



Geometry-Independent Reduced Order Model For CFD Using Immersed Damping Source And Neural Networks

This work presents a geometry-independent reduced-order modeling strategy, denoted FlowROM, for transforming CFD simulation data into a machine-learning-based surrogate that approximates the behavior of the Navier-Stokes equations while significantly reducing computational cost.

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Introduction

The central idea is to replace explicit geometry parameterization by an immersive formulation in a normalized computational domain. Instead of describing solid bodies through boundary-fitted meshes or parameterized shapes, the simulation space is represented as a dimensionless unit domain, e.g., a unit square in 2D and, prospectively, a unit cube in 3D. Geometry is encoded indirectly by a binary voxel mask distinguishing fluid and solid regions . Voxels associated with

solid bodies are not removed from the flow domain; instead, they are assigned a strong momentum-damping source term. This source-term formulation acts as an artificial porous resistance that suppresses local velocity to nearly zero, thereby reproducing the effect of impermeable solid regions and implicitly enforcing no-slip-like behavior without explicit boundary-condition tracking.

Pressure and flow field Visualization

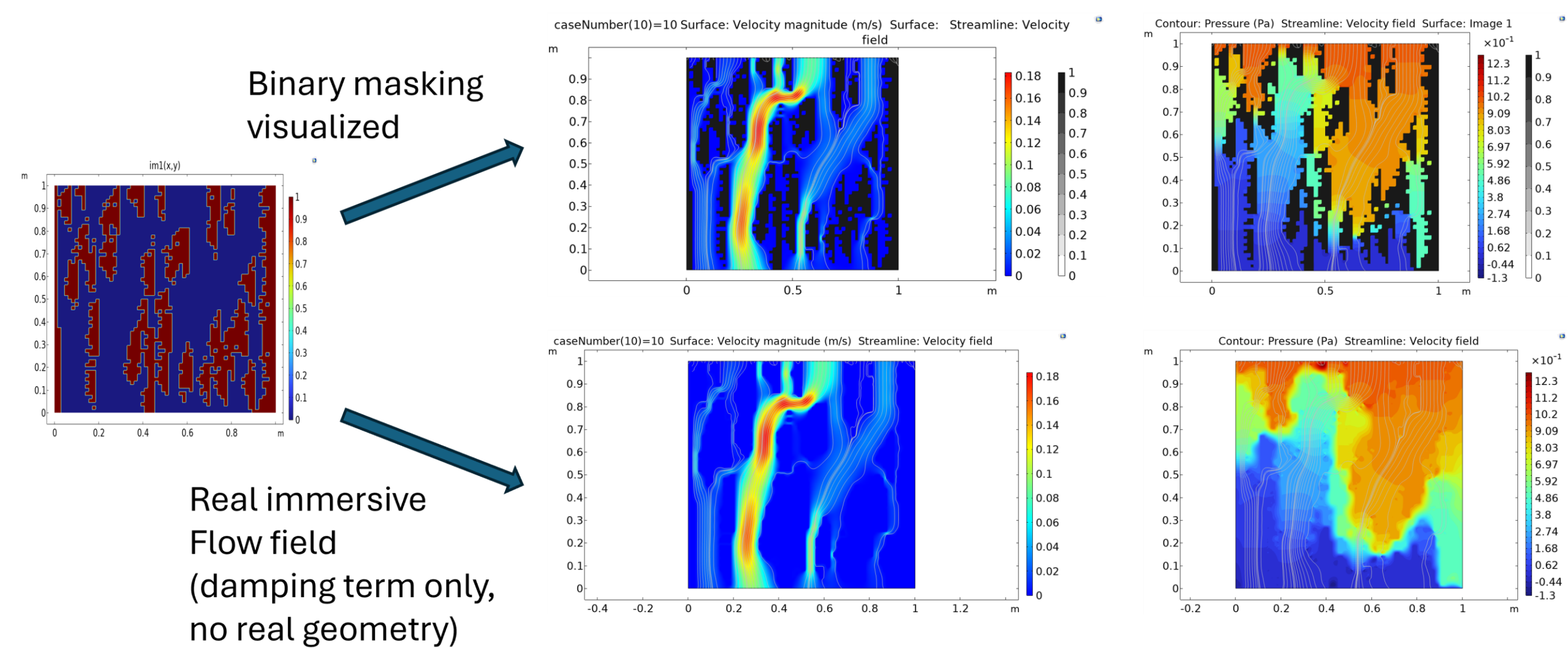


Figure 1. Training Data Generation Workflow

Methodology

Training data are generated with COMSOL Multiphysics® using classical CFD simulations in the normalized domain. The exported fields include spatial coordinates, velocity components, pressure, and the binary geometry mask, which together form the input-output basis for the neural-network workflow. The presented workflow therefore combines CFD-based field generation, geometry masking, and supervised learning into a reduced-order framework that is independent of conventional geometric parameterization. This makes the method suitable not only for simple parametric configurations but also for complex, irregular, and nonparameterizable shapes. Several neural network architectures were tested for this task, including a simple fully connected network, Deep ResNet, FlowCNN, and U-Net.

Results

The comparison of training behavior and flow-field predictions indicates that the U-Net architecture provides the most accurate overall reconstruction quality, with predictions that most closely match the target velocity components and flow magnitude fields across the tested obstacle configurations. The training-history plots and prediction comparisons further support this ranking, showing that U-Net achieves the strongest validation performance among the evaluated models. The visualized results indicate that the immersive damping-term approach reproduces meaningful pressure and velocity field structures while preserving the encoded obstacle topology through the binary mask. Compared with conventional CFD only workflows, the method is intended to reduce simulation effort drastically while retaining the dominant physical flow features. The broader implication is a practical route toward fast engineering prediction tools based on CFD-trained machine learning, with the potential to accelerate flow analysis by orders of magnitude and to extend efficiently toward more advanced validation studies, pressure-aware learning targets, turbulence extensions, and future 3D implementations.

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Current results with U-NET convince

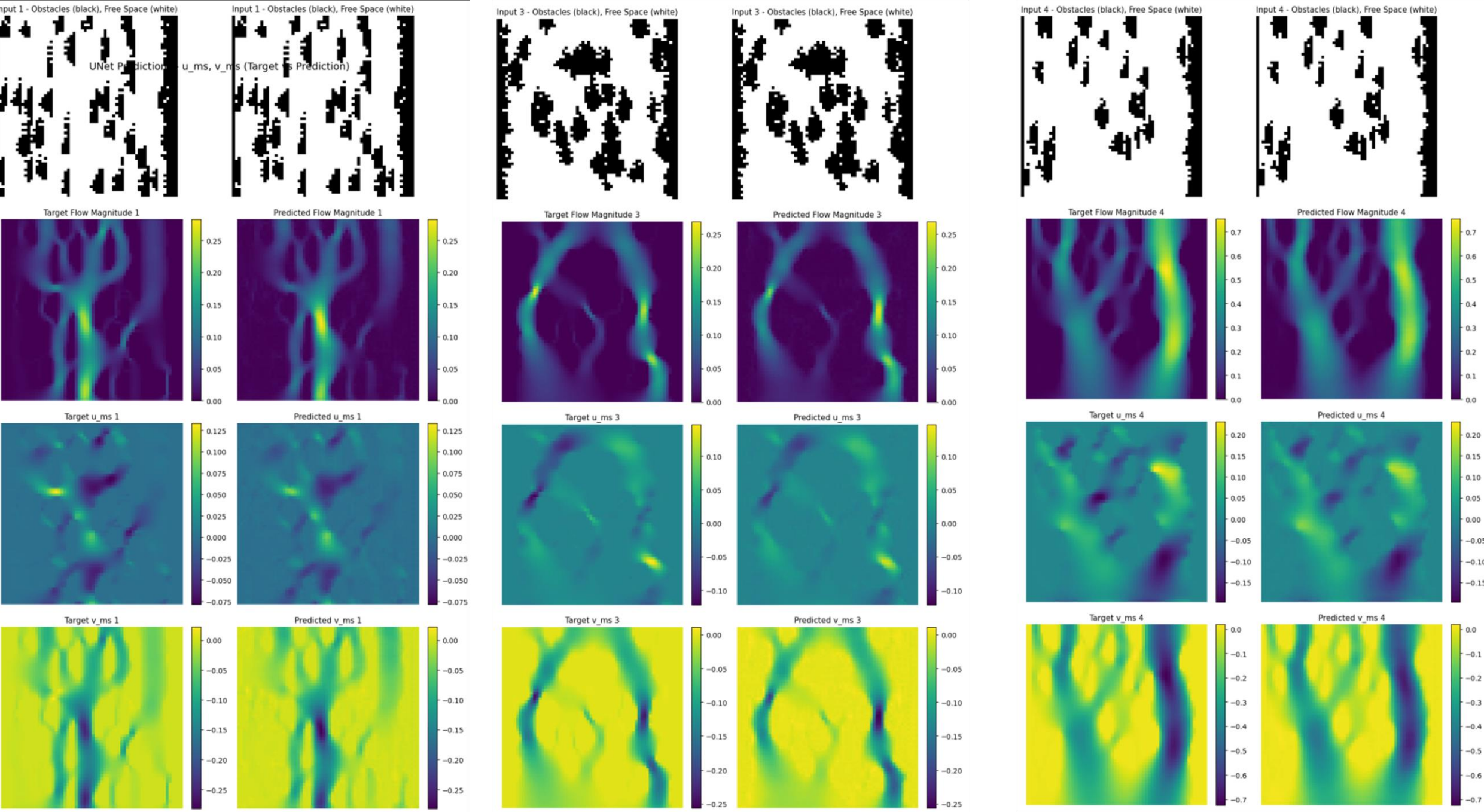


Figure 2. U-NET predicted Data vs. Comsol Trainings Data Results