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Solving natural convection problem in annulus pipes using physics informed neural network

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Investigation of natural convection problems in horizontal annuli has been one of the topic of interest for decades because of its versatility for example in solar collector-receiver, underground electric transmission cables and food process devices. Conventional CFD methods has been widely used for addressing the heat transfer problems, however these methods are still costly when it comes to new cases with varying boundary conditions. Recent advancements of data science has facilitated the emergence of new methods like physics informed neural network [1] for solving forward and inverse PDEs problems. In this study, we verify the capability of this novel technique in solving natural convection problem in the annulus pipes. One of the main challenges of solving partial equations using PINN model concerns imposing the boundary conditions into model, which can be done through a soft manner by feeding the values into PINN model or hard constraints via a predefined function representing the general form of the solution. We propose a new ansatz model for the solution and compare its performance with the previous model in literature [2]. Once the model has been trained it can make prediction for given input values with no extra cost. The numerical investigation is carried out for different governing parameters namely, Rayleigh number and .Our preliminary results have been validated against those obtained from CFD results and showed an acceptable accuracy while demanding for lower computational costs.

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