AUGMENTED MESH REFINEMENT IN PHYSICS-INFORMED NEURAL NETWORKS FOR EFFICIENT SOLUTION OF STIFF PARTIAL DIFFERENTIAL EQUATIONS

Nursyiva Irsalinda [1,2], Maharani Abu Bakar[1,3] *

[1] *Faculty of Computer Science and Mathematics, Universiti Malaysia Terengganu, Kuala Nerus, Terengganu, 21030, Malaysia*
[2] *Faculty of Applied Sciences and Technology, Universitas Ahmad Dahlan, Banguntapan, Bantul, 55166, Indonesia*
[3] *Special Interest Group Modelling and Data Analytics, Faculty of Computer Science and Mathematics, Universiti Malaysia Terengganu, Kuala Nerus, Terengganu, 21030, Malaysia*

ABSTRACT

Physics-Informed Neural Networks (PINNs) have emerged as a promising approach for solving partial differential equations; however, their performance often degrades when applied to stiff PDEs due to the inability of uniform training meshes to accurately capture localized sharp gradients without incurring high computational cost. This limitation leads to inefficient learning and slow convergence, particularly in regions with highly nonlinear behavior. To address this issue, this study proposes an Augmented Mesh Refinement Physics-Informed Neural Network (Aug-MR PINN), a novel framework that dynamically reallocates training points toward regions with high residual errors. The proposed method employs residual-based criteria to adaptively refine the mesh during training, enabling the model to focus on critical regions while avoiding unnecessary computation in smoother areas. This adaptive strategy enhances the representation of localized features and improves overall training efficiency. Experimental results demonstrate that Aug-MR PINN consistently achieves lower loss values and faster convergence compared to existing approaches, including AMR-FEM, standard PINN, R-PINN, and X-PINN. Furthermore, the proposed refinement strategies exhibit comparable performance, highlighting the robustness and flexibility of the framework.Overall, this work provides an effective and scalable solution for solving stiff PDEs and offers strong potential for broader applications in computational physics, including fluid dynamics, wave propagation, and multiphase systems.

***K*eywords** Mesh refinement · Physics Informed Neural Networks · Stiff PDE · Mesh grid

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* *Corresponding Author's E-mail: maharani@umt.edu.my*

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