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Hydraulic modeling and deep learning based flow forecasting for optimizing inter catchment wastewater transfer

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A B S T R A C T

Sewer overflow is a priority concern for many cities. Owing to the high density of buildings and populations, constructing new storage tanks in urban areas is getting more and more difficult. Therefore, this paper proposes a novel Inter Catchment Wastewater Transfer (ICWT) method for sewer overflow mitigation. The ICWT method aims at redistributing the spatial mismatched sewer flow according to the treatment capacity of Wastewater Treatment Plant (WWTP). Three tasks are involved in the development of ICWT. First, test the effectiveness of ICWT. Second, study how to properly redistribute inflow to the WWTP. Third, the operation of ICWT highly depends on inflow to the WWTP, to support the management of ICWT, it is imperative to construct a flow rate prediction model. A hydraulic model is used for task 1 and 2, individual and combined effects of the storage tank and ICWT on sewer overflow are investigated. The simulation results show that less overflow is obtained. In considering the deficiencies of hydraulic model, one of the most promising deep learning techniques, Long Short-Term Memory (LSTM), is employed to undertake task 3. Experiments demonstrated that LSTM could be of great use in predicting sewer flow.

1. Introduction

Sewer overflow refers to a condition in which untreated sewage is discharged directly into the environment from sewer outlets or bypass structures of the wastewater treatment plant (WWTP), when the sewage volume exceeds the capacity of the sewer system or WWTP. More frequent sewer overflow can be expected with the increased impermeable surface, extreme rainfall events and urbanization. Consequently, better ways of mitigating sewer overflow will be required.

Storage units such as retention basins or storage tanks are the most straightforward solution to reduce sewer overflow. However, constructing new storage units in metropolitan cities can be a complicated and costly task. The locations and sizes of storage units are limited by densely populated urban space and need to be selected appropriately. Constructing storage units require significant investment. Besides, the disruption to residences and businesses due to construction works cause social and economic cost (Ganora et al., 2017; Ngo et al., 2016). The drawbacks of constructing new storage units have motivated the research for cost-effective methods for mitigating sewer overflow. These alternative approaches mainly focus on aggregating the spatial and temporal dynamic free space of the sewer system, thus maximizing the capacity of the sewer system with minimum construction works.

Several studies have been conducted to explore the in-line storage capacities of sewer systems rather than construct new storage facilities (Darsono et al., 2007; Grum et al., 2011; Garofalo et al., 2017). The in-line storage control solution aims at exploiting the full storage capacity of the sewer system through regulating gates, pumps, and weirs. For example, in a less overloaded conduit, a moveable weir could accumulate storm water temporarily by increasing the weir height during a rainfall event. This approach could efficiently reduce infrastructure investments.

Similarly, sewer overflow can be mitigated by operating existing storage tanks proactively. Lee et al. (2017) investigated a novel pump operating method for the storage tank on urban flood control in Daerim sewer network, Seoul, Korea. The operating method considers both the storage tank and sewer conduit, it implements two monitoring nodes, one in the storage tank and the other one in sewer conduit. The pumps in a storage tank will proactively discharge reserved volume until the water level of the conduit rises up to the maximum level. This method lets the existed storage tank accommodate to unprecedented flow rates and reduce flood successfully.

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Owing to the high density of urbanized areas in modern cities, it is difficult to construct storage units or separate sewer systems. In some developed cities, deep tunnel systems have been used as an alternative solution. The deep tunnel could temporally transport storm water and sewage during heavy rainfall events, thereby reducing downstream peak flows. In a recent case study in Guangzhou city, China, engineers found that the deep tunnel could improve the flood control and drainage capacities of the basin successfully (Wu et al., 2016).

It can be summarized from the above literature that recently proposed methods for improving sewer management mainly emphasizes on intelligent control of existing sewer devices, maximum utilization of sewer storage capacity or exploits the underground space. Summarizing previous studies, a novel inter catchment wastewater transfer (ICWT) method is proposed in this paper.

The idea of ICWT is inspired by the concept of inter-basin water transfer (IBWT). IBWT refers to transfer water from basins having sufficient water (donor basin) to basins facing water shortages (receiving basin). The purpose of IBWT is to counterpoise the uneven distribution of water resources and imbalanced water demand in different basins. IBWT could create a win-win situation by utilizing the differences of flow regime in different basins (Wang et al., 2015; Yevjevich, 2001). Since the 20 th century, in order to meet growing residential, commercial and agricultural demand, many large-scale IBWT projects have been proposed, such as the South-North Water Transfer Project, which aims to transfer 44.8 billion cubic meters of water annually from the Yangtze River in southern China to the north.

This study generalizes the concept of IBWT to allocate inflow to WWTPs in different catchments. The ICWT method takes both the sewer systems and WWTPs into consideration. Most developed cities have more than one WWTPs (Vrebos et al., 2014), each of WWTPs receives sewage collected from the sewer systems of the associated catchments, these sewer systems and catchments have different behaviors against rainfall events, the WWTPs also have different treatment capabilities. A catchment with a more overflowed WWTP can be regarded as the donor basin. On the contrary, a catchment with a less overflowed WWTP can be regarded as the receiving basin. The essence of ICWT is to address the spatial mismatch between sewer flow and WWTP treatment capacities in different catchments.

The development of the proposed ICWT solution is a complex task. In general, there are three tasks in this study. First, the effectiveness of ICWT method should be tested and compared with traditional solutions such as construct new storage tank (task 1). Second, control rules should be derived to ensure adequate redistribution of the sewage stream (task 2). Third, the operation of ICWT involves a series of sewer control structures and highly depends on the flow information of its associated catchment, it is imperative to forecast inflow to the WWTP, thus providing sufficient response time and enhancing ICWT control (task 3) (Liu et al., 2016; Chen et al., 2014; Duchesne et al., 2001).

In this study, the hydraulic model is used for task 1 and 2. Hydraulic models are the most common tools in terms of design and test sewer control (Autixier et al., 2014; Lucas et al., 2015; Seggelke et al., 2005). Hydraulic models can supply high-quality information about the sewer system's behavior and give insight into the effects of different control strategies (Chiang et al., 2010). So that the output of hydraulic models is suitable for hydraulic planning and design. However, hydraulic models require complete knowledge of sewer systems and rainfall patterns; it can only provide sewer hydraulic information based on current or previous rainfall events. Additionally, the calibration of hydraulic models requires adjusting many parameters. Carrying out simulations by using hydraulic models demands manual operation. For a large sewer system, the hydraulic model also needs long computational time. These features make hydraulic models limited adequate for application in task 3 (El-Din et al., 2002).

To predict sewer flow and enable real-time operation (task 3), deep learning is among the top methods. Unlike hydraulic models, which adopt hydrological and hydraulic principles, deep learning avoids sophisticated theories by making data-driven predictions through learning from data. As a breakthrough of artificial neural network, deep learning has solved problems that have resisted artificial intelligence for decades. One exciting news of deep learning is Google DeepMind's AlphaGo (Silver et al., 2016) beat the world's best human Go game player Ke Jie in 2017. A deep learning technique that has made revolutionary strides in the sequential data modeling domain is the Long Short-Term Memory (LSTM) (Hochreiter and Schmidhuber, 1997). The latest Google translation system powered by LSTM has vastly improved the translation quality, brought service nearly to the level of human translators (Google, 2016). The information contained in language is a kind of sequential data, when undertaking translation tasks, the correct word to use depends on the context, and the other words in the sentence or even paragraph. Time series data such as the inflow to the WWTP is also a kind of typical sequential data. LSTM has shown its superior performance for prediction of traffic time series (Ma et al., 2015), and has been adopted by Uber for extreme event ride requests forecasting (Laptev et al., 2017). However, to the best of the author's knowledge, there are very few studies about the application of LSTM in the water recourse related domain, given the success of the LSTM reported by both academia and industry, the effectiveness of LSTM need to be investigated. In this paper, LSTM was employed to construct a model for WWTP inflow prediction to support the management of ICWT.

Combining the advantages of hydraulic models and machine learning/deep learning methods is a trend in nowadays research (Yu et al., 2013; Chiang et al., 2010; Darsono et al., 2007). The present work aims at describing a systematic sewer system management approach using ICWT in order to improve the whole system behavior with minimal construction, and looking at the efficiency of LSTM on flow prediction. The remainder of this paper is organized as follows: the first part is a general description about study area, hydraulic model and LSTM. The second part is simulation results for different control scenarios based on the hydraulic model. The third part presents the prediction efficiency of the LSTM. Conclusion and future envision are discussed at the end of this paper.

2. Method and materials

2.1. Description of case study area and the proposed ICWT scheme

Drammen is located in the southeast of Norway. With more than 150,000 inhabitants, Drammen is the fourth largest city in Norway, and the largest city and capital in Buskerud County. The catchment area of Drammen's sewer system is around 15 km^2 and the total length of the sewer system is approximately 500 km. There are two WWTPs in Drammen, the Muusøya WWTP and the Solumstrand WWTP. Fig. 1 is an overview of the Drammen city.

The traditional city center distributes along the Drammen Fjord. There are two major catchments on the north bank of the Drammen Fjord, the Muusøya catchment and the Bragernes catchment, the curve in Fig.1 (a) indicating the boundary of these two catchments. The Muusøya WWTP treat sewage collected from the Muusøya catchment (Fig.1 (b)). Wastewater aggregated from the Bragernes catchment is transported by the Søren Lemmich pump station (Fig.1 (c)) from the north bank to the Strømsø catchment,

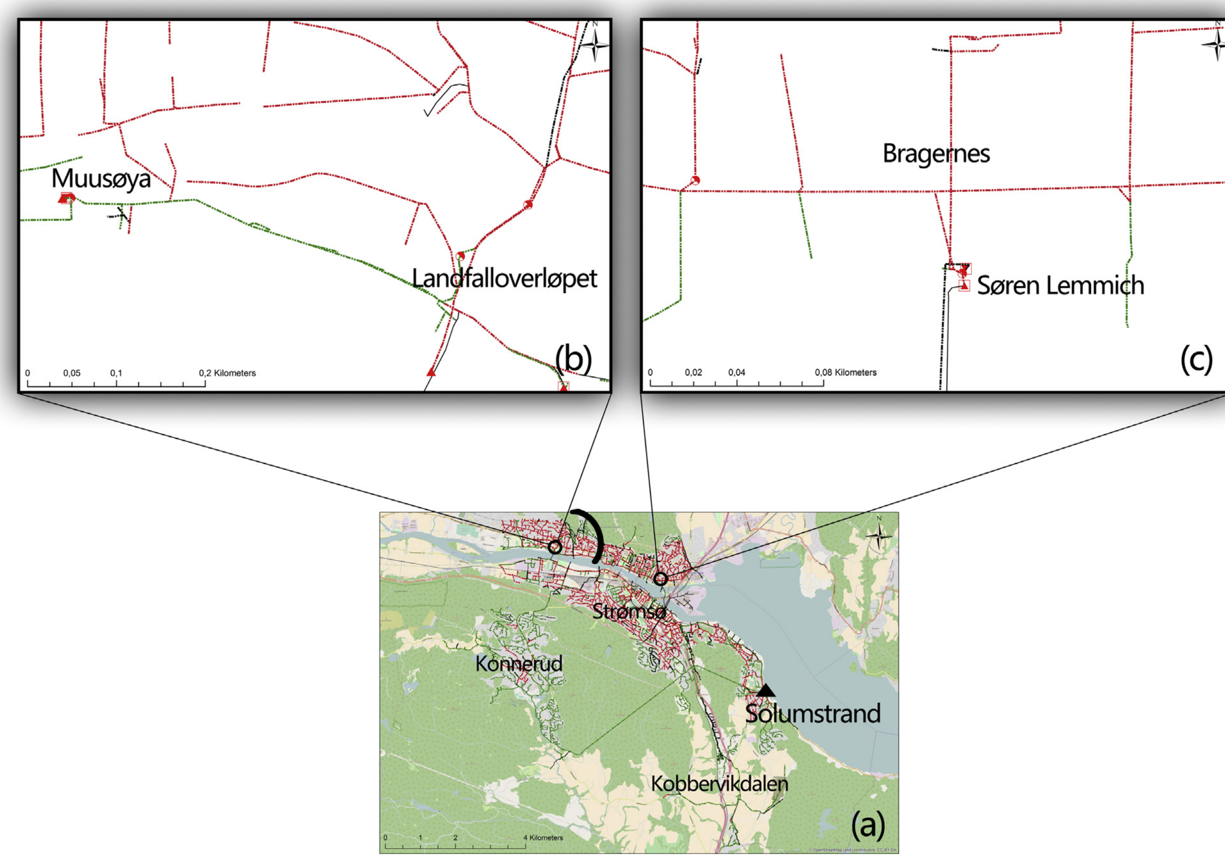

Fig. 1. Overview of Drammen, Muusøya WWTP and Søren Lemmich pump station.

which is on the south bank of Drammen Fjord. Afterward, sewage stream merges with wastewater collected from the Konnerud catchment and the Kobbervikdalen catchment, and finally discharged to the Solumstrand WWTP.

To reduce overflow from the sewer system and the WWTPs, the government of the Drammen city launched an innovative project: Regnbyge 3 M. The ultimate goal of the Regnbyge 3 M project is to integrates intelligent monitoring, modeling and control solutions, manage sewer system and WWTP in a holistic way.

The capacities of the sewer system and WWTPs are unevenly distributed in different catchments of Drammen. More than 80% of sewer system in the Muusøya catchment are combined sewer, while combined sewer in the sewer system associated with Solumstrand WWTP only accounts for less than 50%. For Muusøya WWTP, the designed treatment capacity is 33,000 PE (population equivalents), the dimensioning flow (Qdim) is 780 m^3/h, and the maximum flow (Qmax) is 1200 m^3/h. The Solumstrand WWTP is the major WWTP in Drammen, with a designed treatment capacity of 130,000 PE, the Qdim and Qmax is 2000 m^3/h and 4000 m^3/h respectively. Moreover, as a part of the traditional city center, the Muusøya catchment has a denser population than the rest of catchments. Because of combined sewer, lower WWTP capacity and higher population density, the Muusøya WWTP is suffering from the severe overflow. In the current phase, the Drammen municipality is planning to construct a storage tank to reduce overflow from the Muusøya WWTP. Due to the high density of buildings, there is very limited space for constructing storage tanks in the Muusøya catchment. Suggested by experts, the Landfalloverløpet was selected as the appropriate location for the storage tank, but the maximum dimension of the storage tank is restricted to 20,000 m^3, which is insufficient to deal with the current overflow situation. The ICWT is proposed in order to compensate insufficient capacity of the storage tank. The purpose of the ICWT schemes is to convey part of the WWTP inflow from the Muusøya WWTP to the Solumstrand WWTP.

2.2. The Regnbyge.no sewer monitoring system

To monitor the sewer system in real time, as well as provide data for model construction and calibration. A web based sewer monitoring system, called Regnbyge.no, was developed at the beginning of the Regnbyge 3M project. The Regnbyge.no sewer monitoring system is comprised of water level sensors, velocity sensors (NIVUS GmbH; Germany) and rain gauges deployed all around the Drammen city. The data collected by these sensors are transmitted to the data center of the Rosim AS. A spatial database was designed to manage the collected data, and ease the process of searching and editing data. The collected data is visualized by a web-based Geographic Information System (GIS), which supplies a user-friendly way to check the real-time and historical information. Fig. 2 is the screenshot of the regnbyge.no sewer monitoring system. Please note that the flow shown in the user interface is calculated according to water level, velocity and the pipe shapes.

2.3. Hydraulic model

To test the effectiveness of ICWT and derive proper control rules (task 1 and 2), a full detailed hydraulic model, with 9113 pipes, 9094 manholes, 129 weirs, 78 pumps and 39 outlets, is developed. Fig.3 is the hydraulic model for the Drammen sewer system. The sewer hydraulic model used in this study is Rosie. Rosie is an

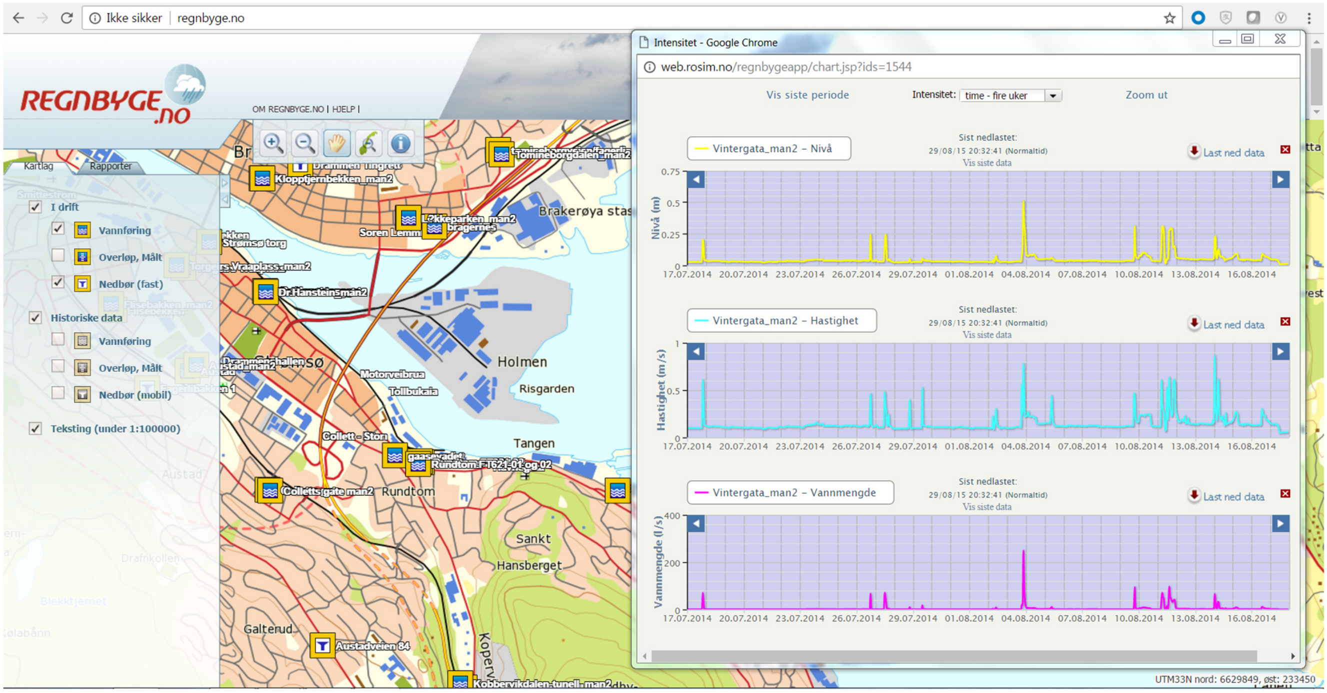

Fig. 2. The user interface of the Regnbyge.no sewer monitoring system.

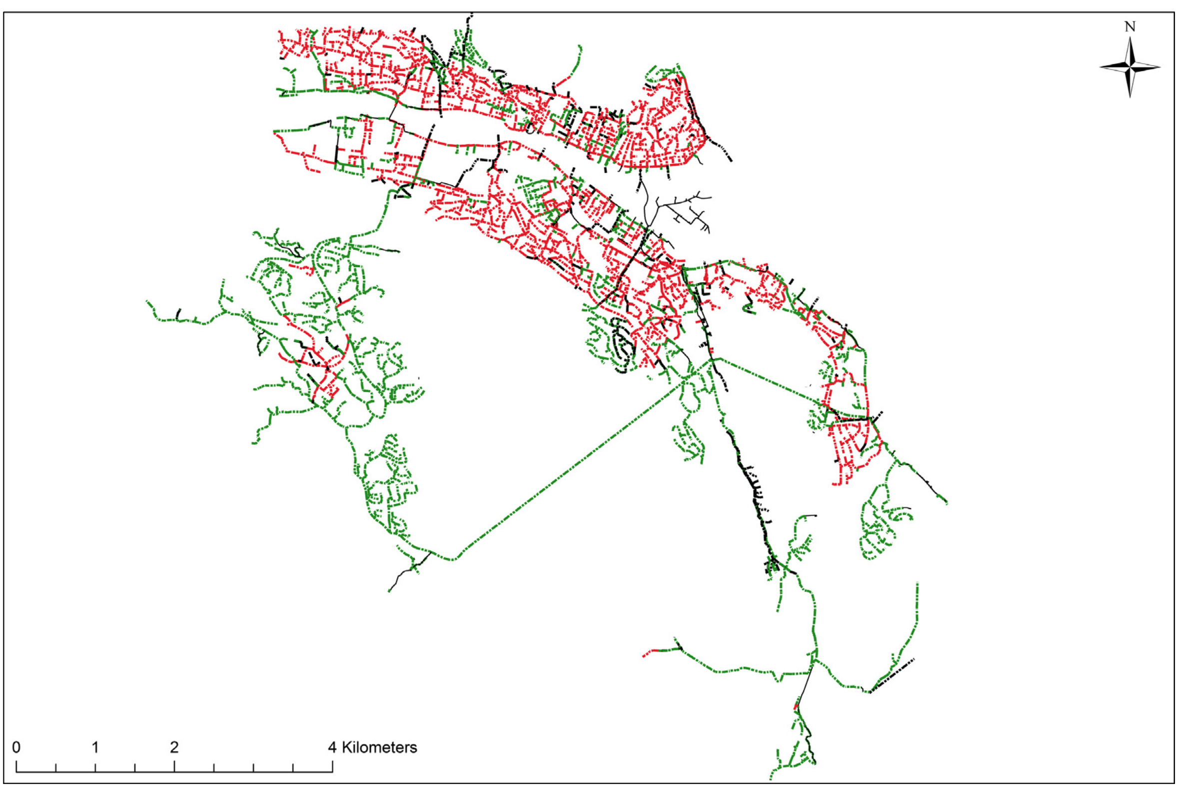

Fig. 3. The Hydraulic model for sewer system of Drammen.

ArcGIS additional application for planning, sizing and modeling of water distribution and sewerage systems developed by Rosim AS. The Rosie software maintains the interface and all the functions of ArcGIS, while using the MOUSE DHI as the computational engine to simulate the sewer system.

The runoff consists of two major components: the fast response component (FRC) and the slow response component (SRC). The FRC is the direct response from rainfall, which is calculated by the time–area (T-A) curve method in Rosie. Runoff model A is selected in this study. The SRC is the runoff generated gradually from the previous hydrological processes and accumulated as interflow and baseflow. The Rosie use the rainfall dependent infiltration (RDI) method to calculate SRC. The pipe hydrodynamic (HD) flow is simulated by one dimension free surface Saint Venant continuity and momentum equations. The MOUSE real-time control (RTC) module is used to simulate sewer control. In the MOUSE RTC module, the operation of control structures, such as pumps, moveable weirs or orifices, are designed by a curve that provides the relationship between water level (H) and water flow (Q).

There are two types of weirs available in Rosie. One type of weir define it as a structure that connects two sewer nodes and the other type of weir diverts sewage out of the system once the sewage level in the pipe exceeds the weir crest level. Sewer overflow is calculated by summarizing discharges from the latter type of weirs using the HD model.

2.4. LSTM

This study employs a novel neural network architecture, LSTM, to undertake task 3 (inflow prediction for the Muusøya WWTP). The neural network is usually comprised of input layer, hidden layer and output layer. Parameters that connect input values with hidden neurons, as well as link hidden neurons with outputs called weights.

In the most widely used feedforward neural network (FFNN), the FFNN first computes a weighted sum of its input values and weights:

$$s = \sum_{i=1}^{n} w_i x_i + b \tag{1}$$

Then the weighted sum s is fed into the hidden layer. The hidden layer is made up of a number of hidden neurons, which contain an activation function. The hidden neurons transfer weighted sum s into output by using the activation function, such as the sigmoid function:

$$f(s) = \frac{1}{1 + e^{-s}} \tag{2}$$

In the above equations, w_i represents the weights, x_i is the input values, b is the bias.

The LSTM is a special type of recurrent neural network (RNN), Fig.4 (a) is a schematic of the Elman RNN (Elman, 1990), which is one of the earliest RNN architecture. RNN feeds not only the weighted sum of inputs and weights, but also the states of the hidden neurons at the previous time steps into hidden neurons at the present time step. As shown in Fig.4 (a), the hidden neuron output at time step t is calculated by the equation:

$$h_t = f(w_h h_{t-1} + w_i x_t + b) \tag{3}$$

Where h_t is state of the hidden neuron at the time step t, h_{t-1} is state of the hidden neuron at the time step t-1, w_i and w_h are weights between input values and hidden neurons, and between hidden neurons respectively, $f()$ is the activation function.

Usually, neural network are trained by using the Back propagation (BP) method, BP use chain rule of differentiation to calculate the gradients of the error corresponding to the weights. In FFNN, BP propagates the error between predicted and observed values backward to the hidden layer, then to the weights. The neural network reduces differences between observed and predicted values through adjusting the weights.

The training of RNN uses an extended version of BP, also known as backpropagation through time (BPTT). BPTT adjust w_i and w_h during training, it means the chain rule of differentiation not only along the direction of hidden layer and input weights w_i, but also along previous time steps. When using the BPTT method, because the error of derivation accumulates through time, it will be extremely hard to learn and tune the parameters of the earlier layers. Because the gradient going through the network either gets very small and vanish, or get very large and explode. This is commonly known as the vanishing and exploding gradient problem.

Different from RNN, the LSTM use a memory cell and three gates to control information in the hidden neuron. The function of forget gate is to reset memory cell. The input gate permits inputs to modify the memory cell state. The output gate allows or obstructs the memory cell state from influencing other neurons. The memory cell can impede outside interference, which further allows the LSTM to learn time series with long spans.

Fig.4 (b) shows the hidden unit of LSTM. The i, f and o in Fig.4 denote the input, forget and output gate. The c and $\bar{c}$ represent the memory cell state and the new memory cell state. The mathematical representation of LSTM is written in the following equations:

Input gate:

$$i_t = \sigma_g(W_i * x_t + U_i * h_{t-1} + V_i^{\circ} c_{t-1} + b_i) \tag{4}$$

Forget gate:

$$f_t = \sigma_g(W_f * x_t + U_f * h_{t-1} + V_f^{\circ} c_{t-1} + b_f) \tag{5}$$

Output gate:

$$o_t = \sigma_g(W_o * x_t + U_o * h_{t-1} + V_o^{\circ} c_{t-1} + b_o) \tag{6}$$

Cell state:

$$c_t = f_t^{\circ} c_{t-1} + i_t^{\circ} \bar{c}_t \tag{7}$$

$$\bar{c}_t = \sigma_c(W_c * x_t + U_c * h_{t-1} + b_c) \tag{8}$$

Output vector:

$$h_t = o_t^{\circ} \sigma_h(c_t) \tag{9}$$

Where x_t is the input vector. W, U, V, and b are parameters for weights and bias. $^{\circ}$ represents the scalar product of two vectors, σ_g is the sigmoid function, σ_h and σ_c are the hyperbolic tangent function, for a given input z, the output of the hyperbolic tangent function is:

$$f(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}} \tag{10}$$

In this study, the LSTM is implemented using Keras. The Docker Toolbox is used to setup a development environment to let different deep learning software and libraries coexist and function

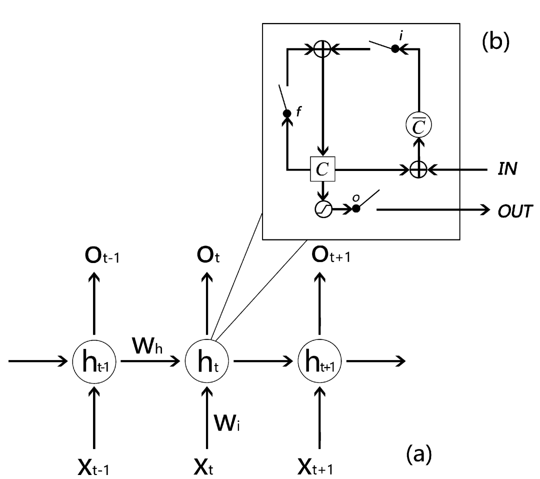

Fig. 4. Schematic of RNN and hidden units of LSTM.

correctly. The Jupyter notebook is used as the programming interface. Keras is a Python based high-level deep learning library. It is running on top of TensorFlow or Theano. TensorFlow is used as the backend of Keras in this study. TensorFlow is an open-source deep learning software released by Google in 2015. Other Python based machine learning libraries, includes Pandas, NumPy, Scikit-learn and Matplotlib are also used. Specifically, Pandas and NumPy are used to load the dataset as the data frame and prepare the raw data in the format of the desired array. Scikit-learn is used for model selection and preprocessing, such as tuning parameters and data normalization. Matplotlib is used for visualization.

2.5. Model performance criteria

Three model performance criteria are used in this study, i.e. root mean square error (RMSE), Nash-Sutcliffe Efficiency (NSE) and the coefficient of determination (R^2). The calculation of RMSE as shown below:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right)^2}{n}} \tag{11}$$

NSE is a parameter that determines the relative importance of residual variance (noise) compare with the variance in the measured data (information). The NSE is calculated by the following equation:

$$NSE = 1 - \left[\frac{\sum_{i=1}^{n}(Y_i^{obs} - Y_i^{sim})^2}{\sum_{i=1}^{n}(Y_i^{obs} - Y^{mean})^2}\right] \tag{12}$$

NSE varies from $-\infty$ to 1, NSE = 1 indicates a perfect correlation between simulated and observed data, values between 0.0 and 1.0 is generally acceptable.

The equation for R^2 is:

$$R^2 = \left[\frac{\left(\sum_{i=1}^{n}\left(Y_i^{sim} - Y_{sim}^{mean}\right)\left(Y_i^{obs} - Y^{mean}\right)\right)^2}{\sum_{i=1}^{n}\left(Y_i^{sim} - Y_{sim}^{mean}\right)^2\sum_{i=1}^{n}\left(Y_i^{obs} - Y^{mean}\right)^2}\right] \tag{13}$$

In the three above listed equations:

Y_i^{obs} = the i -th observed data.
Y_i^{sim} = the i -th simulated data.
Y^{mean} = mean value of observed data.
Y_{sim}^{mean} = mean value of simulated data.
n = number of observed data.

3. Results

3.1. Calibration of the hydraulic model

The historical flow data obtained from the Regnbyge.no sewer monitoring system is used to validate the hydraulic model. Fig. 5 shows the hydrographs of the hydraulic model outputs versus the recorded values at five monitoring sites. The recorded values cover both dry weather season and wet weather season. It clearly indicates that the flow rate simulated by the hydraulic model is consistent with the real values. Table 1 is the model performance criteria of the hydraulic model. All the criteria show acceptable values. Results displayed in Fig. 5 and Table 1 confirm the high reliability of the hydraulic model simulations. The calibrated model is then used in the following scenario analyses.

3.2. Scenario simulations of the hydraulic model

The observed precipitation in 2014 with a temporal resolution of 1 min is used for the hydraulic simulation. The simulation runs continuously from Jan. 01, 2014 to Dec. 31, 2014 as a baseline scenario against different control scenarios.

The total overflow volume of the Drammen sewer system for the baseline scenario is 2,096,668 m^3. Table 2 shows the simulated overflow volume through weirs associated to the Muusøya WWTP under the baseline scenario. The 507_Landfall is the major bypass structure of the Muusøya WWTP, which is the weir that takes away most of the peak flows to the Muusøya WWTP. The simulation result illustrates that weirs relate to the Muusøya WWTP contribute 22.7% of the total overflow. As the baseline scenario simulation indicates, implement overflow control solutions towards the Muusøya WWTP could bring the most immediate and significant result. Table 3 is simulated overflow volume in every month of 2014. One can observe that the overflow volume is significantly higher during the rainy season of Drammen from June to August.

In order to test the feasibility of ICWT, and compare its efficiency with the storage tank, seven control scenarios are designed. Table 4 gives a description of different control scenarios. The main goal of the control is to: 1) reduce the total overflow, 2) reduce overflow from the Muusøya WWTP and 3) avoid bringing extra burden to the Solumstrand WWTP. In the control scenarios, the distribution of sewage is determined according to the principal of the greedy algorithm. Greedy algorithm refers to for the solution to a problem builds up a solution step by step, always taking the action that gets the most immediate benefit at the next step (local optimal solution) within the specified constraints step by step rather than considering the global optimum (Cormen, 2009).

According to the principal of the greedy algorithm, the control structures such as pump first maximum inflow to Muusøya WWTP during peak flow events, as it is the easiest way to deal with peak flow. If the influent flow rate exceeds the maximum designed treatment capacity of the Muusøya WWTP, the exceeded volume is drained to the storage tank (except scenario 4, which activate ICWT directly). If the storage tank is still insufficient to dealing with the inflow, for scenario 5–7, the ICWT is activated to divert sewage to the adjacent Brageners catchment.

The impact of the different control scenarios on the total overflow is investigated. Fig. 6 displays the reduction of total overflow volume compare with the baseline scenario. Table 5 lists the percentage of total overflow reduction of control scenarios compare with the baseline scenario.

As expected, no matter only use storage tank or applying the ICWT, all seven control scenarios reduced overflow volume compare with the baseline scenario. There is a clear tradeoff between storage tank sizes and overflow volume, with the total overflow decreasing as the storage tank size increases. With the smallest storage tank dimension, the total overflow of scenario 1 is close to the baseline scenario, the relative percentage is only 1.20%, which indicates that the effect of scenario 1 is not distinct. When the storage tank is built with the maximum available size of 20000 m^3 (scenario 3), the overflow reduction is 258,895 m^3, a reduction of 12.35%.

The storage tank is less efficient compared with ICWT. As shown in Fig. 6, in scenario 1 and scenario 2, using a storage tank with a volume of 1000 m^3 and 5000 m^3, the volume of reduced overflow is less than only implementing the ICWT (scenario 4). Scenario 4 with only ICWT implemented gives an overflow reduction of 120,504 m^3, 5.75% less than the total overflow volume of the baseline scenario. ICWT enhances the capability of the storage tank dramatically. Overflow reduction of scenario 1 and scenario 2 increase from 25,146 m^3 and 95,412 m^3 to 141,741 m^3 (scenario 5) and 201,011 m^3 (scenario 6) respectively. Scenario 7 yields the highest

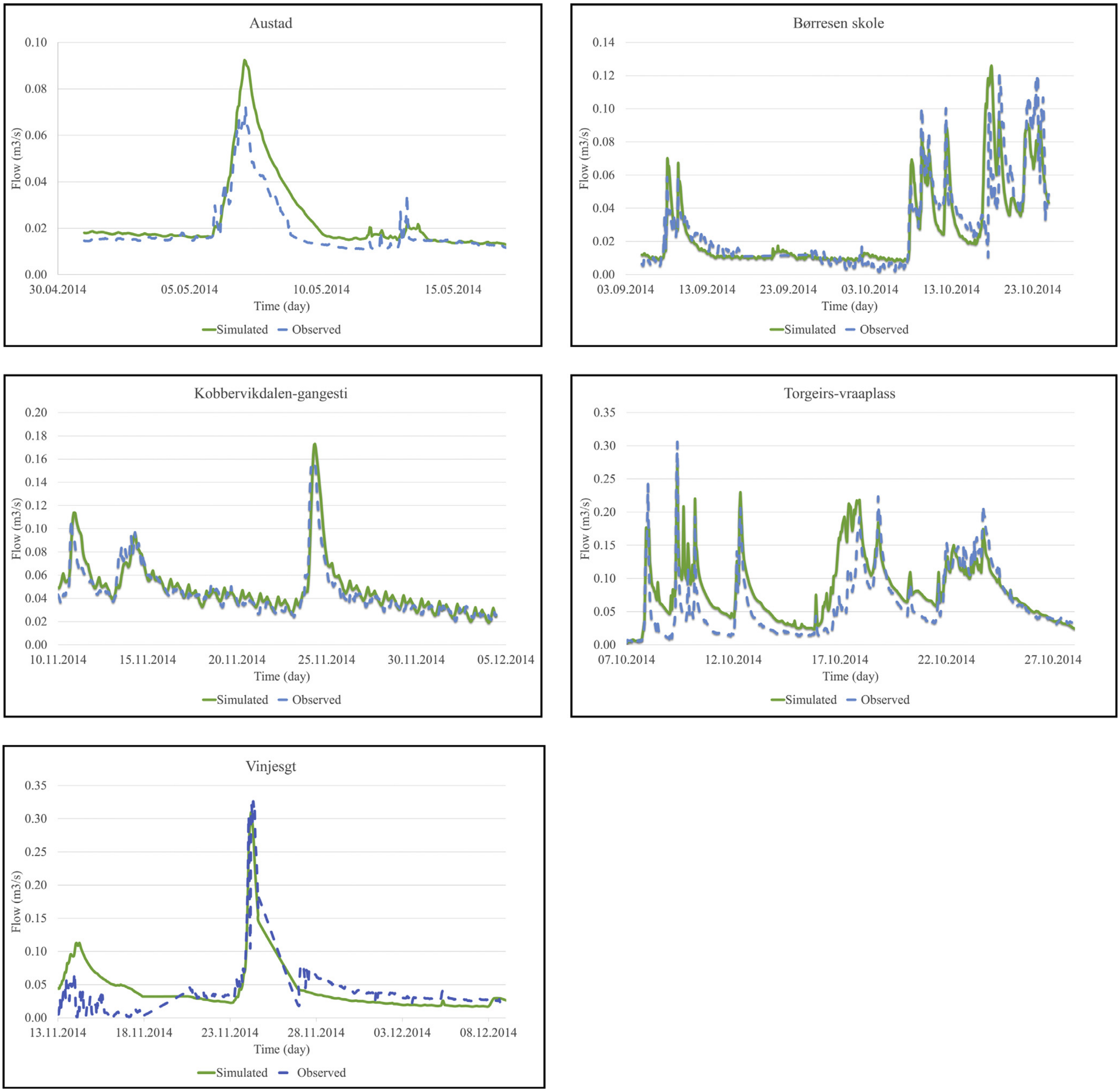

Fig. 5. Hydrographs of observed versus simulated flow at five stations.

Table 1
Values of model calibration criteria at five stations.

Measurement point	NSE	R^2	RMSE
Austad	0.54	0.91	0.008
Børresen skole	0.68	0.71	0.014
Kobbervikdalen-gangsti	0.80	0.85	0.010
Torgeir-vraaplass	0.51	0.67	0.036
Vinjesgt	0.53	0.57	0.029

Table 2
Overflow volume of outlets associated to the Musøya WWTP for the baseline scenario.

Weir ID	Simulated overflow volume (m^3)
50433_w_1	5751
505_Store Landfall	6016
507_Landfall	456,171
508_Landfall	7113

overflow reduction, i.e. a reduction of 15.51%. Nevertheless, it should be noticed that using a storage tank of 5000 m^3 (only one-fourth of the maximum dimension used by scenario 7), scenario 6 achieves over half the effect of scenario 7, i.e. 9.6%.

Although implementing storage tank and ICWT resulted in significant reduction of total overflow, one obvious concern for ICWT is whether it will bring extra burden to the Solumstrand WWTP. The volume of overflow from the bypass structures of the two WWTPs under different scenarios is listed in Table 6. The overflow from the bypass structure of Muusøya WWTP is reduced substantially. For the Solumstrand WWTP, the impact of ICWT is almost negligible.

Table 3
Overflow volume in every month of 2014 for the baseline scenario.

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Overflow volume (m^3)	7929	4216	58,633	422,122	56,382	120,189	116,986	149,685	92,498	737,182	329,652	1195

Table 4
Description of the control scenarios.

Scenario	Description
Scenario 1	Only construct a 1000 m^3 storage tank at Landfalloverløpet
Scenario 2	Only construct a 5000 m^3 storage tank at Landfalloverløpet
Scenario 3	Only construct a 20,000 m^3 storage tank at Landfalloverløpet
Scenario 4	Only implement the ICWT between the Muusøya catchment and the Brageners catchment
Scenario 5	1000 m^3 storage tank + ICWT
Scenario 6	5000 m^3 storage tank + ICWT
Scenario 7	20,000 m^3 storage tank + ICWT

Table 7 is the total overflow volume of different control scenarios from March to November. It can be seen that the overflow reduction is most significant during the rainy season of Drammen.

3.3. LSTM

The hydraulic simulations of the eight scenarios clearly demonstrate the viability of ICWT. However, since these hydraulic simulations are based on perfect foreknowledge of the rainfall events, they cannot be implemented for the actual real-time purpose. To achieve successful control of the storage tank and ICWT, the overflow control facilities should open/close timely in order to redistribute WWTP inflow. For the better operation of the storage tank and ICWT, it is essential to anticipate the future WWTP inflow, thus enhancing decision-making and giving enough response time for the operation.

To overcome the aforementioned disadvantages of hydraulic model and traditional neural network, LSTM is employed to predict inflow to the Muusøya WWTP. The training data for LSTM development were collected from Jan. 1, 2014 to Dec. 31, 2014 with a temporal resolution of 1 min. The raw data have over 500,000 records. To validate the generalization ability of the proposed LSTM algorithm, the raw data are divided into two subsets: training set and testing set. Data from the first 75% is used for training, and the remaining 25% is used for testing. The difference between training and testing is regularization mechanisms, which is used as penalize to limit overfitting, are turned off during the testing stage. Table 8 is summarized statistics of the training data.

Considering technical details of the pump operation, the proposed models aim at predicting flow rate in the next hour based on the flow rate and rainfall in the past hour. During dry weather, the flow rate is stable and the pump can be operated at a lower frequency, while during wet weather, it is essential to predicate flow rate with a higher resolution. To fulfill pump operation requirements, the raw data is resampled to frequencies of 10 min, 15 min, half hour and one hour, models with corresponding frequencies are developed.

There are primarily four modes of LSTM application (Karpathy, 2016). The one to one mode such as image classification, have one input (image) and one output (image label). The one to many mode generates many outputs using one input, e.g. image captioning, which takes an image and outputs a sentence of words. The many to one mode receive sequence input and output one label (e.g. sentiment analysis where a given sentence is classified as expressing positive or negative sentiment). The many to many mode (or sequence to sequence, Abbreviated as seq2seq) is the method for machine translation or chat robot, with a sentence in one language as input and a sentence in the target language as output. The one hour frequency model is defined as a one to one problem, i.e. predicting flow rate of the next hour by using the values from

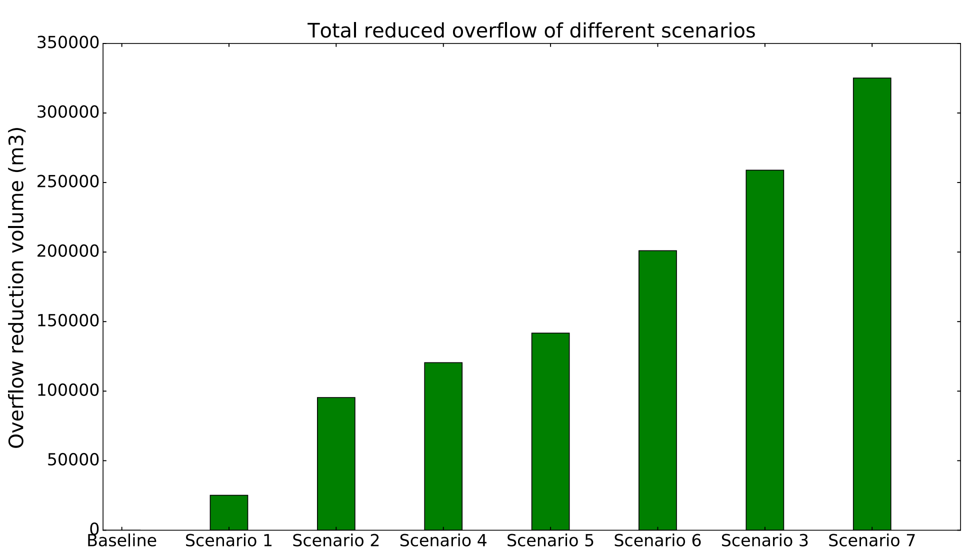

Fig. 6. Total overflow volume reduction of different scenarios.

Table 5
Relative percentage of total overflow reduction of control scenarios compares to the baseline scenario.

Scenario	Relative percentage compare with the baseline scenario (%)
Baseline scenario	0.00%
Scenario 1	1.20%
Scenario 2	4.55%
Scenario 4	5.75%
Scenario 5	6.76%
Scenario 6	9.59%
Scenario 3	12.35%
Scenario 7	15.51%

Table 6
Volume of overflow from the bypass structures of the Muusøya WWTP and the Solumstrand WWTP.

	Muusøya WWTP (m^3)	Solumstrand WWTP (m^3)
Baseline scenario	456,171	6214
Scenario 1	438,595	6174
Scenario 2	372,403	6170
Scenario 3	215,059	6144
Scenario 4	323,404	6182
Scenario 5	311,159	6197
Scenario 6	266,370	6165
Scenario 7	162,722	6193

the previous hour. LSTM models with other three frequencies are defined as a seq2seq problem (Zaytar et al., 2016), e.g. for the 10 min frequency data, the model uses the values of the past 6 steps to predict the next 6 steps.

Several state-of-the-art techniques such as dropout and RMSprop are used to optimize the LSTM. Dropout (Hinton et al., 2012) is a simple but effective way to increase the generalization ability of neural network. Traditional neural network training usually uses the ensemble method to prevent overfitting, but it could significantly increase CPU consumption. The key idea of dropout is temporary discard part of units (either hidden neurons or visible inputs) from the neural network during training. Dropout generates a number of different "thinned" networks during training, and in the testing stage, a single un-thinned network is used (Srivastava et al., 2014). RMSprop is an unpublished, adaptive learning rate method proposed by Geoff Hinton in Lecture 6e of his Coursera course. RMSprop utilizes the magnitude of recent gradients to normalize the gradients, and keeps a moving average over the root mean squared gradients for each weight. RMSprop also divides the learning rate by an exponentially decaying average of squared gradients.

Through trial and error experiments, the final LSTM architecture used in this paper has three hidden layers with 10 LSTM units in each hidden layer, dropout layer is implemented between hidden layers. After ascertaining the optimum structure of LSTM, the model is used to predict the inflow to the Muusøya WWTP. Furthermore, the LSTM is compared with two of the most widely used machine learning models in the water resource field: FFNN and support vector regression (SVR). To make a fair comparison, the FFNN remains the same deep structure with LSTM. The kernels and parameters of SVR are confirmed using the grid search method, the optimal SVR used in this study is an RBF kernel SVR with a gamma value of 0.5 and C value of 5.

Table 9 presents the model performance. The results imply that LSTM outperforms FFNN and SVR. LSTM produces a high NSE value

Table 7
Total overflow volume from March to November under different control scenarios.

Model	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov
Scenario 1	57,784	420,834	54,732	119,065	108,576	146,716	91,541	732,503	326,433
Scenario 2	54,162	414,206	51,236	111,459	97,531	139,422	86,532	716,762	316,609
Scenario 3	52,430	375,023	45,310	91,576	82,197	123,216	73,105	679,867	301,713
Scenario 4	54,199	342,789	51,937	116,375	106,363	143,005	88,476	731,620	328,060
Scenario 5	53,723	341,477	51,350	115,340	100,775	140,273	86,817	726,333	325,481
Scenario 6	52,430	338,330	48,020	106,239	93,774	133,414	82,536	711,645	315,933
Scenario 7	52,430	328,623	45,353	87,710	81,837	119,563	68,936	675,431	298,298

Table 8
Summary statistics of the datasets.

Model stage	Max flow rate (m^3/s)	Average flow rate (m^3/s)	Standard deviation of flow rate	Max rainfall (mm/s)	Average rainfall (mm/s)	Standard deviation of rainfall
Training	1.50	0.18	0.12	33.33	2.41	5.36
Testing	1.79	0.14	0.09	25.29	1.94	4.47

Table 9
Model performance of LSTM, FFNN and SVR with different sampling frequencies.

Model	Performance criteria	Sampling frequency			
		One hour	Half hour	15 min	10 min
	R^2	0.9677	0.9555	0.9426	0.9396
LSTM	RMSE	0.0150	0.0176	0.0203	0.0208
	NSE	0.9668	0.9549	0.9406	0.9378
FFNN	R^2	0.9607	0.9321	0.9330	0.8962
	RMSE	0.0235	0.0236	0.0277	0.0319
	NSE	0.9181	0.9188	0.8798	0.8542
SVR	R^2	0.9660	0.9533	0.9433	0.9413
	RMSE	0.0496	0.0435	0.0410	0.0392
	NSE	0.6357	0.7224	0.7570	0.7792

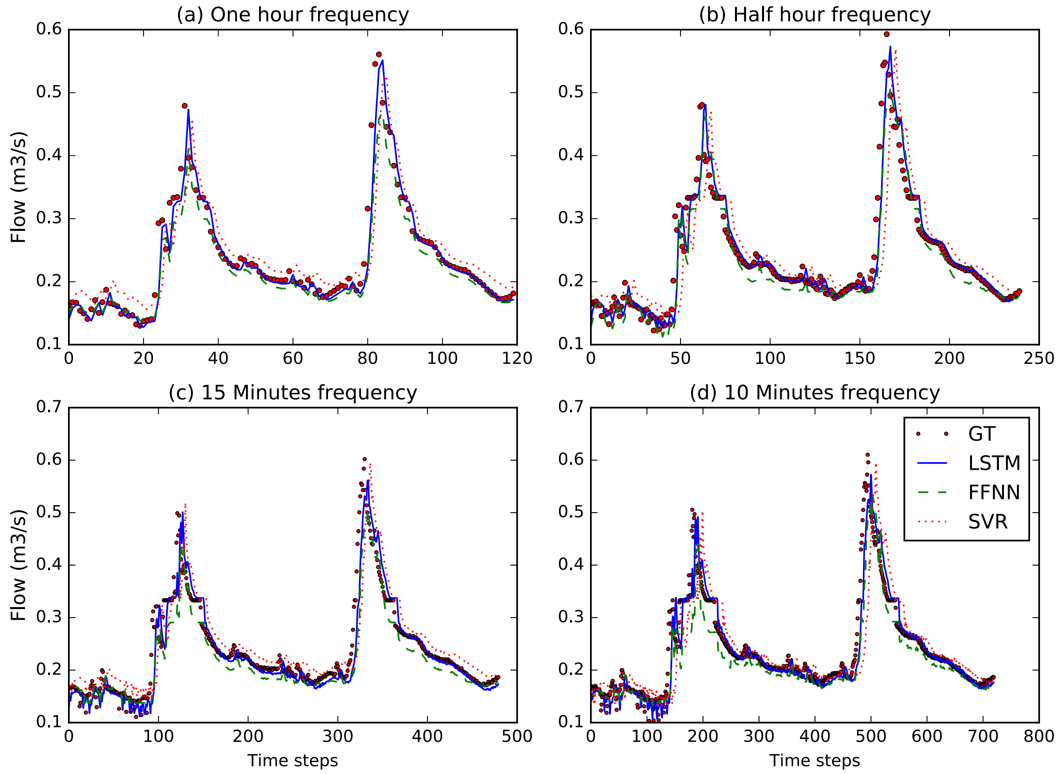

Fig. 7. Hydrographs of LSTM, FFNN and SVR outputs versus the ground truth (GT) values for 10 min, 15 min, half hour and one hour frequency models from Nov. 7, 2014 to Nov. 12, 2014.

(close to 0.95), high R^2 value (higher than 0.93) and low RMSE value (around 0.02). The values of the three criteria indicate that the LSTM has the ability to predict highly nonlinear and variable time series, such as WWTP inflow.

To illustrate the performance of the developed LSTM, FFNN and SVR models in a more intuitive way, hydrographs of ground truth (GT) versus forecasted flow from Nov. 7, 2014 to Nov. 12, 2014 are drawn in Fig. 7. It can be seen from Fig. 7 that LSTM is capable of predicting the inflow to the Muusøya WWTP in spite of significant variations in flow rate during these days. The LSTM is able to capture the major trends and peaks of observations, while the FFNN model underestimates the peak value. It also can be observed that for the periods of rainfall, the LSTM anticipate two increases in flow rate timely, while the SVR presents a time delay problem.

4. Discussion and Conclusion

The increase of urbanization and extreme rainfall events are inducing more frequent sewer overflow. At the same time, the treatment capacity of WWTP also seriously affected. Efficient sewer management measures have to be applied to mitigate sewer overflow. For existing sewer system, although storage tank could supply a straightforward solution for overflow reduction, their locations and dimensions are highly constrained. In densely populated cities, alternative solutions should be investigated.

This paper describes a novel ICWT solution. The effectiveness of ICWT is evaluated by a case study for a real sewer system in Drammen, Norway. The hydraulic behaviors of the sewer system with different control scenarios are assessed using hydraulic model. Annual long simulations of eight scenarios show that the ICWT could provide extra benefits for overflow mitigation.

This study also demonstrates that LSTM is able to provide precise time series predictions for sewer system management. LSTM can be a powerful tool for managers or engineers of the sewer system, who can take advantage of the prediction to improve their decision-making. Intelligent urban infrastructures will become the backbone of future cities. Sensors, actuators and algorithms are integrating together to enhance important infrastructures such as sewer system or WWTP. There are many possible scenarios to complement urban infrastructure control with deep learning.

In recent years, deep learning methods such as LSTM are gaining more and more successes in many industries. However, the sophisticated mathematical knowledge and programming skill behind deep learning limit its application in the water resource field. Even so, the potential power of deep learning still fascinating, and more studies about absorbing deep learning into the water resource field is necessary.

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