# Physics-informed neural networks for modelling groundwater flow in unconfined aquifers

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**Résumé**

Physics-informed neural networks (PINNs) are a class of machine learning models that incorporate physical laws or principles into the neural network architecture(1). These models aim to combine the power of data-driven approaches, like neural networks, with the governing equations of physical processes to improve accuracy and generalization, particularly in scenarios with limited or noisy data.
PINNs are receiving increasing interest in simulating flow in porous media(2). However, to the best of our knowledge, it has never been used to simulate flow in unconfined aquifers. In this work, we show how PINNs can be used in such a case. We suggest a time scaling approach to normalize the space and time domains.

The flow processes in unconfined aquifers are governed by Darcy's law and the continuity equation with the Dupuit approximation.With PINNs, the pressure head($H$) is approximated using a deep neural network. The network is trained to satisfy the governing partial differential equation (PDE) on a given number of collocation points. Since PINNs do not utilize any predefined datasets, the neural network is trained by creating data points in line with the initial and boundary conditions. The partial derivatives required are obtained using automatic differentiators.

As a first step, the PINN-based method has been applied to a 1D case. The application to 2D problems is under development. A sample of the results obtained with PINNs in a 1D scenario is presented. It concerns flow in unconfined aquifer with imposed head charges at the left and right sides. The aquifer is homogenous and isotropic.

Several runs have been performed to select the parameters used for the NN and the optimizer. The results which will be presented are obtained with 32,786 collocation points in the spatial and temporal domain and 256 points for the initial conditions. The NN model is a 4-layer feed-forward deep neural network with hyperbolic tangent activation function. The network utilizes two optimizers. The model is initially trained using Adam optimizer and then followed by LBFGS optimizer for further reducing and stabilizing the loss function. The Adam optimizer works with a learning rate of 0.001 over 30,000 epochs while

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the LBFGS optimizer operates over 300 epochs with a learning rate of 0.1. PINNs cannot provide good results without normalizing the space and time domains. In our case, this is done by defining a new variable for the time ($t^*$) that is equal to the time divide by 1000 ($t^* = t/1000$). The results of PINNs have been compared with the results of the finite element model COMSOL. The results obtained show good agreement with the COMSOL counterpart.

## References

(1) M. Raissi et. Al., Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations, Journal of Computational Physics, Volume 378, Pages 686-707 (2019).

(2) Lal Dangi et al. Predicting flow in porous media: a comparison of physics-driven neural network approaches, Mathematical Models in Engineering, Vol. 9, No. 2 (2023).