# Partial-Physics Pretraining for Transfer-Learning in Computational Aerodynamics

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## 1. Introduction

In applied aerodynamics, machine-learning has demonstrated immense potential for various domains, including aerodynamic shape optimization [1] and flow control [2]. However, up-scaling these aerodynamic surrogates can be expensive, or even impractical, due to the associated costs of constructing high-fidelity and whole-physics training sets. Notably, data acquisition methods are typically constrained, ranging from intractable computations to resolve turbulent length scales at high Reynolds numbers ($Re$) [3] to physical limitations in experiments [4]. While there is a growing number of online databases describing fluid mechanics [5, 6], their utility may be less universal than large image datasets due to the sensitivity of flow physics towards operating conditions, geometry, and time scale, among many other parameters. Ultimately, building robust models that can generalize well in such data-scarce environments is not straightforward.

In this study, a partial-physics pretraining into transfer-learning strategy is explored in the context of a fundamental aerodynamic flow over airfoil problem, followed by application in empirical settings, including satellite rarefied aerodynamics and quadrotor agile flight.

## 2. Case Study A: Fundamental Flow Over Airfoil

*Reynolds-Averaged Navier Stokes (RANS)*. The whole-physics, mean aerodynamic performance of an airfoil operating at a given $Re$ and pitch ($\alpha$) is described by the surface distribution of pressure ($C_p$) and skin friction coefficients ($C_f$), obtained from the finite-volume flow field solution of the two-dimensional, steady and incompressible RANS equations, i.e.

$$\rho \nabla \cdot (\overline{\boldsymbol{u}} \otimes \overline{\boldsymbol{u}}) + \nabla \overline{p} = \mu \nabla^2 \overline{\boldsymbol{u}} + \nabla \cdot \boldsymbol{\tau} \tag{1}$$

$$\nabla \cdot \overline{\boldsymbol{u}} = 0 \tag{2}$$

where $\overline{\boldsymbol{u}}$ and $\overline{p}$ is the mean velocity vector and pressure, and $\boldsymbol{\tau}$ is the Reynolds stress, in an environment of density $\rho$ and dynamic viscosity $\mu$.

*Potential Flow*. By introducing the assumption of inviscid and irrotational flow, the flow field can be simply described by its velocity potential ($\overline{\boldsymbol{u}} = \nabla\phi$) and streamfunction ($\overline{\boldsymbol{u}} = \nabla\times\psi$) to satisfy the Laplace equation, i.e.,

$$\nabla^2\phi = \nabla^2\psi = 0 \tag{3}$$

An inviscid, partial-physics equivalent of surface pressure ($C_{p,\mathrm{inv}}$) can be obtained from this environment, whereby compute time per sample is equivalent to only 0.2% of the whole-physics cost. As such, prediction models can be massively pretrained before transfer-learning towards the sparse whole-physics samples.

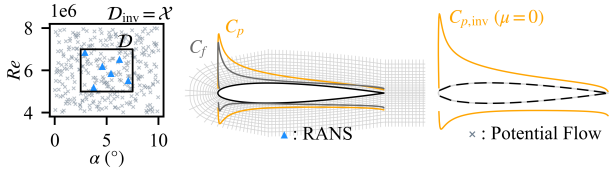


Fig. 1: Pretraining with partial-physics $C_{p,\mathrm{inv}}$ followed by transfer-learning towards sparse samples of whole-physics $C_p$ and $C_f$ [7].

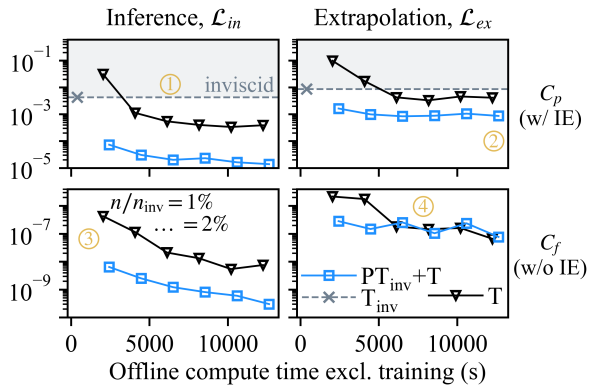


Fig. 2: Partial-physics pretraining leads to consistent improvements to model performance in both inference and extrapolation, under both similar and distant transfer settings.

## 3. Case Study B: Satellite Rarefied Aerodynamics

The partial-physics strategy is applied to the simulation of satellites operating in very low Earth orbits. At such low altitudes, high-fidelity and affordable aerodynamics modelling is imperative for reliable satellite design and mission planning due to the presence of atmospheric drag. Herein, models are first pre-trained in a partial-physics environment derived by theoretical panels, then transfer-learned towards sparse samples of whole-physics, particle-based simulations.

## 4. Case Study C: Quadrotor Agile Aerodynamics

In quadrotor agile aerodynamics, the flight regime of high-speed agile maneuvers is dominated by unsteady aerodynamic influences which are challenging to empirically model and compensate for, while CFD is limited by its costs. Improved surrogates for agile aerodynamics can be obtained by first pre-training in aerodynamics-free motion, then transfer-learning of unsteady CFD aerodynamics.

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