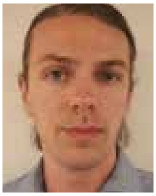
PROGNOSTISERING AV KOMBINERAT AVLOPPSVATTENFLÖDE MED X-BANDRADAR OCH NEURALA NÄTVERK – EN FALLSTUDIE I LUND

FORECASTING COMBINED SEWER FLOW USING X-BAND RADAR WITH A NEURAL NETWORK – A CASE STUDY IN LUND




Filip Faust, Per Nelsson

Dept. Water Resour. Eng. Lund University, Box 118 221 00 Lund, Sweden

Abstract

This study aimed to forecast combined sewer flow into a wastewater treatment plant in Lund, Sweden by using uncalibrated X-band radar data with a neural network. Neural networks have proved themselves useful in the field of forecasting as they can solve multiple kinds of problems and recognise patterns in the data as well as model complex real-world problems. In 2018, an X-band radar unit was installed in the proximity of Lund which provides precipitation data with high spatial resolution, thus making it suitable for studying precipitation events on a smaller scale. The study concluded that it is possible to accurately forecast combined sewer flow up to 1 h ahead of time by only using input variables connected to the catchment of the treatment plant. It was indicated that the prediction time could potentially be extended by adding forecasts of the precipitation as input to the network. The most important input variables were information about the sewage system, a nearby watercourse, the flow at the plant itself as well as information from a rain gauge. The radar is affected by attenuation, degrading the performance of the neural network during large flows.

Keywords: X-band radar, neural network, combined sewer flow

Sammanfattning

Denna studie syftade till att prognostisera det kombinerade spillvattenflödet in till reningsverket i Lund genom att använda okalibrerad X-bandradardata tillsammans med ett neuralt nätverk. Neurala nätverk har visat sig vara användbara inom prognostisering då de kan lösa en mängd olika problem genom att identifiera mönster i data och även modellera komplexa naturliga fenomen. År 2018 installerades en X-bandradarenhet i närheten av Lund som förser området med högupplöst nederbördsdata vilken är lämplig att använda vid analys av regnhändelser på mindre ytor. Studien slog fast att det är möjligt att göra noggranna prognoser av kombinerat spillvattenflöde upp till 1 timme in i framtiden genom att endast använda variabler knutna till reningsverkets avrinningsområde. De mest hjälpsamma variablerna för att förbättra prognosen var information om spillvattenflödet i avloppsnätet, flödet i ett närliggande vattendrag, inflödet till Källby reningsverk samt nederbördsinformation från närliggande regnmätare. Radarn påverkas av attenuering, vilket försämrar prognoserna vid stora flöden.

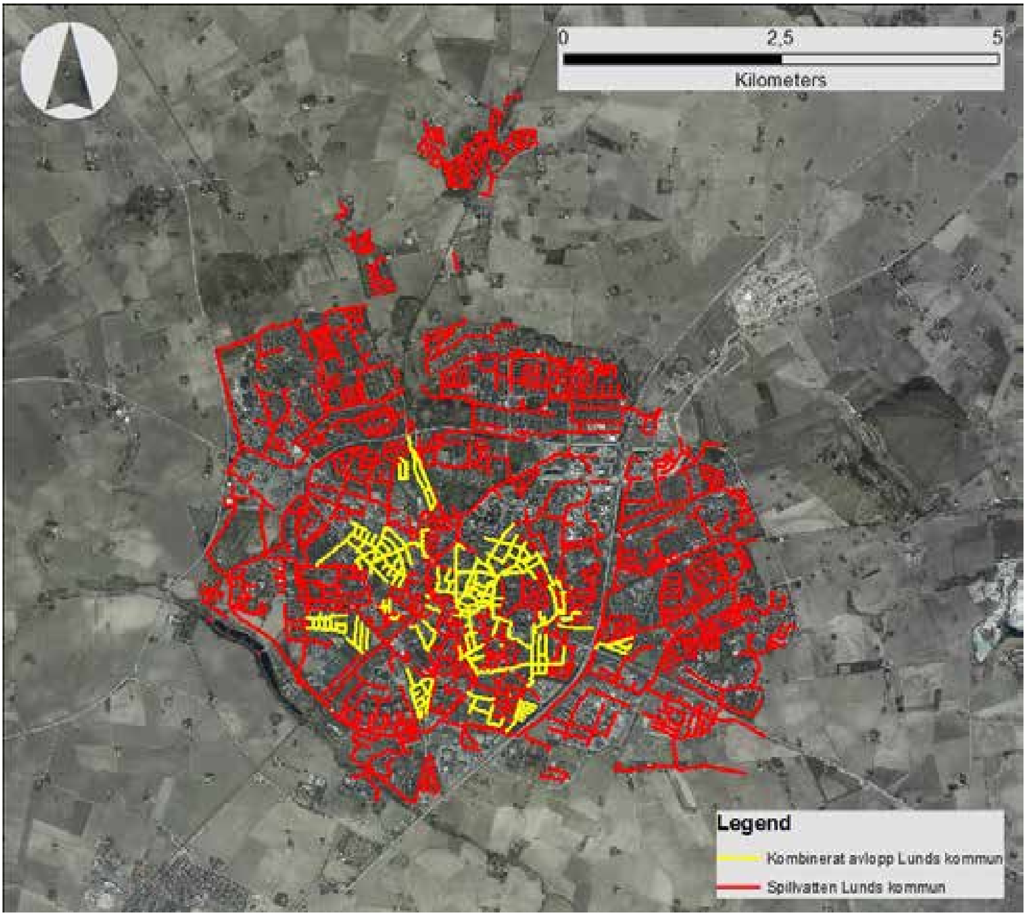


Figure 1. *Division of sewer type in Lund. Red indicates separated sewers and yellow indicates combined sewers.*

Introduction

Källby wastewater treatment plant is located in Scania in southern Sweden and it treats the wastewater from the city of Lund and surrounding villages. As parts of the sewer system in Lund consist of combined sewers, the inflow to the treatment plant does not only consist of wastewater but also stormwater. The sewer types in Lund is visible in figure 1. This means that in case of a large rain event, the inflow to the treatment plant may increase greatly which is troublesome as the plant operates best at a stable inflow of water. To avoid problems and ease the operations at the plant, a forecast of the inflow is of great value to know the severity of what is to come. An indication of when the flow is about to increase due to a rain event could also be used to monitor the flow status in the entire sewer system and further warn when there is risk of flooding or combined sewer overflow.

In the summer of 2018, an X-band radar unit was installed in Dalby, 10 km southeast of Lund. The X-band radar produces large quantities of data that requires treatment such as a bias-correction, which makes it inconvenient and time consuming to use with a conventional physics-based model. However, there are other types of models called neural networks, that excel at using large data sets and do not need extensive pre-processing of the data.

Neural networks have become popular in many different kinds of research fields including forecasting, as they provide benefits compared to other conventional methods. Zhang (1998) and Hill et al. (1993) argue that neural networks could perform well, or even outperform, classical models in tasks related to forecasting. However, the neural network approach is by many still seen as something more experimental in engineering practice and is unfortunately therefore not very common in practical applications. However, this is subject to change as large progress is being made in the field of machine learning, refining the models and allowing use in new applications.

Previous studies on the X-band radar in Dalby have been done by Hedell and Kalm (2019), who combined neural networks and radar data for grid points to evaluate the potential to use the network for urban flood forecasts. Further, Olsson (2019) used the X-band radar data to simulate runoff with a MIKE URBAN model. Both studies gave promising results for the application of the Dalby X-band radar in urban hydrology.

The purpose of this paper is to evaluate the potential to forecast the inflow to Källby wastewater treatment plant with a neural network, by using spatially aggregated X-band radar data together with other input variables. The paper mainly aims to investigate how far into the future a reliable forecast can be made, which variables are most useful to produce a qualitative forecast and lastly see if the X-band radar data alone is enough information for the network to make a good forecast. The present paper is based on a Master Thesis (Faust and Nelsson, 2020), where more detailed information can be found.

Method, Model and Data Treatment

The Neural Network

A neural network is a data driven model that tries to mimic the human brain in a sense that nodes, similar to neurons, make up the model in different layers. The nodes are arranged in one input layer, one or several hidden layers and an output layer. The input information passes through the layers and the output layer finally produces a prediction of the most likely output, solely based on historical data which has been used to set up the model (Zhang, 2012; Solomatine et al., 2008). This approach enables the model to solve multiple kinds of problems and recognise patterns in the data (Alemu et al., 2018). There is a weight connected to each node which is constantly changed as the network is optimised in a process called training. The training aims to minimise the error between the model's prediction and the target that it tries to predict, all in order to change the weights connected to the nodes in an optimal way (Zhang, 2012). This means that the weights in the hidden layer(s) are tweaked and iterated until the output is considered most satisfactory. The network is trained on a data set and after tested on an independent data set to verify the output of the model. Further, a validation is included in the training which also evaluates the output of the network (Zhang, 2012).

The neural network in this project is Python-based in the platform Tensorflow and was developed by the company Informetics (Copenhagen, Denmark). The model has one hidden layer with 8 nodes and produces a forecast 60 min ahead of time if nothing else is specified. Certain features are built into the script to improve the performance of the model, such as sine functions with periods corresponding to the length of 1 day and 1 week. These were implemented with the purpose to represent the daily and weekly patterns that the wastewater flow generally shows.

X-Band Radar

Precipitation data is the main input to the network and is measured with a weather radar. Whereas a conventional rain gauge measures the accumulated volume of precipitation in a container, the weather radar measures the reflectivity of rain particles in the air (Einfalt et al., 2004) as the radar unit rotates and scans the air in 360 degrees at several inclinations, giving an almost full picture of the atmosphere (South et al., 2019). A special kind of radar, well suited for analysing intense rain events on a small scale, is the X-band radar. Compared to C- and S-band radars, which are commonly used in meteorology, an X-band radar provides more detailed information about the precipitation within a shorter range. Generally, the resolution is 0.25 – 2 km for C-band, 1 – 4 km for S-band and down to 50 m for the X-band (South et al., 2019). The X-band radar unit in Dalby is a Compact Dual Polarimetric X-band Doppler weather radar WR-2100 with a range of 60 km which rotates at a maximum of 16 revolutions per minute with a frequency of 9.4 GHz (Furuno, 2020).

Presentation of Cases

As previous studies by Calm & Hedell (2019) and Olsson (2019) have shown are there certain issues with the radar and the data that it produces. The problems mainly concern areas where the precipitation is either vastly overestimated or affected by clutter. Because of this, three different cases with different spatial aggregations of radar data were tested to see if the performance of the network is affected by adjusting the spatiality of the radar data. The first case included data for the entire area aggregated in one large polygon, including the malfunctioning areas. The second case was similar to the first one, but the malfunctioning areas were excluded. The third case used the same area as the second case, but the area was further divided into four sub-catchments to see if the network benefited from receiving input individually from separate areas. All cases used the hydrological boundary of the urban area of Lund, defined by VA SYD, as outer catchment boundary. Further, a fourth case was used as a reference case which only used precipitation information from rain gauges and not from the radar unit.

Evaluation of Data Variables

Several other input variables additional to the precipitation information from the radar unit were tested. The variables all relate to the catchment in different ways and could potentially provide valuable information to the network which would improve the forecast. The input variables tested were:

- X-band radar: precipitation information
- Dalby: flow information from sewer system outside of radar coverage
- Höje å: discharge in receiving watercourse
- Wind speed and wind direction near Lund
- Groundwater level variation
- Precipitation information from rain gauges
- Källby: current flow at the WWTP

Method of Analysis

The input variables and their impact on the forecasts were evaluated in two ways, by comparing the evaluation parameters RMSE, R2 and loss and by visually inspecting the performance during the peak flows. The loss function is a function displaying the error in the model, measuring the difference between the predicted output and the actual value of the target it tries to predict (Wu et al., 2019). The general performance is well indicated by the evaluation parameters but as most days are uneventful with no rain, these parameters might not evaluate the peak performance satisfyingly. The performance during events with large flows is of most interest which is why the largest individual flow events are visually evaluated. During the larger flows, the timing and value of the peaks are considered of most importance, and not the correct total volume of discharge. The input variables were put together in different tests which further were evaluated, see table 1.

Table 1. *The different tests which all include different combinations of input variables.*

Test nr.	Input variables
0	Radar
1	Radar, Dalby
2	Radar, Höje å
3	Radar, Dalby, Höje å
4	Radar, rain gauge
5	Radar, rain gauge, Dalby, Höje å
6	Radar, wind information
7	Radar, groundwater level
8	Radar, Källby
9	Radar, Källby, Dalby, Höje å
10	Radar, rain gauge, Källby, Dalby, Höje å

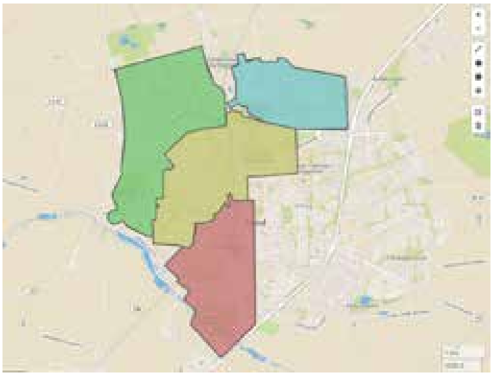


Figure 2. *Map of Lund and the sub-catchments used when aggregating the radar data. The eastern parts of Lund are excluded as the precipitation is not measured accurately for these areas.*

Figure 3. *The loss for each test. A low loss implies a low error in the forecasts made by the model in comparison to the corresponding value to be forecasted.*

The longest possible prediction time with input related to Lund was evaluated. A visual inspection of the forecast was conducted as the prediction time was increased in 15-min steps from 45 min to 120 min. Furthermore, the possibility to extend the prediction time even further was evaluated. Precipitation data from a rain gauge was used as a perfect forecast of the precipitation and put 4 h ahead of time while the prediction time is increased to 4 h. The purpose was to see if the network could produce such a lengthy forecast with perfect conditions, which could be useful for many purposes and later further studied.

For all different objectives of the project, the training period was selected to May – November 2019 and the validation period December 2019 – January 2020.

Results

This results section is an abridged summary of the produced results, and only a few, representative figures are included.

Cases

After evaluating the cases with different spatial aggregations of radar data it was concluded that the first case performed significantly worse than the other cases. This indicates that the network benefits from removing data from the areas with incorrect measurements of the precipitation. Further, additional division of the data into sub-catchments had a close to negligible effect on the results. Case 3 was concluded the best performing case after both evaluating the cases visually and with the evaluation parameters. The spatial aggregation of radar data for case 3 was further used in the evaluation of the tests, illustrated in figure 2. The value of the loss can be seen in figure 3 for all tests and cases.

Input variables

The network responded differently to the various variables tested, as seen in the variation in loss in figure 3. Both the groundwater level variation and wind information were indicated to not improve the forecast by their relatively high loss, which further was confirmed by a visual inspection of the events. The variation in groundwater level could be a process too slow to help forecast the quick response of a precipitation event and the network further did not seem to find patterns between the wind information and measured flow at Källby WWTP.

The other input variables tested all improved the model in different ways. Figure 4 shows the forecasts of tests 0, 1, 2 and 3 where all variables to different extents improved the forecast. The prediction from test 3, which included information

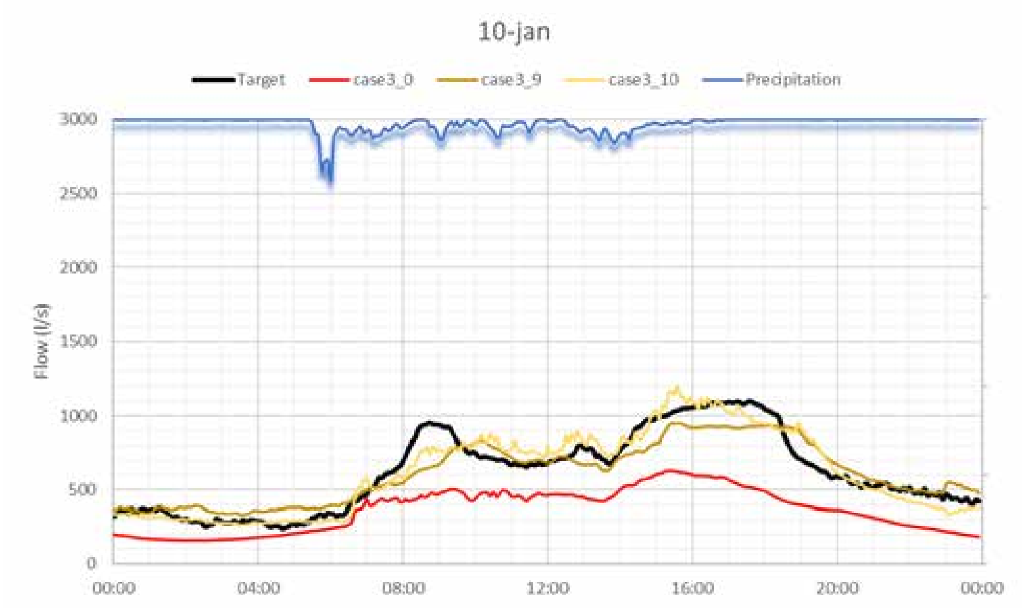


Figure 4. *Forecasts made by the models. The black line, the target, is the flow at Källby WWTP which the models try to predict. Precipitation is illustrated without units in the top of the figure, just to visualise the timing of the response. The curves case3_0, case3_1, case3_2 and case3_3 refer to case 3 of spatial radar aggregation and tests 0, 1, 2, and 3 with regard to additional data variables.*

from both Dalby and Höje å, seemed to be closest to the target.

After comparing all tests regarding the score from the evaluation parameters and by visual inspection, it was concluded that the best performing tests were test 9 and 10. This indicates that the model greatly benefits from information about the wastewater system (Källby and Dalby), discharge in the catchment recipient (Höje å) as well as precipitation information from nearby rain gauges together with the radar data. The difference between test 9 and 10 is that test 10 included rain gauge information.

Figure 5 illustrates the large rain event on the 11th of October where test 0, which only used radar data, struggled to forecast the peak in the evening and overestimated the flow during the day. Test 9 and 10 better predicted the flow where test 10 further outperformed test 9 during the large peak at 20.00, likely thanks to the additional rain gauge information as the radar is affected by attenuation during the heavy rains.

Figure 6 shows a direct comparison of the forecasted flow and the measured target flow at Källby WWTP for every timestamp in the time period. As seen in the figure, the vast majority of the data points have values lower than 500 l/s. As indicated by the line pattern on the right side of the figure, there is a limit for how large flows can be measured at Källby WWTP, which is roughly 2 200 l/s.

All tests generally underestimated the flow to different extents but test 10 was most accurate as the trend line is rather close to the 1:1 line, compared to test 0 and 9. The width of the cloud of points indicates the general variation in error for all data points. The fairly narrow cloud for test 10 suggests that the forecasted values do not deviate from the respective measured values as much as for the other tests.

The scatter plots give no information about the

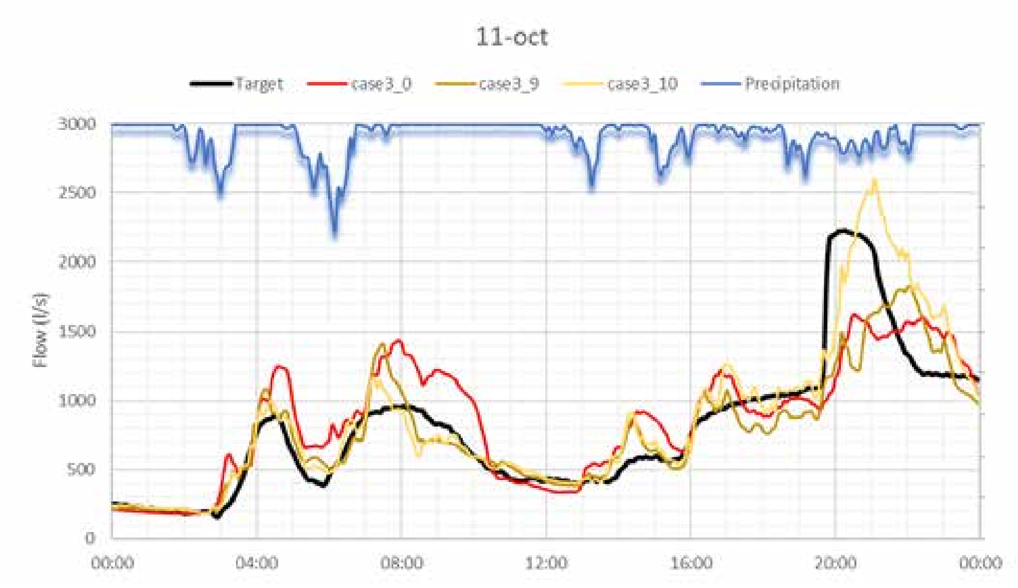


Figure 5. *Observed and forecasted flow at Källby WWTP on the 11th of October 2019.*

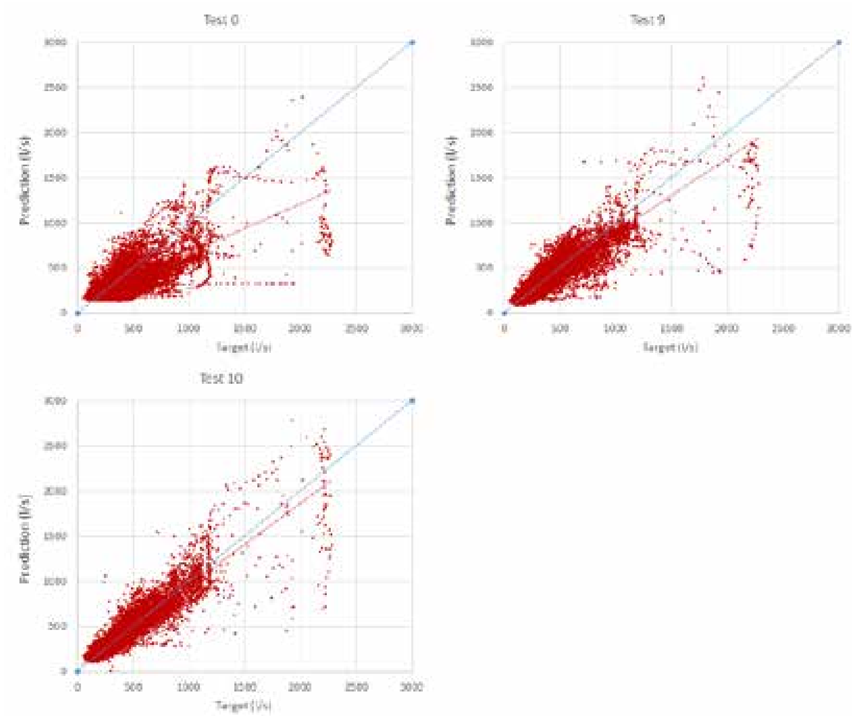


Figure 6. *Forecasted values for tests 0, 9 and 10 in relation to the corresponding measured value for the same timestamp. The 1:1 regression is illustrated in blue, and the calculated regression for each test is illustrated in red.*

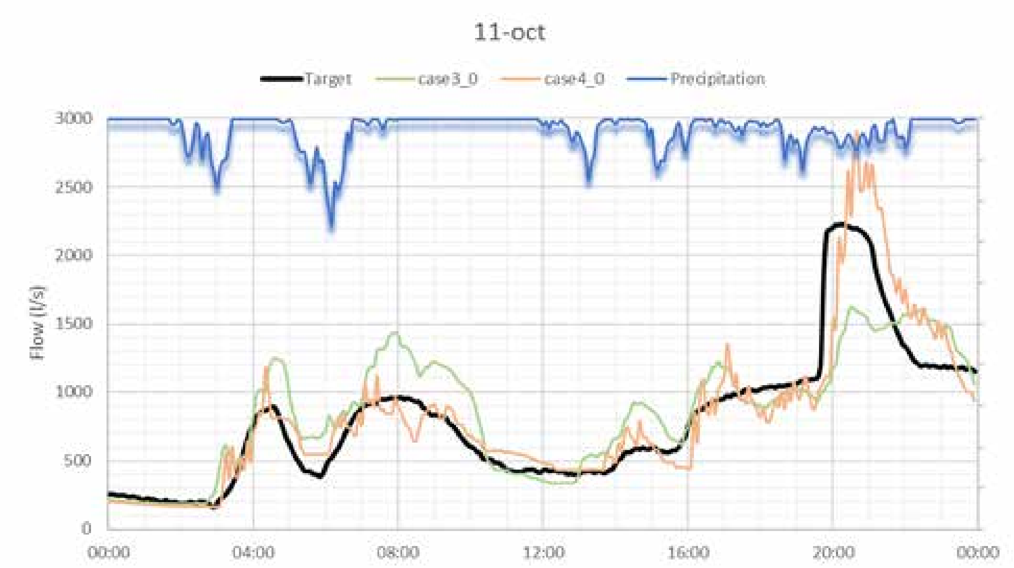


Figure 7. *Two forecasts made with radar data (case 3_0) and rain gauge data (case 4_0) for the precipitation event on the 11th of October 2019.*

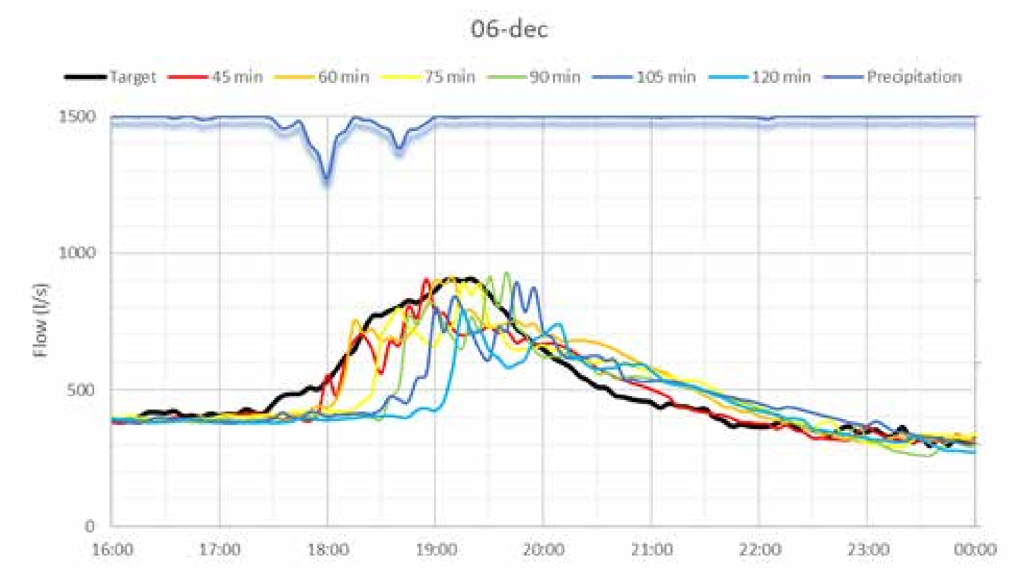


Figure 8. *Forecasts made with different forecasting times. As the forecasting time increases over 1 h, the forecasts get increasingly delayed.*

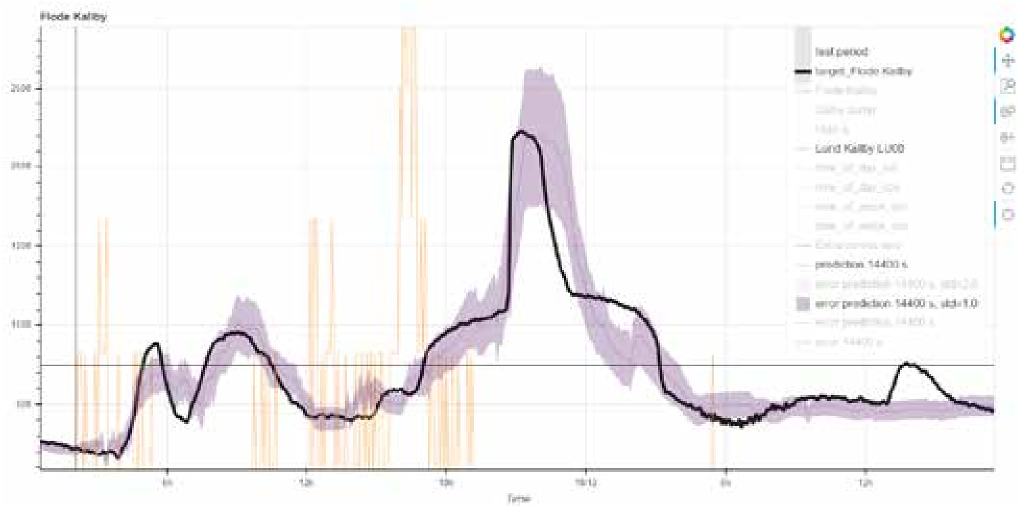


Figure 9. *A 4 h forecast using rain gauge information as a perfect forecast of the precipitation data for the 11th of October 2019. The black line is the measured flow at Källby WWTP and the thinner grey line is the prediction. The yellow lines illustrate precipitation and the purple field is the uncertainty in the prediction.*

timing of the peaks. However, the large number of underestimations, including for test 10, indicates that the forecasts of the largest flows are regularly inaccurate. This is likely due to that the model is trained on flows that never exceed 2 200 l/s, when they in reality do. Underestimations are also likely related to the low quality of the radar data during the larger rain events.

Reference case using rain gauges

A forecast using only radar data is compared with a forecast using only rain gauge data. It is concluded that without any other sources of input information, the rain gauge model outperformed the radar one, see figure 7.

The poor performance of the radar forecast is likely related to the various issues with the data during the larger precipitation events. However, as more input variables are added, the performance of the radar forecast greatly improved while the rain gauge forecast only slightly improved. Further, the model that used precipitation information from both the radar and rain gauge (test 10) performed even better than the other ones.

Investigation of forecasting time

The investigation of the maximal prediction time, with input variables related to Lund catchment, concluded that it is possible to accurately forecast the flow up to 1 h ahead of time. As the prediction time increased over 1 h, the quality of the forecasts worsened and got gradually delayed, which is illustrated in figure 8. There was no major difference in the forecasts of the 60- and 45-min prediction, which indicates that prediction times lower than 60-min does not drastically improve the performance of the model and that the 60-min forecast could be somewhat reliable.

It was further investigated if the forecast time could be extended with a perfect forecast of the precipitation. As illustrated in figure 9, which shows a 4 h forecast, both the timing and the peak of the flow is accurate. This indicates that the network indeed is capable of making such a lengthy forecast. However, as the prediction is based on a perfect precipitation forecast, there are reasons to suspect that the neural network would perform worse in reality where the forecasts are more uncertain.

Discussion

The finding that a neural network can be trained to make hydrological forecasts of waste- and stormwater flow based on non-bias-corrected radar data is considered a success for the project. Further, the results are promising if the low quality of the radar data is considered, indicating that the model has much room to improve with better data. Källby WWTP was used as a case and in theory the relationship between measured precipitation and forecasted flow could be applied to many other instances. Additionally, the versatility of a neural network gives it potential as both an urban planning and flood warning tool.

However, if the model is to reach its full potential, the performance is dependent on the quality of the radar data. This is also the largest identified issue in the project, where perhaps the most important factor is the observed attenuation effect during heavy rains which leads to that no or incorrect amounts of precipitation are being recorded. This is unfortunate, as heavy rains are the most important events to study and train for the purpose of the project.

Despite the issues related to the radar was it possible to produce a forecast by only using radar data, even though the quality was significantly lower compared to the best model that also used multiple other inputs. Depending on the user and their demands a forecast like this might still be of use.

Sources of Errors

Ideally, the measured flow at Källby WWTP is a function of only the waste- and stormwater that naturally flows into the plant. However, this is not the case, as there are technical complications and measures taken by operators that affect the inflow to the plant. For example, there are several pumping stations around the sewage system that can regulate the flow. Information about how and when these stations operate were not available for this project.

The time period which the network is trained on stretched from May 2019 – January 2020, which is a relatively short period of time. As the time period does not encompass several years, eventual seasonal patterns in both the wastewater flow and the precipitation cannot be captured. A longer time series of data would likely have improved the model as these issues then would have been addressed. Further, the neural network prefers large data series for the training process in order to produce an optimal model.

Future studies

This study is limited to only looking at variables connected directly to Lund, which may be why forecasts longer than 60 min ahead of time could not be made satisfactory. To achieve a model with longer prediction times, precipitation data from areas outside of Lund would be required. In such a case, the wind speed and wind direction together with precipitation information from these areas could be useful information for the network.

An application that was not included in this study, but could be of interest for future studies, was to develop a model that calculates the probability of exceeding a certain forecasted flow at a given time. A model like this could be programmed to give a warning whenever a certain flow is believed to be reached with a certain probability. This could be used as a safety measure which always would be running in the background at for example, Källby WWTP.

Furthermore, a similar study with higher quality radar data could be conducted to investigate the true potential of the neural networks ability to forecast the flow. As of now, precipitation information from a rain gauge is more reliable than the information from the radar during large precipitation events. This could be a subject of change, or the gap between the data sources could at least be slightly bridged, if the radar is properly calibrated.

Conclusions

The purpose of the study was to evaluate the potential to forecast the inflow to Källby WWTP by using X-band radar data with a neural network. The study concluded that it is possible to train a neural network with non-bias-corrected radar data to forecast the flow up to 60 min ahead in Lund. Prediction times longer than 60 min degraded the result and caused a delay in the forecast. It was further indicated that the prediction time could potentially be increased by adding forecasted or measured precipitation information from areas outside of Lund.

The performance of the model was improved by adding more input variables, and the combination of variables that gave the best performance was:

- precipitation information from X-band radar
- flow information from sewer system outside of radar coverage (Dalby)
- discharge in receiving watercourse (Höje å)
- rain gauge information
- current flow at the WWTP (Källby)

The model using only rain gauge information performed better than the model using only radar data, which is believed to be mainly related to attenuation issues in the radar data. As a rain gauge provides more consistent data for high-intensity rainfalls, it might be more reliable for the neural network. However, a model combining both radar and rain gauge data performed even better as it benefits from both the spatially high-resolution radar and the consistent performance of the rain gauge, especially when attenuation is affecting the radar.

For the purpose of forecasting, aggregating the radar data in sub-catchments instead of one large catchment made little, if any, improvements to the result. However, removing areas with problems connected to the radar data was important for the performance of the model.

It was possible to make a forecast by only using radar data, although it yielded significantly worse results without the other input variables. However, depending on the purpose and demands of the user, a forecast like this might still be useful.

References

Alemu, H. Z., Wu, W., Zhao, J. (2018) Feedforward Neural Networks with a Hidden Layer Regularization Method, Symmetry, 525 – 543. doi:10.3390/sym10100525

Einfalt, T., Arnbjerg-Nielsen, K., Golz, C., Jensen, N-E., Quirmbach, M., Vaes, G., Vieux, B. (2004) Towards a roadmap for use of rada rainfall data in urban drainage, Journal of Hydrology, 186 – 202. doi: 10.1016/j.jhydrol.2004.08.004

Faust, F., Nelsson, P. (2020) Using X-band Radar with a Neural Network to Forecast Combined Sewer Flow - A case study in Lund. Dept. Water Resour. Eng., Master Thesis TVVR 20/5008, Lund University.

Furuno. (2020) WR-2100 Brochure. https://www.furuno.no/Userfiles/Sites/files/WR-2100_E.pdf (Accessed: 23 January, 2020).

Hill, T., Marquez, L., O'Connor, M., Remus, W. (1993) Artificial neural networks for forecasting and decision making, International Journal of Forecasting, 10(1): 5 – 15. doi: 10.1016/0169-2070(94)90045-0

Hedell, C., Kalm, A. (2019) Applying X-band radar data in urban hydrology - Adjusting data for a neural network model, based on the pilot project in Dalby 2018. Dept. Water Resour. Eng., Master Thesis TVVR 19/5004, Lund University.

Lengfeld, K., Clemens, M., Münster, H. and Ament, F. (2014) Performance of high-resolution X-band weather radar networks – the PATTERN example, Atmospheric Measurement Techniques, 4151 – 4166. doi:10.5194/amt-7-4151-2014.

Olsson, L. (2019) Flow simulation in MIKE URBAN based on high-resolution X-band radar data. Dept. Water Resour. Eng., Master Thesis TVVR 19/5005, Lund University.

Wu, Y., Liu, L., Bae, J., Chow, K-H., Iyengar, A., Pu, C., Wei, W., Yu, L., Zhang, Q. (2019) Demystifying Learning Rate Policies for High Accuracy Training of Deep Neural Networks. arXiv:1908.06477.

Zhang, G.P., Patuwo, E., Hu, M.Y. (1998) Forecasting with artificial neural networks: the state of the art, International journal of forecasting, 14(1): 35 – 62. doi: 10.1016/S0169-2070(97)00044-7

Zhang, G.P. (2012) Neural Networks for Time-Series Forecasting, Handbook of Natural Computing, pp. 461-477. doi:10.1007/978-3-540-92910-9_14