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Fast and detailed emulation of urban drainage flows using physics-guided machine learning

Roland Löwe[1], Rocco Palmitessa[1], Allan Peter Engsig-Karup[2], and Morten Grum[3]
[1]Technical University of Denmark, Department of Environmental Engineering, Kgs. Lyngby, Denmark (rolo@env.dtu.dk, rocp@env.dtu.dk)
[2]Technical University of Denmark, Department of Applied Mathematics and Computer Science, Section of Scientific Computing, Kgs. Lyngby, Denmark (apek@dtu.dk)
[3]WaterZerv, Brønshøj, Denmark (mortengrum@waterzerv.com)

Hydrodynamic models (numerical solutions of the Saint Venant equations) are at the core of simulating water movements in natural streams and drainage systems. They enable realistic simulations of water movement and are directly linked to physical system characteristics such as channel slope and diameter. This feature is important for man-made drainage structures as it enables straightforward testing of the effects of varying channel designs. In cities, models with hundreds up to tens of thousands of pipes are commonly used for drainage infrastructure. Their computational expense remains high and they are not suited for a systematic screening of design options, discussing water management options in workshops, as well as many real-time applications such as data assimilation.

Hydrologists have developed many approaches to enable faster simulations. All of these do, however, compromise on the physical detail of the simulated processes (for example, by simulating only flows using linear reservoirs), and usually also on the spatial and temporal resolution of the models (for example, by simulating only flows between key points in the system). The link to physical system characteristics is thus lost. Therefore, it is challenging to incorporate such approaches into planning workflows where changing city plans require a constant revision of water management options.

Recent advances in scientific machine learning enable the creation of fast machine learning surrogates for complex systems that preserve a high spatio-temporal detail and a physically accurate simulation. We present such an approach that employs generalized residue networks for the simulation of hydraulics in drainage systems. The key concept is to train neural networks that learn how hydraulic states (level, flow and surcharge volume) at all nodes and pipes in the drainage network evolve from one time step to another, given a set of boundary conditions (surface runoff). Training is performed against the output of a hydrodynamic model for a short time series.

Once trained, the surrogates generate the same results as a hydrodynamic model in the same level of detail, and they can be used to quickly simulate the effect of many different rain events

and climate scenarios. Considering pipe networks with 50 to 100 pipes, our approach achieves NSE values in the order of 0.95 for the testing dataset. Simulations are performed 10 to 50 times faster than the hydrodynamic model. Training times are in the order of 25 minutes on a single CPU. The surrogates are system specific and need to be retrained when the physical system changes. To minimize this overhead, we train surrogates for small subsystems which can subsequently be linked into a model for a large drainage network.

Our approach is an initial application of scientific machine learning for the simulation of hydraulics that is readily combined with other recent developments. Future research should, in particular, explore the application of physics-informed loss functions for bypassing the generation of training data from hydrodynamic simulations, and of graph neural networks to exploit spatial correlation structures in the pipe network.