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Using weather radar to improve the prediction accuracy of LSTM neural networks for anomaly detection of water level measurements in UDS

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Highlights

- Water level measurements are becoming increasingly abundant in urban drainage systems, and methods for anomaly detection are needed to ensure the quality of the recorded observations
- Long Short-Term Memory (LSTM) neural networks is a promising technology that may become better and easier to set up for automated anomaly detection than conventional methods
- Using weather radar instead of rain gauges improves the accuracy and stability of LSTM neural networks for generalizing the predicting of water levels on unseen data

Introduction

Large amounts of data are currently collected in urban drainage systems in the process of digitalizing the water sector. The data is to be used in decision-making when moving towards a more data-driven urban water management (Eggimann et al., 2017). The large amount of data also poses a threat if wrong, leading to potentially wrong decisions, hence anomalies in the data need to be identified and the process automated for it to be scalable. In order to have a well-functioning anomaly detection, models with a high prediction accuracy are needed to avoid wrong classifications of the data.

Feed-Forward Neural Networks (FFNN) have been used before to predict time series in urban drainage systems (Savic et al., 2013; Karimi et al., 2019). Recent studies have shown that Long Short-Term Memory (LSTM) networks, which is a sub-type of Recurrent Neural Networks (RNNs) can learn time-dependencies through gating mechanisms and be used to predict water levels and flows using rain gauges as a predictor (Palmitessa et al., 2021). However, the models are still prone to the spatial distribution of precipitation when using rain gauges or cannot be used if rain gauges are not present. To solve this, we here proposed to use weather radars as a predictor. This is tested and compared to using rain gauges when predicting water levels in a sewer overflow chamber in Bellinge, Denmark using data from a 9 month period in 2019.

Methodology

Case area and data sources

The proposed models were tested on data from the combined sewer system of Bellinge, which is a suburban town outside Odense, Denmark that covers approximately 55.25 km^2. The rain gauge data, weather radar data and water level data are part of the open data set described in Pedersen et al. (2021), which also describe the catchment delineation. The rain gauge is quality controlled by the Water Pollution Committee and operated by the Danish Meteorological Institute (DMI) (Jørgensen et al., 1998). The weather radar is also operated by DMI, and the water level sensor is operated by the utility company VandCenter Syd (VCS) and comes pre-filtered as described in Pedersen et al. (2021).

Model considerations

When comparing the rain gauge input with the weather radar we used the same ANN architecture used in Palmitessa et al., (2021). Here, two LSTM layers with a latent dimension of 64 were used followed by a feed-forward layer with 64 neurons before the output layer, and we used an input window length of 2 hours. Since the weather radar input consists of 58 radar cells a mean of these cells was used as an input. Other inputs used were the time of the day (to represent the daily wastewater fluctuations) and the 5% quantile of the previous 24 hours of the water level (in order to give the model a baseline value for dry conditions). Furthermore, it was explored if the model could benefit from having the full spatial input of the radar by using all the radar cells as input. The latent dimension and neurons was in this case doubled to 128 to accommodate the larger number of inputs.

Training, validation, and testing periods

In order to train and assess the ANN 9 months of data from the period from January-October 2019 was split up into three datasets – a training set (5 first months), a validation set (2 following months) and a test set (2 last months). The validation set was used for assessing the model performance after each training epoch in order to stop the training before overfitting. The test set was kept for assessing the model generalization to unseen data.

Results and discussion

The LSTM model results during three different events in the testing period are plotted in Figure 1. During the first event the models with rain gauge (LSTM gauge) and mean of the weather radar (LSTM radar) overestimates the peak water level by 0.08-0.1m whereas the model with all the radar cells as input (LSTM radar all) overestimates the peak water level by 0.01-0.02m. The declining water level after the event is also overestimated by the models with rain gauge and mean weather radar inputs. The overestimation likely stems from the rain intensity input, which is larger than for the second event, even though the second event has a higher peak water level. The model with all the weather radar cells seems to have learned some dynamics in the spatial distribution of the rain in other to predict the lower water level. During the second event, both models with radar as input incorrectly estimate the beginning of the event. The reason for this can, again, be found in the rain intensity input where the radar observes rainfall before the increased water levels are registered. The models with mean weather radar and all the weather radar cells underestimate the peak water level by 0.03-0.05m and the model with the rain gauge input underestimates the peak water level by an additional 0.01m. During the last event the model with the rain gauge input overestimates the first peak water level by 0.1m, whereas both the models containing weather radar input predict the event with good accuracy. The second peak is overestimated by the models using weather radar as input and the model with rain gauge input performs the best. The third peak is only reacted upon by the models containing the radar, although it is overestimated. Due to the spatial distribution of the rain the rain gauge does not detect any precipitation at that point in time.

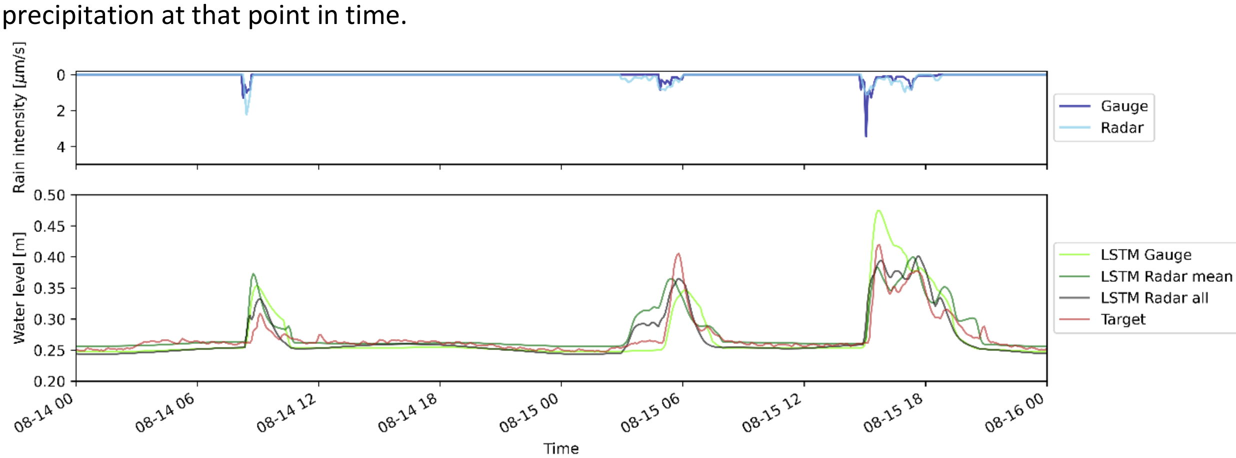

Figure 1. LSTM model predictions plotted against the observed water level (Target, lower panel) together with the rain gauge intensity and mean weather radar intensity (upper panel).

From the figure it also becomes clear that during longer events where the memory (i.e. 2 hours in this case) of the network is exceeded the prediction accuracy of the models decreases. As discussed above it is difficult to see if one model is better than the others, however, the above results represent just one training and when using ANNs each trained model will be different. Hence, to quantify the influence of uncertain model inputs, 10 models were trained for each input and the Root Mean Squared Error (RMSE) was computed for the training, validation, and test periods. These are shown in Table 1 for the three inputs. The model using the rain gauge input trains to a lower error in general but fails to generalize well to unseen data, whereas using the mean of the radar significantly decreases the error. Using all the radar cells further improves the prediction accuracy.

Table 1. Mean training, validation, and testing RMSE for 10 trainings of each of the models using the rain gauge, a mean of the radar cells or all the radar cells as the predictor of water level.

	RMSE [m]		
	Training	Validation	Testing
LSTM Gauge	0.00327	0.00334	0.0688
LSTM Radar mean	0.00511	0.00477	0.0244
LSTM Radar all	0.00691	0.00487	0.0132

Conclusions and future work

Weather radars have the advantage of covering a large spatial area compared to rain gauges. We here show that by using weather radar as the predictor in LSTM models the prediction accuracy on unseen data is improved. It is expected that the interest in anomaly detection in the water sector will only increase in the years to come as the amount of data collected grows. Hence, our results provide a stepping stone towards models that have sufficient prediction accuracy to be used for anomaly detection. Future investigations could look into finding a predictor for the state of the system during long precipitation event since this could significantly improve the models. Also, testing the model structure on a longer timeframe and across locations could be interesting to confirm the improved model architecture. During the work important lessons learned are:

- By using weather radar both the prediction accuracy and training stability improved.
- In order to improve the models for long duration events a predictor giving the state of the system needs to be identified.

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