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Deep Learning for Modelling of Urban Drainage Networks: A Physics-informed Surrogate Model Using Measured and Simulated Data

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Abstract: City-wide climate adaptation for pluvial flood mitigation requires fast and reliable simulation tools. Considering the limitations of hydrodynamic models at city-scale simulations, data driven models have high potential in the development of surrogate tools. This study explores the Google DeepMind WaveNet™ model architecture to map hydrological response of catchments onto hydraulic parameters of the pipe network in a physically informed approach to deep learning. The WaveNet-based surrogate model successfully predicted hydraulic head and pipe flow in the network at average Normalized Nash-Sutcliffe Model Efficiency Indices of above 0.8, while boosting simulation speed by a factor of 1000. The developed AI model can be used for different assessment and optimization studies on the drainage network, thanks to its physics-informed structure.

Keywords: Artificial Intelligence; Machine Learning; Urban Drainage

Background

Optimization for efficient sizing-siting of blue-green urban infrastructure is an essential step in climate adaptation of drainage in cities, requiring fast and reliable models (Seyedashraf *et al.*, 2021; Haghighatafshar *et al.*, 2019). Current hydrodynamic simulations at the city-scale are expensive; through simplified models, speed can be increased at the cost of spatiotemporal resolution and model reliability. To increase simulation speed while maintaining model reliability, this study aims to develop an AI-based tool that is fast and reliable, to be used as a surrogate-model in lieu of a mechanistic hydrodynamic model for efficient optimization/planning of blue-green urban infrastructure.

Methodology

For the neighbourhood in Malmö, Sweden, which was chosen as the pilot area for this proof-of-concept study, rainfall measurements are available in long timeseries suitable for machine learning, but actual measured pipe flow data is not. Therefore, an existing hydrodynamic model (MIKE+, DHI), was fed measured rainfall data from 2007 (full year) to produce rainfall-runoff and the subsequent hydraulic head and pipe network discharge data (Figure 1.1), similarly as presented by Zahura *et al.* (2020).

This expensive computation was performed *once*, creating a dataset the AI model can be trained on, to replace the hydrodynamic model. A WaveNet-architecture (van den Oord *et al.*, 2016) deep-learning model was developed utilizing Keras and TensorFlow to translate rainfall-runoff timeseries into network hydraulics (levels and flows). The AI model was trained/validated on compiled data of only rainy days from the hydrodynamic simulation dataset corresponding to 11.5 weeks, using the normalized

Nash-Sutcliffe Model Efficiency Index (NNSE) (Nash and Sutcliffe, 1970) for AI model accuracy assessment (compared to the hydrodynamic model results).

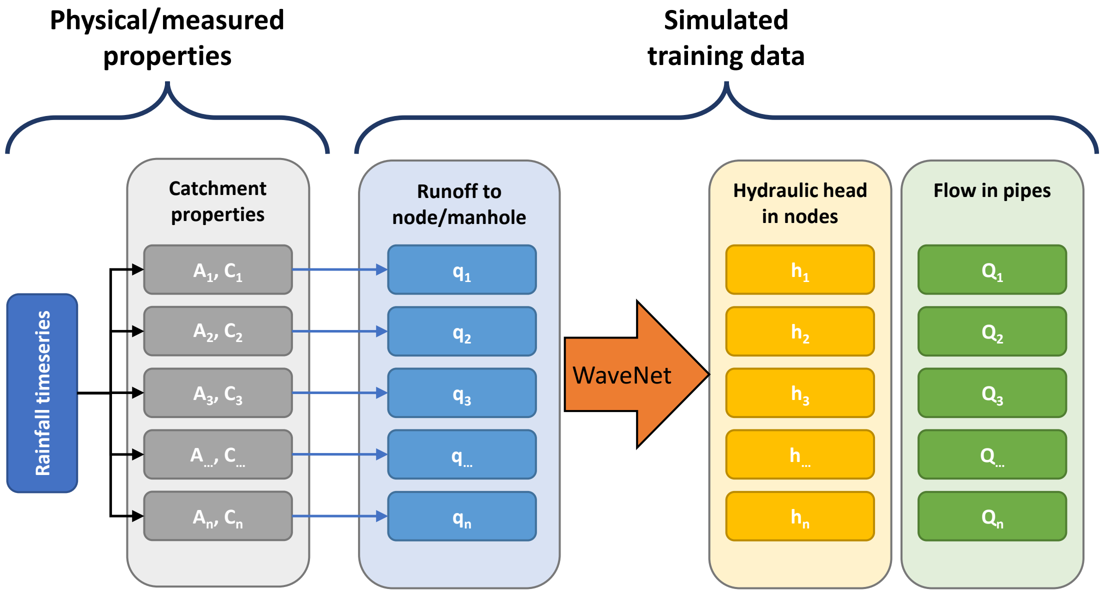

Figure 1.1 A schematic of the physics-informed methodology for the surrogate-modelling data structure. Catchment properties are conventional MIKE+ parameters, e.g. catchment area (A) and runoff coefficient (C).

Results and discussion

Figure 1.2 shows target (hydrodynamic simulation time 21 minutes) and AI-predicted timeseries (WaveNet simulation time 1.2 seconds; boost factor ~1000) over the entire range of the dataset for 3 example manholes with corresponding pipes. As shown, the WaveNet model was able to simulate network hydraulics with high accuracy, i.e., NNSE > 0.7 for level predictions in manholes and NNSE > 0.9 for flow predictions in pipes over the entire dataset.

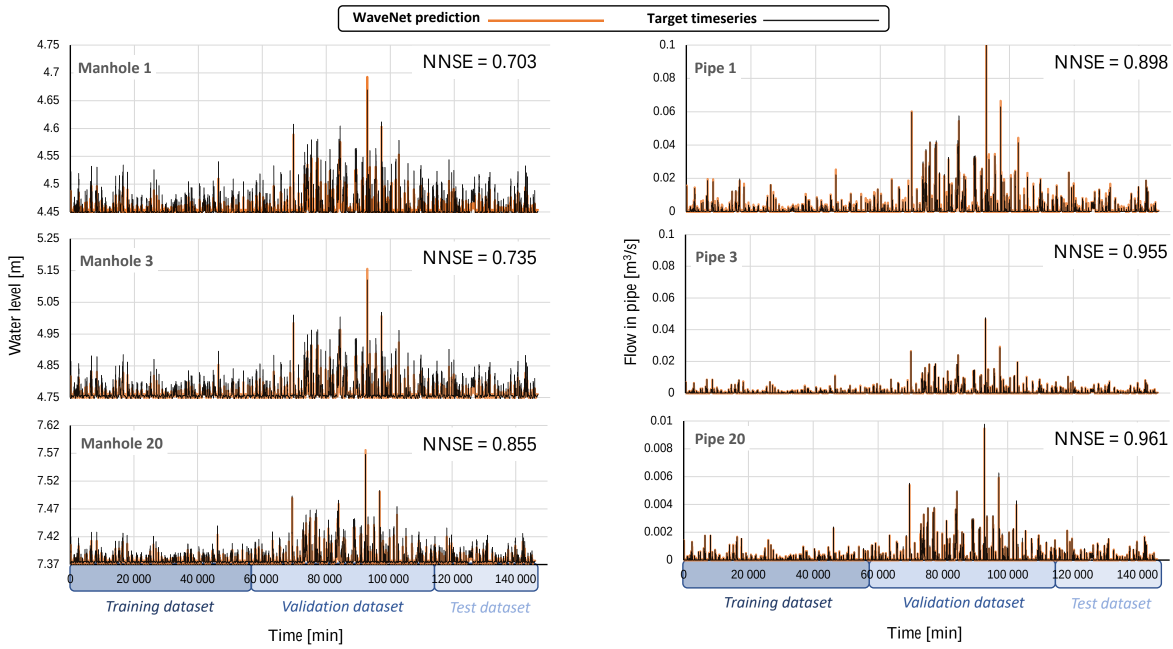

Figure 1.2 Illustration of WaveNet predictions versus target timeseries for water levels in manholes (graphs to the left) and flows in pipes (graphs to the right).

Based on the categories by Moriasi et al. (2007), the predictive skill of the AI model is above *satisfactory/good* for level predictions, and *very good* for flow predictions. Given the boost factor of 1000, the WaveNet-model demonstrates great promise as a surrogate model.

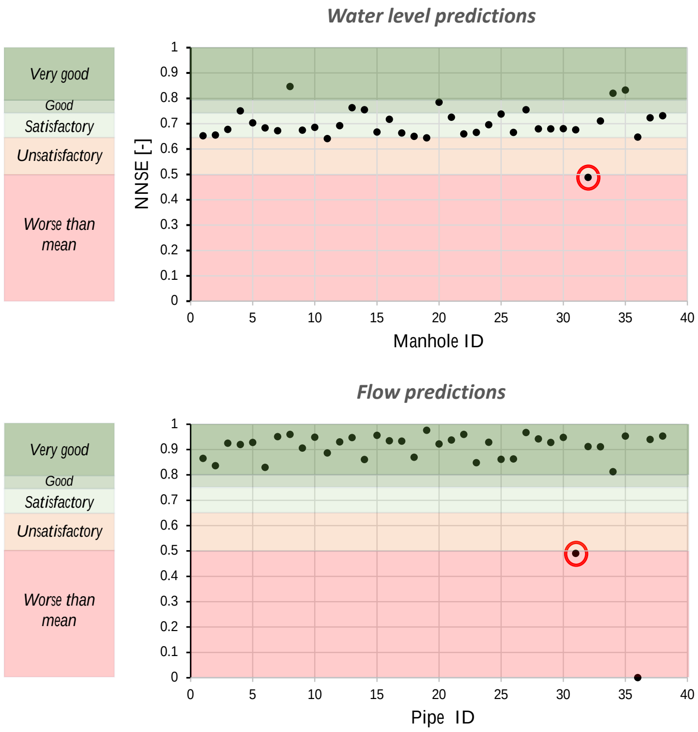

Figure 1.3 Predictive performance of the trained AI-model on the test dataset in terms of NNSE.

To further assess generalizability of the WaveNet model, the NNSE indices presented in Figure 1.3 were computed exclusively over the *Test dataset*, i.e., the final 3 weeks of the full dataset the model did not see during training/validation. The AI-model is highly successful in predicting flows, as expected, (yielding NNSE > 0.8) while level

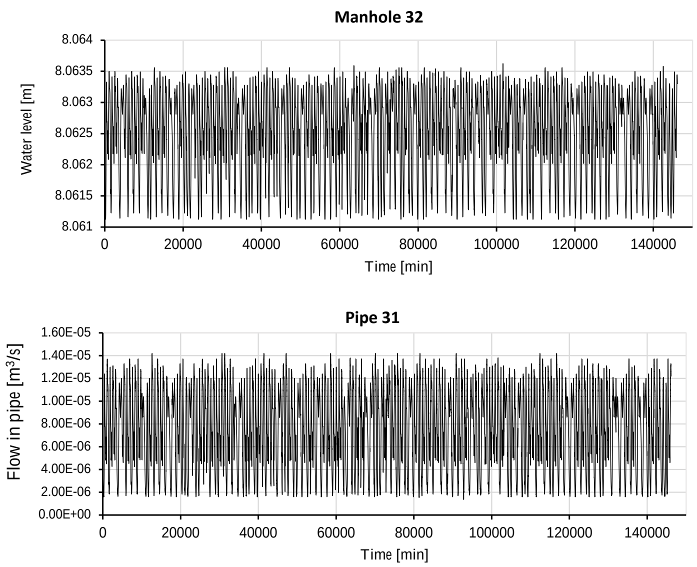

Figure 1.4 Target timeseries of Manhole 32 (8.06 ± 0.0007 m) and Pipe 31 ($7.44\times10^{-6} \pm 3.53\times10^{-6}$ m^3/s) for which the AI model yielded poor NNSE, as marked on Figure 1.3.

prediction is not as accurate (NNSE > 0.65), due to the complexity of hydraulic head dynamics. One possible solution would be to develop two parallel AI models to predict water levels and flows separately.

There are also some outliers with NNSE < 0.5 both in level and flow predictions. The corresponding target timeseries exhibit insignificant dynamic behaviour, being seemingly decoupled from the rainfall-runoff process, (see Figure 1.4). Therefore, these timeseries are difficult to capture by the model because the algorithm learns the common behaviour in the majority of timeseries, ignoring drastically deviating patterns, e.g., near-constant timeseries.

Conclusions

The combined WaveNet model for predicting water levels and flows from rainfall-runoff was found to be a highly interesting alternative for surrogate modelling, providing proof-of-concept. However, the accuracy discrepancy between water level predictions and flow predictions, as shown by the NNSE, suggests that future work should focus on developing methods to improve accuracy for water level prediction in the drainage network.

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