10 submissions for presentation at the workshop. Of these 10 submissions, two were full papers and eight were extended abstracts.

Workshop Summary

Our workshop started with a Keynote Lecture given by Prof. Nils Thürey, Technical University of Munich. Titled "Differentiable PDE Solvers for Numerical Simulations", the talk presented lessons from the area of AI/deep learning for physics simulations with numerical solvers. A key focus was the utilization of solvers that are capable of providing Jacobians, i.e., "differentiable simulations". These solvers seamlessly integrate with deep learning algorithms, presenting numerous advantages arising from AI-based components in solvers, particularly in the context of flow simulations. However, many existing simulation environments do not provide gradients. Avenues for computing them were discussed, as well as fallbacks if they're not available. It was also shown how to leverage differentiable solvers in applications such as closure modeling for Navier-Stokes, accelerated solving and inverse problems.

The contributed talks, filling two 90-minute sessions, presented original contributions, work in progress, and summaries of previously published work. Thematically, we had a strong focus on Bayesian methods, ranging from a new class of physics-informed Gaussian processes, over physics-informed Bayesian optimization to Bayesian inference over function values *and* model parameters. Two contributions in the field of symbolic regression proposed including physics information via finite element simulations, and converting the identified equations to a probabilistic graphical model. Physics information was further used to guide feature engineering in a case study on 3D-printer state estimation, and to speed up reinforcement learning for airflow diffuser design. Obtaining gradient information from a differentiable solver, a contribution showed that surrogate model training can be sped up substantially. Physics-informed neural networks (PINNs) were proposed for estimating active material properties in cardiac models. While this work focused on the inverse problem of estimating parameter fields from data, the forward problem—learning the solution function based on the initial and boundary conditions—-is known to cause problems for PINN training. One paper in our workshop addressed this topic and present an approach to prevent PINNs from converging to unstable fixed points of ordinary differential equations. Recognizing the relevance of this problem, this paper was awarded the Best Paper Award at AIRoV 2026.

Outlook

Given the substantial interest in the topic of physics-informed machine learning and hybrid modeling, we aim at giving this workshop a regular presence at future AIRoV Symposia. Future installments shall reserve time for breakout sessions, during which synergies between ongoing projects can be discussed in more detail.

Acknowledgments

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