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Enhanced Physics-Informed Neural Networks for Efficient Solution of 2D Shallow Water Models

Communication Info

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Abstract

Physics-informed neural networks (PINNs) provide a flexible framework for solving nonlinear partial differential equations by embedding physical laws into neural network training [1]. This study presents an enhanced PINN approach for efficiently solving the two-dimensional shallow water equations (SWE) on a flat bed. The proposed enhancement introduces a dynamic mesh-refinement strategy that adaptively increases the density of collocation points in regions with steep gradients and propagating wave fronts, where standard PINNs often lose accuracy [2,3]. The SWE are enforced as soft constraints in the loss function, together with initial and boundary conditions, resulting in a data-free formulation without labeled targets. Fully connected neural networks are trained using a hybrid optimization scheme combining Adam and L-BFGS to improve convergence [4,5]. The enhanced PINN is evaluated against a standard PINN, with a finite difference method (FDM) used as a reference solution. Numerical results show that adaptive refinement improves accuracy near wave fronts and accelerates convergence, producing solutions closer to the FDM benchmark. These results demonstrate that dynamic refinement significantly enhances the efficiency and reliability of PINN-based shallow water modeling.

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