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A Comparison of Physics- and Data-based Modeling of Rural Drainage Systems ⋆

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Abstract: Rural drainage systems are often large and complex systems, which are difficult to model. In this work, a physical model based on the hydrology and hydraulic laws and a data-driven modeling approach with an ARX structure are created for the rural drainage system in Eiderstedt, Germany. Thereupon, the prediction accuracy for real measurement data of both models is investigated and the respective advantages and disadvantages are discussed. It is shown that both models are able to predict the water level quite well, with the physical and data-based model being more accurate for long- and short-term predictions, respectively.

Keywords: Data-based modeling, physical modeling, rural drainage systems.

1. INTRODUCTION

Proper drainage is essential for a healthy environment and productive agriculture [Vlotman et al. (2020)]. While too fast drainage yields undesired distribution of pesticides and loss of nutrients, poor drainage can yield flooding and salinization [Singh (2018)]. In rural areas, the drainage system is typically a combination of open ditches and pipes, which are used to transport the water into a river or the open sea. Usually, less intense, but continuous precipitation, which typically occurs in winter is a major issue as shown in Loritz et al. (2021). In contrast to that, in urban areas short but intense rain events, which typically occur in the summer time cause the hazard of flooding. Additionally, rural drainage is rather slow compared to the flow in urban drainage systems, where the water discharge typically takes only a few hours. Hence, different levels of detail and impact factors should be considered, when modeling the two type of systems.

In recent decades, as more sensors have been installed and more information has been made available, data-based modeling has become increasingly important in water systems, especially with the aim to control the system as desired [Putri et al. (2024); Baumann et al. (2022b, 2024)]. Depending on the prior knowledge of the modeled system white, gray or black box models can be used. The first two take the transportation behavior of the drainage system into account, whereas black-box approaches are purely data-based and do not consider any physical laws. Remesan and Mathew (2014) give an extensive overview of the different black-box data-based modeling approaches in hydrology. At the same time, however, the classic physics-based drainage modeling has evolved as well, especially with respect to implementation and computational efficiency [Jensen et al. (2010); Baumann et al. (2022a)].

Even though a variety of works regarding physical and data-based modeling with application to drainage systems have been published, the urban area is investigated intensively [Jóhannesson et al. (2021); Bach et al. (2014); Garzón et al. (2022)] compared to rural areas [Gurovich and Oyarce (2015); Hadid et al. (2020)]. However, due to the different conditions and requirements occurring in these systems, special attention should also be paid to modeling the water drainage of rural systems, which is done in this work. In detail, this includes the derivation of a data-driven model from the physical model, which to the best of the authors' knowledge has not yet been presented. The resulting model has an ARX structure and is compared with the physics-based model in terms of prediction accuracy. Further, the potentials of both approaches for modeling rural drainage modeling are compared and discussed. To illustrate the use of the method, it is applied to a subarea of the drainage system of Eiderstedt, a marshland area in northern Germany, by using available historical measurement data from the project region for model calibration and validation.

After a brief presentation of the project region, both a physical and a data-based modeling approach is described in Section 2. The results of both approaches are presented

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and compared in Section 3 before their potentials are discussed in Section 4. Finally, Section 5 concludes this work with a small summary and possible future research directions.

2. DESCRIPTION OF THE PROJECT REGION AND MODELING APPROACHES

2.1 Description of the project region

The project region Eiderstedt is a half island in northern Germany, which has been successively won from the North Sea by building dikes. It has a total area of 249 km^2, most of which is marshland, with drainage ditches totaling more than 1000 km in length. These drainage ditches and tide gates, which are tunnels underneath the dikes, are utilized to transport water to the next compartment of the dike cascade and finally release it to the open sea. In general, the water flow is rather slow, since mainly free surface flow drives the water discharge. Unfortunately, some areas are even located below sea level, which makes it rather difficult to drain the water to the open sea. Hence, the tides are crucial. In a time span of approximately 4 h when the sea level is below the level of the water stored behind the dike, the tide gates are opened to release the water. In this work the subarea, which drains to the Everschop tide gate is further investigated since multiple sensors are installed there and it is prone to flooding especially in the winter months. In Figure 1a the project region is shown, while Figure 1b displays the area, which drains to the Everschop tide gate and the available sensor location.

2.2 Physical model

In general, the movement of water accelerated by gravitational force can be described by the equations of Saint-Venant (1871), which read

$$\partial_t A + \partial_x Q = 0 \tag{1a}$$

$$\partial_t Q + \partial_x \left(\frac{Q^2}{A} \right) + gA(\partial_x h + S_f - S_0) = Q_l \tag{1b}$$

with the initial conditions

$$A(x,0) = A_0, \qquad x \in [0, L], \tag{1c}$$

$$Q(x,0) = Q_0, \qquad x \in [0, L] \tag{1d}$$

and the up-/downstream boundary conditions

$$h(0,t) = h_{\mathrm{up}}(t), \qquad t \in \mathbb{R}_0^+, \tag{1e}$$

$$h(L,t) = h_{\mathrm{down}}(t), \qquad t \in \mathbb{R}_0^+. \tag{1f}$$

These form a set of hyperbolic partial differential equations, which describe the conservation of mass and momentum of the water flow. The states Q and A describe the discharge and the wetted area of the ditch, while the water level is given by h. Moreover, Q_l denotes the lateral inflow, while the parameters g, S_0 and S_f are the gravitational acceleration, the bed slope and the friction slope, which can be described by the Manning-Strickler relation as

$$S_f = n_M^2 \frac{Q|Q|}{A^2 R^{4/3}}. \tag{2}$$

Therein, the friction coefficient n_M is used to take the friction of the channel bed into account [Litrico and Fromion (2009)]. Finally, the hydraulic radius R is given by the quotient between the wetted perimeter and A.

When two or more ditches are connected, the coupling of these ditches has to be considered such that the water level of the connecting node changes with its in- and outflows. Thus, the mass balance equation of each node is given by

$$\dot{V}_n = A_n \dot{h}_n = \sum_{i=1}^{N} Q_i \tag{3}$$

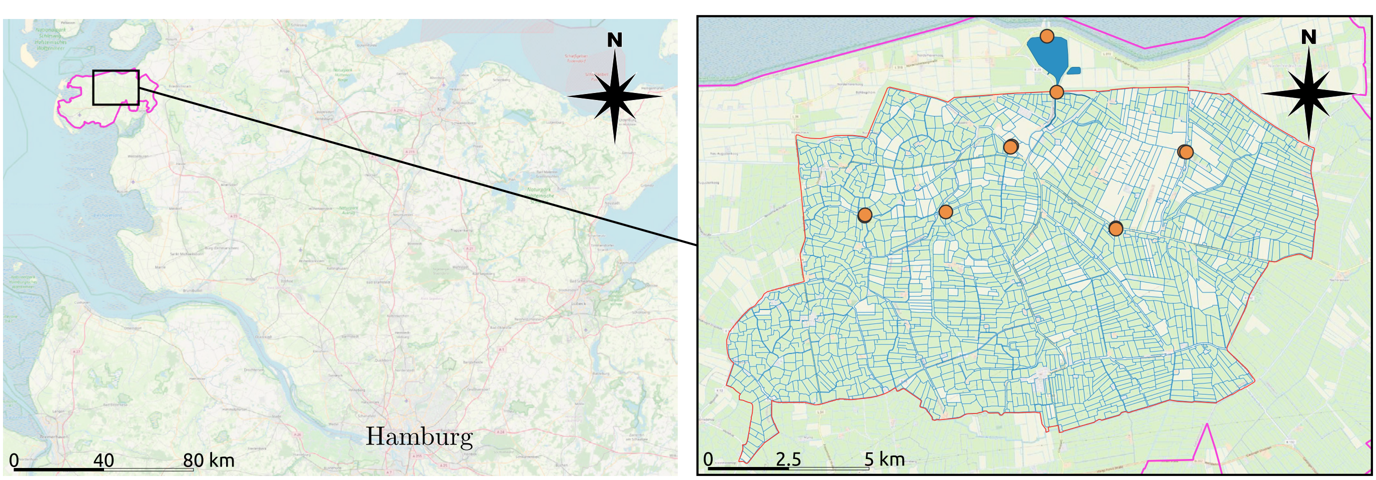
with the node volume V_n, node area A_n and the boundary discharges Q_i of the N connected ditches.

Regarding the gates, different formulations apply depending on the gate setting with respect to the up- and downstream water level. If the upstream water level of the gate is submerged, the gate flow is modeled as

$$Q = C_s L_o h_o \sqrt{2gh_e}. \tag{4}$$

Otherwise the wire type flow can be described using

$$Q = C_w L_o h_e^{3/2}, \tag{5}$$



(a) Map of northern Germany with Eiderstedt outlined in pink.

(b) Ditches (blue lines) and available sensors (orange dots) in the project area (outlined in red).

Fig. 1. Geographical location of the project region Eiderstedt on the left and the project area, which drains to the Everschop tide gate on the right.

where the gate and weir coefficients are denoted as C_s and C_w, while L_o and h_o are the opening width and height, respectively. Moreover, h_e denotes the effective water head, which depends on the upstream and – in the submerged case – downstream water level.

Finally, to take the precipitation into account, the infiltration and runoff of the sub-catchment areas has to be considered. Therefore, a variety of methods like the Green-Ampt model, Horton's method or unit hydrograph have been introduced [Beven (2011)]. They define the inflow and thus the boundary conditions for the nodes of the drainage system, that are connected to catchment areas. In this work Horton's method is used, which assumes that the infiltration rate decreases exponentially with time since the soil moisture gets saturated.

The open-source software tool Stormwater Management Model (SWMM) is a suitable choice to model such a system. In SWMM the ditches are modeled by the discretized 1D shallow water equation. By interconnecting the 1D elements in a grid, even surface flows can be modeled precisely [Jensen et al. (2010)]. For a detailed description of the simulation in SWMM 5, the reader is referred to the hydrology and hydraulics manual [Rossman and Huber (2016, 2017)]. In order to obtain a simulation model with a reasonable balance between accuracy and computational effort, not all ditches but the major branches are modeled. Unfortunately, the local association DHSV Eiderstedt, which is responsible for the proper drainage of the area, does not have accurate information on the ditch dimensions, so this data has to be obtained from other sources. For the given project area Open Street Maps and satellite images from Google Maps combined were used to extract the ditch length and width. Thereupon, the procedure described in Baumann et al. (2022a) is used for automated model creation. It yields the SWMM model of the project region, shown in Figure 2. Due to the branch structure of

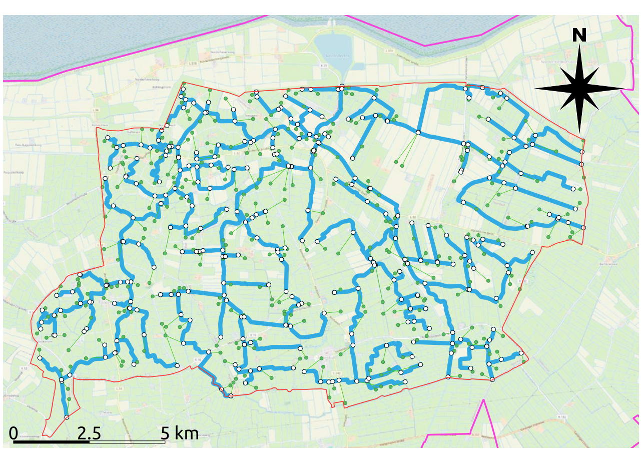


Fig. 2. SWMM model of the rural drainage system from Figure 1b. Links are marked in light blue, nodes in white and the rainfall-runoff elements in green.

the drainage system the whole model can be divided into six subareas, which are shown in Figure 3. Each of the subareas has a controllable gate at the downstream end, marked in white. These gates are the only points where water can be exchanged between the areas.

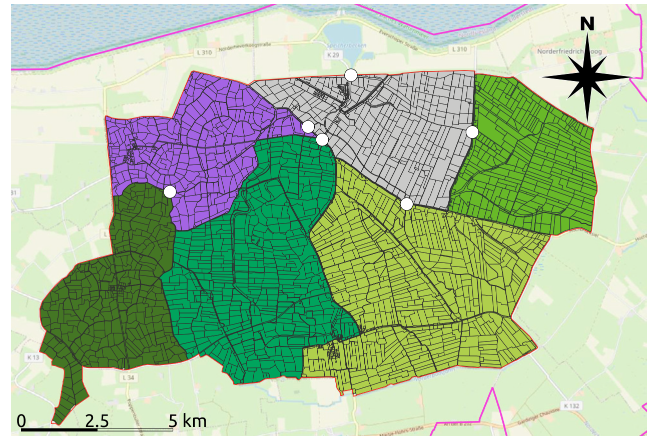


Fig. 3. Catchment areas of the SWMM model from Figure 2. The gates are marked as white dots.

2.3 Data-based model

When it comes to data-based modeling, different approaches can be applied, depending on the prior knowledge of the given system. Since the governing physical principles are known, the structure of the data-based approach should be chosen accordingly.

As shown in the previous subsection a network of open channels can be modeled by interconnected shallow water equations. However, instead of using junction nodes in between merging channels as in (3), the confluence can be described as a lateral inflow included in Q_l of (1b). Hence, the total water flow towards the outlet is similar to a cascade of interconnected pools, with external inflows [Weyer (2001)]. With the aim of achieving such a formulation, (1a) and (1b) are first considered in quasi-linear form

$$\frac{\partial U}{\partial t} + \mathcal{A}\frac{\partial U}{\partial x} = S(U), \tag{6}$$

where U is the vector of the states, $\mathcal{A}$ is the Jacobian matrix of the flux and S denotes the source term including external inflows [Machalińska-Murawska and Szydłowski (2013)]. Subsequently, the system is discretized by using a numerical scheme like the finite volume or finite difference method as in Lacasta et al. (2018), which reads

$$\begin{aligned} U_{k+1}^i = U_k^i &- \frac{\Delta t}{\Delta x}\alpha\left(\mathcal{A}_k^i U_k^i - \mathcal{A}_k^{i-1} U_k^{i-1}\right) \\ &- \frac{\Delta t}{\Delta x}(1-\alpha)\left(\mathcal{A}_k^{i+1} U_k^{i+1} - \mathcal{A}_k^i U_k^i\right) + \Delta t S_k^i. \end{aligned} \tag{7}$$

when applying the upwind scheme, with

$$\alpha = \begin{cases} 1, & \mathcal{A} > 0 \\ 0, & \mathcal{A} < 0. \end{cases} \tag{8}$$

The temporal and spatial index are denoted as k and i, respectively. When (7) is resorted and the N previous solutions of the neighboring elements $i \pm 1$ are calculated similarly until time step k, the scheme can be brought to

$$\begin{aligned} U_{k+1}^i = &\left(1 + \frac{\Delta t}{\Delta x}(1-2\alpha)\mathcal{A}_k^i\right) U_k^i + \Delta t S_k^i \\ &+ \sum_{j=1}^{N} a_j^i U_{k-j}^i + \sum_{j=1}^{N} b_j^i S_{k-j}^i + \mathcal{R}^i \end{aligned} \tag{9}$$

for each element i. While a^i_j and b^i_j denote the influence factors of the neighboring elements, the residuum from time steps older than $k-N$ is captured in $\mathcal{R}^i$. Finally, when all parameters are linearized around a stationary solution, which is also referred to as normal flow, it yields

$$U^i_{k+1} = \sum_{j=0}^{N} a^i_j U^i_{k-j} + \sum_{j=0}^{N} b^i_j S^i_{k-j} + \mathcal{R}^i \tag{10}$$

which is basically a linear state-space auto-regression model with external inputs (ARX model) [Ljung (1998); Hannan and Deistler (2012)]. Note that the applied numerical scheme is only used to exemplify the derivation. Other approaches that yield a stable solution scheme of (6) result in the same structure as (10).

To formulate a data-based model, the structure of (10) is utilized to create a model, which can predict the water levels based on historic water levels and precipitation measurements. The water levels form the model states. Additionally, the current and historic precipitation form the source term, such that after concatenating the local elements i the model can be written as

$$\boldsymbol{h}_{k+1} = \sum_{j=0}^{N_a} A_j \boldsymbol{h}_{k-j} + \sum_{l=0}^{N_b} \boldsymbol{b}_l p_{k-l}. \tag{11}$$

Therein, N_a and N_b are the number of historic water levels and precipitation measurements, respectively, while the coefficients in A_j and $\boldsymbol{b}_l$ are the auto-regressive and exogenous parameters, respectively. The bold notation is used for column vectors. Finally, to additionally be able to predict water levels for up to N_p days and therefore also include precipitation forecasts $\hat{p}$, the model is extended to

$$\begin{bmatrix} \boldsymbol{h}_{k+1} \\ \vdots \\ \boldsymbol{h}_{k+N_p} \end{bmatrix} = \sum_{j=0}^{N_a} A^*_j \boldsymbol{h}_{k-j} + \sum_{l=0}^{N_b} \boldsymbol{b}^*_l p_{k-l} + \sum_{m=1}^{N_p} \boldsymbol{c}^*_m \hat{p}_{k+m}, \tag{12}$$

where the asterisk denotes the vertically extended parameters. By horizontal concatenation (12) can be brought to

$$H^+ = [A^* \;\; B^* \;\; C^*] \left[H \;\; P \;\; \hat{P}\right]^T, \tag{13}$$

which can be implemented straightforward. After collecting the snapshots of the historic water levels, precipitation and forecasted precipitation, the ARX parameter can be identified by solving the matrix inversion problem. When creating the data-driven model N_a and N_b are the degrees of freedom that have to be tuned during model creation.

2.4 Available data and model calibration

Since the goal is to create a model, which predicts the water levels on a daily basis, a data-set with daily measurements of the water level and the precipitation is sufficient for the parameter identification of the data-based approach. These data are freely available online on the environmental portal of Schleswig-Holstein [MEKUN (2022)] and on the website of the German weather service [DWD Climate Data Center (2023)], respectively. For the calibration of the data-based model, data from the period from 2014 to 2016 is used. Thereupon, the number of historic water levels and precipitation days are tuned during model creation based on the training set prediction accuracy and are finally chosen to be $N_a = 2$ and $N_b = 10$, respectively.

When it comes to the calibration of the physical model, a more narrow data sampling is required. Therefore, another precipitation data set from the portal of the German weather service was used with a 10-minute sample time. Additionally, the local association provided their measurements of the project area including a data set that covers the years 2019 and 2020, which was used for calibration of the physical model. With these measurement data the missing parameters, namely the friction and gate coefficients and the channel depth have been identified. Based on the structure of the project area a successive calibration has been carried out. Therefore, the four outer subareas from Figure 3, which are colored in shades of green, are calibrated separately for a period, when the respective downstream gate was closed. Subsequently, the downstream subareas were calibrated. In this way, the number of tunable parameters within a single step reduces and thus the calibration process simplifies.

3. RESULTS

After the models have been created and calibrated, they are used to predict the water level in the drainage system for a one, two and three day period. Therefore, a validation data set from 2013 is used, which has not been taken into account during the calibration of the models. In order to update the SWMM model with the latest measurements, the corresponding nodes are reinitialized with the measured water level before each prediction. Such an update is not required for the ARX model, since the latest measurements are used for the prediction anyway. Figure 4, 5 and 6 show the one, two and three day prediction of both models compared to the real measurements. The corresponding precipitation of the prediction period is shown in Figure A.1. It can be seen that both models capture the water

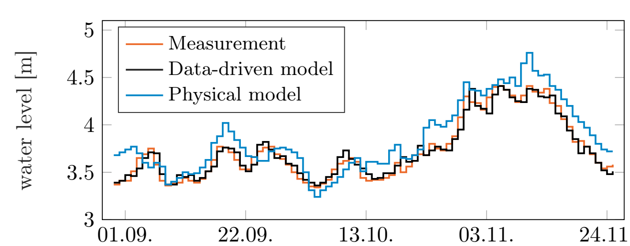


Fig. 4. Comparison of the measurements with the one day prediction results of the ARX and SWMM model.

level variations during September and the rise during the end of October, the resulting peak and the decrease quite precisely. The ARX model is able to predict the water level

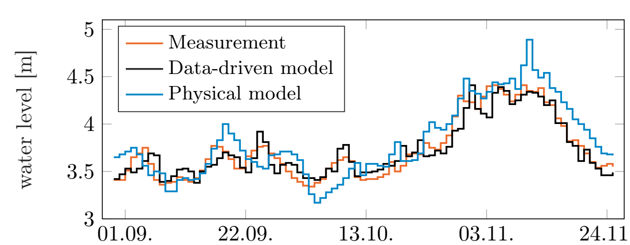


Fig. 5. Comparison of the measurements with the two day prediction results of the ARX and SWMM model.

for the next day with RMSE ≈ 6.2 cm, while the prediction becomes slightly less accurate for the second and third day, with RMSE ≈ 10.9 cm and RMSE ≈ 14.9 cm, respectively. The physical model shows less accurate results for the three prediction horizons, each with a RMSE around 16.5 cm. However, for a long term prediction this model has shown to be by far more accurate than the uncorrected propagation of the ARX model predictions. When simulating the whole evaluation period of 90 days, the physical model yields a prediction accuracy of RMSE ≈ 20.4 cm. Note that for comparison the results of the physics-based

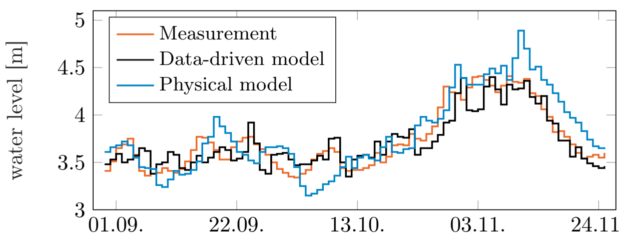


Fig. 6. Comparison of the measurements with the three day prediction results of the ARX and SWMM model.

model are compressed to a daily sample rate. Nevertheless, it is also capable to capture tide-related variations that become visible at a higher sample rate.

4. DISCUSSION

As shown in the previous section, both the physical and the data-based model are able to predict the water level in the drainage system. While the data-driven model allows accurate predictions for a few days, the physical model is able to predict the water level for a longer period.

Regarding the spatial resolution, the physical model has the ability to predict the water levels and even discharges in the whole drainage system due to its detailed description of the rainfall-runoff behavior and ditch flow. Therefrom, even flood maps can be created to display flooded areas. In contrast, the data-based model is only able to predict the water level at the measurement points. With respect to the temporal level of detail, the physical model is able to predict the water level in the drainage system for every time step, whereas the data-based model can only predict the water level at the frequency used for training. The required temporal resolution depends on the application. For the project region, daily predictions are sufficient, since the water level in the drainage system does not change rapidly. However, for other regions, a higher temporal resolution might be required.

When creating the physical model, all physical parameters must be known. If some are unavailable, their determination from available measurements can be a time-consuming process. Especially in flat areas like in the project region, a few centimeters of inaccuracy in the physical parameters can have a big impact of the simulation results. Hence, the availability and the accuracy of measurement data is crucial. Contrary to the physical model, the data-based model can be created and trained within a few lines of code and some milliseconds of calculation time, after a suitable training data set has been identified. Thus, modeling and calibration comes in one step and constitutes a major advantage of the data-based approach.

One question that may arise is what happens when the drainage system is redesigned. Regarding the physical model, the new parameters have to be identified, which again might be a time-consuming process depending on the changes. Similarly to its creation, the data-based model enables quick recreation and recalibration. However, no measurement data is available directly after the change. Thus, both models require a certain amount of time to adapt to the new situation, whereby the physical model has the potential to be additionally used to plan and evaluate outcomes of the structural changes.

Finally, due to the high level of detail of the physical model, the computational effort is higher than for the data-based model. However, in this work the computational effort of the physical model is still suitable, since the model shown in Figure 2 is a strongly simplified representation of the real drainage system displayed in Figure 1b.

After all, it can be said that both models have their advantages and disadvantages. Which modeling approach to choose mainly depends on the application and its requirements. In any case, the model can only be as good as the measurement data used for training and calibration.

5. CONCLUSION

A data-driven modeling approach based on auto-regression with external inputs and a physical model based on the hydrology and hydraulic laws have been applied to the rural drainage system in Eiderstedt, Germany. The results show that both models are able to reproduce the behavior of the system with a high accuracy, but with a slight decrease in accuracy over the days of the prediction when using the data-driven approach. Nevertheless, the effort to create and calibrate this model is significantly lower than for the physics-based model. However, the drawback of the physics-based model namely the creation and calibration effort, finally yields the possibility to obtain accurate results even for long-term predictions and for the whole system. This is not possible with the ARX model, since only the measurement location can be predicted. Hence, the choice which model to use depends on the requirements of the application.

In the future to improve the physical model accuracy some parameters like the elevation of the bottom of each gate and some upstream points should be measured. The data-driven approach holds further potential which can be exploited by including the gate opening as external input as well. Additionally, a control and state estimation scheme for the drainage system should be developed to support the operator's control decisions. Since external disturbances arise a model predictive control scheme seams to be a suitable choice to additionally be able to reduce the energy consumption of the actuators. However, this has to be further analyzed in more detail.

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For all maps, data from OpenStreetMap contributors (2017) were used.

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Appendix A. PRECIPITATION

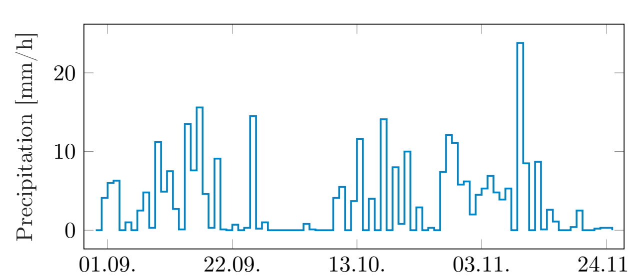

Fig. A.1. Precipitation of the evaluation period in 2013.