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PREDICTION OF HYDRAULIC LOAD FOR URBAN STORM CONTROL OF A MUNICIPAL WWT PLANT

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ABSTRACT

Three different methodologies are assessed which provide predictions of the hydraulic load to the treatment plant one hour ahead. The three models represent three different levels of complexity ranging from a simple regression model over an adaptive grey-box model to a complex hydrological and full dynamical wave model (Chow *et al.*, 1988). The simple regression model is estimated as a transfer function model of rainfall intensity to influent flow. It also provides a model for the base flow. The grey-box model is a state space model which incorporates adaptation to the dry weather flow as well as the rainfall runoff. The full dynamical flow model is a distributed deterministic model with many parameters, which has been calibrated based on extensive measurement campaigns in the sewer system. The three models are compared by the ability to predict the hydraulic load one hour ahead. Five rain events in a test period are used for evaluating the three different methods. The predictions are compared to the actual measured flow at the plant one hour later. The results show that the simple regression model and the adaptive grey-box model which are identified and estimated on measured data perform significantly better than the hydrological and full dynamical flow model which is not identifiable and needs calibration by hand. For frontal rains no significant difference in the prediction performance between the simple regression model and the adaptive grey-box model is observed. This is due to a rather uniform distribution of frontal rains. A single convective rain justifies the adaptivity of the grey-box model for non-uniformly distributed rain, i.e. the predictions of the grey-box model were significantly better than the predictions of the simple regression model for this rain event. In general, models for model-based predictive control should be kept simple and identifiable from measured data.

KEYWORDS

ATS; dynamical wave theory; grey-box modelling; identification; model-based predictive control; regression models; software sensor.

INTRODUCTION

The municipal wastewater project was initiated in Denmark in 1991 with the objective of controlling the sewer system and treatment plant in real time. For this purpose two control systems - MOUSE ONLINE

(Nielsen *et al.*, 1993) and STAR (Nielsen and Lynggaard-Jensen, 1993) - were developed. The interface between the two systems is the hydraulic load of the sewer system on the treatment plant and the hydraulic capacity of the plant's biological treatment capacity. STAR estimates the hydraulic load capacity depending on the sludge balance of the plant and sludge settleability, and the hydraulic load capacity is increased by control if predictions of the incoming flow are high. Similarly, MOUSE ONLINE retains water in the upstream sewer system to avoid plant overloading and sends predictions to STAR of the hydraulic load to the treatment plant. The control systems MOUSE ONLINE and STAR have been implemented and are presently operating in the Aalborg West catchment.

In STAR the Aeration Tank Settling (ATS) control principle was developed to increase the hydraulic capacity of the biological treatment by 25-75% without reducing the removal capacity of nutrients or organic carbon (Nielsen *et al.*, 1996; Bundgaard *et al.*, 1996) as is the case with step feed control. ATS control can be initiated directly as the inlet flow to the treatment plant in the event that rain exceeds a given threshold for ATS control. However, the control is much more effective if sludge is moved from the clarifiers to the aeration tanks before large hydraulic loads occur. For this reason predictions of incoming flow to the plant are a valuable source of information for initiating the ATS control more effectively.

The Aalborg West WWTP was set in operation in 1989 and serves the western and central part of the city of Aalborg with a population of approximately 150,000 inhabitants and many large industries. The plant is designed for 330,000 PE (85% fractile). The average dry weather flow is approximately 36.000 m^3 per day, and the reduced impervious area of the catchment is estimated from figures of the catchment to be 1329 ha. The plant can process up to 15,000 m^3/h during rainy weather, but the capacity of the biological treatment is designed to 5,800 m^3/h in ordinary operation and 8,700 m^3/h with ATS. Thus, the flow exceeding the biological capacity limit is only processed mechanically and bypasses the biological treatment.

SOFTWARE SENSOR OF FLOW

Electromagnetic flow transmitters are installed to monitor the flow through the biological treatment and plant bypass flow. The combination of these two on-line measurements gives the total load of the treatment plant. However, these two measurements of flow are affected by the operation of pumps and weirs at the treatment plant. This complicates the identification of a model for the rainfall runoff without taking the operation of pumps and weirs into account. Thus, a software sensor of flow using the inlet pumping station as a flow gauge (see Carstensen *et al.*, 1996) has been identified and implemented in order to obtain a more representative measurement signal for the hydraulic load of the plant. Although there are some major pumping stations in the upstream sewer system, these will only have a minor effect on the software sensor.

Table 1. Operating characteristics of the Aalborg west inlet pumps

Maximum pumping capacity			
Pump 1	Pump 2	Pump 3	Pump 4
3500 m^3/h	1500 m^3/h	5000 m^3/h	5000 m^3/h

The inlet pumping station has four screw pumps operating at different levels. Data for the four pumps are given in Table 1. Pump 1 and 2 are in operation for the dry weather flow while pump 3 and 4 are in operation for rain events only. When all four pumps are in operation the maximum hydraulic capacity of the treatment plant is reached (15,000 m^3/h). If the hydraulic load to the inlet pumping station exceeds the pumping capacity, water will be stored in the upstream sewer system until the water level reaches a combined sewer overflow crest in level 1.0 m. However, this combined sewer overflow is rarely in use because the hydraulic load of the inlet pumping station almost never exceeds the maximum inlet pumping capacity. The retention volume of the sewer system upstream of the inlet pumping station is approximately 7,700 m^3 and is currently not used for storm water control. For most rain events only 2,000-3,000 m^3 of the potential retention volume is in use. A small maintenance bridge in the pumping well will be flooded if the total retention volume in the upstream sewer system is used for control.

In the inlet pumping station the water level is measured on-line and the operation of the pumps is registrered. Knowing the relationship between stored volume and water level, the incoming flow can be found in discrete time

$$Q_{inlet,t} = Q_{pump1,t} + Q_{pump2,t} + Q_{pump3,t} + Q_{pump4,t} + \frac{\Delta V_t}{\Delta t} \tag{1}$$

where $Q_{pumpi,t}$ (i=1...4) are given by the four pumping characteristics of the inlet pumps as a function of the water level in the well and pump operation. The change in volume over time acts as a smoothening term for the software sensor, because the pump flow terms induce systematic and less smooth variations in the software sensor.

The initial step is to identify the characteristics of the fours pumps (level to flow relationships). For this purpose four simple two-parameter models of the flow into the plant have been estimated against the measured flow through biological treatment and wastewater plant bypass. The delay through the primary treatment is found to be approximately 2 samples (~12 minutes).

Thus, equation (1) provides a software sensor of flow to the treatment plant. The model has a standard deviation of 251 m^3/h compared to the measured flow through biological treatment and wastewater plant bypass. The software sensor provides a smooth signal of flow except for transient phenomena occuring during starts and stops of pumps. These transient phenomena are caused by the inertia of water in the pipe system. It also gives an earlier warning of increasing flow than the measured flow at the plant due to the information on increasing water level in the pump wet well (as seen in Figure 2).

THE SIMPLE REGRESSION MODEL APPROACH

A simple regression model for predicting the flow to the plant was estimated beginning of 1994. This model was implemented in STAR as an alternative to the predictions provided by MOUSE ONLINE, because the communication between STAR and MOUSE ONLINE was periodicly unstable. The data used for the regression model were rainfall measurements at the treatment plant as input and measurements of the flow through the biological treatment and the wastewater plant bypass combined into one flow signal as output. The time series covered one month with several rain events. The flow prediction model consists of two components - a diurnal flow profile and a rainfall-runoff transfer function.

$$Q_t = Q_{wastewater,t} + Q_{runoff,t} \tag{2}$$

where

$$Q_{wastewater,t} = \mu_{wastewater} \cdot \left(1 + \sum_{i=1}^{2} \alpha_i \cos\frac{2\pi it}{1440} + \beta_i \sin\frac{2\pi it}{1440}\right) \tag{3}$$

and

$$Q_{runoff,t} = \frac{\omega(B) \cdot B^{10}}{1 - \phi B} \cdot I_{rain,t} \tag{4}$$

In the transfer function above, the backshift operator of the time series analysis terminology, B ($BX_t = X_{t-1}$), is used.

It is also seen that there is a delay of 10 samples (~60 minutes) from the rain input to the runoff output. The one hour prediction is thus easily obtained by shifting time 10 samples ahead.

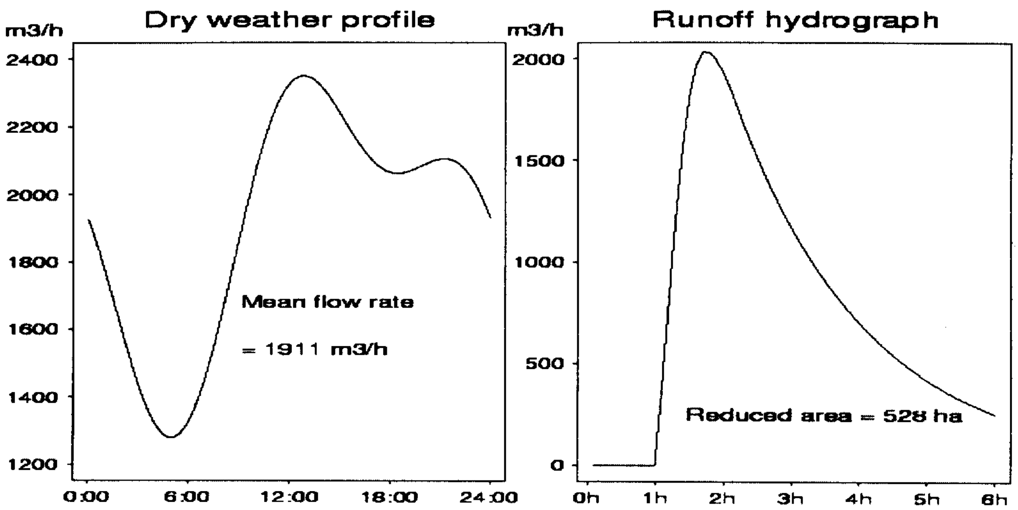

Figure 1. The two estimated components of the simple regression model.

Figure 1 shows the estimated diurnal profile and rainfall-runoff transfer function (hydrograph). The exponential decay of the transfer function is due to the denominator in (4). The average dry weather flow is 1,911 m^3/h, and integration of the transfer function results in an estimate of the contributing impervious area in the catchment of 528 ha. This estimate is somewhat lower than the estimate based on the catchment figures as this estimate does not take combined sewer overflows into account.

THE GREY-BOX MODEL APPROACH

The simple regression model above is a deterministic model giving exactly the same output for every mm of rain measured at the rain gauge. The rainfall distributed over the total catchment, however, may differ significantly from the measured rainfall at the treatment plant. Thus, the simple regression model can be improved by adding stochastic black-box elements to the model in order to make the model capable of adapting to the measured flow. This is achieved by adding noise terms to (3) and (4) which are stochastic processes. Thus, the stochastic part of the model describes the deviations between measured data and the deterministic part of the model.

For simplicity the stochastic process added to (3) is an AR(1)-process (autoregressive process of order 1), i.e. $(1+(\varphi B)e_t=(\varepsilon_t$ where ε_t is an independent identical distributed (IID) process with an estimated standard deviation of 65 m^3/h. The stochastic process added to (4) is also an AR(1)-process with the characteristic that the variance of the process innovation, $\sigma^2_{\varepsilon,t}$, is zero in dry weather and different from zero in rainy weather (standard deviation=284 m^3/h). Finally, the flow measurement is uncertain and the standard deviation of the measurement noise is estimated to be 49 m^3/h. A Kalman filter is used for updating the two states of the model (dry weather flow and rainfall-runoff). Due to the variance characteristic of the noise process in (4), only the state of the dry weather model is updated in dry weather. Similarly, updating in rainy weather is performed with most weight on the rainfall-runoff model, since the innovation variance of this model is significantly larger than that of the dry weather model.

As described previously the combined flow signal of the measured flow through the biological treatment and the wastewater plant bypass is affected by the operation of the inlet pumps. The stochastic AR-processes of the grey-box model would adapt to the inlet pump operation as well, if this flow signal were used for estimation. Hence, the grey-box model is estimated using data from the software flow sensor of the inlet pumping station. The estimated diurnal profile has an appearance similar to that of the simple regression model in Figure 2 with an average dry weather flow of 1,390 m^3/h. The estimated hydrograph corresponds to a reduced impervious area of 447 ha. As above, this estimate does not take the combined sewer overflow in the sewer system into account. However, the delay from the rain input to the runoff output in the transfer function (3) is only 7 samples (~42 minutes). This is due to the fact that there is an estimated delay of 18 minutes from the software sensor of flow based on the inlet pumping station to the measured flow to the biological treatment and the wastewater bypass. Prediction κ steps ahead with the grey-box model is a little more complicated than the simple regression model, because it requires κ iterations with the model. The grey-box model is recently implemented in STAR.

THE FULL DYNAMICAL WAVE APPROACH

A hydrological and full dynamical wave model for the Aalborg West catchment is implemented in the control system MOUSE ONLINE. The control loop in MOUSE ONLINE consists of four basic tasks (Kjær *et al.*, 1996):

A: Measurements, operator settings and objectives
B: Prediction
C: Control
D: Settings and setpoints

Tasks A and D handle the system interface with inputs and outputs to operator and SCADA-system. Task C evaluates different control strategies using the prediction information from task B.

The hydraulic load prediction is derived from three different models implemented in MOUSE ONLINE for the runoff of rain:

- a rainfall prediction model
- a hydrological simulation model (rainfall/runoff)
- a hydraulic simulation model (sewer pipeflow)

The rainfall predictions are very important as they are the basis for the two succeeding models. The rainfall/runoff model uses the rainfall prediction as input and a description of the catchment which can vary in detail from simple surface models to advanced hydrological models which take into account the humidity of the soil based on previous rain events (Amdisen *et al.*, 1994). The sewer pipeflow model uses runoff as input and a description of the geometry of the drainage network. The on-line hydraulic model is a simplified model of a 'high fidelity' model which can replace the actual urban drainage system and act as simulator in off-line mode. The simple on-line model is chosen for computational reasons in order to predict future states of the system conditional on a set of selected control strategies (Kjær *et al.*, 1996). However, the simple model is still a fully nonlinear hydraulic system based on the dynamical wave theory (Chow *et al.*, 1988). A model for the dry weather flow is also implemented to improve the predictions of the model. The on-line model is activated in the event of rain, i.e. in dry weather predictions of the hydraulic load are not calculated. Even though the predictions of MOUSE ONLINE are based on three different models, we shall refer to the combined model as the full dynamical wave approach.

The MOUSE ONLINE model in the Aalborg West catchment has access to information from 4 rain gauges in the actual and surrounding catchments, 12 level transmitters and 2 flow transmitters in the sewer system. This information is used as input to the model and for updating of the model. The simplified hydrodynamic model consists of 115 pipes where the partial differential equations are solved numerically using a grid system of 1151 points with step length ranging from 7.5 to 81 meters in distance and between 10 and 15 seconds in time. Extensive measurement campaigns have been carried out to obtain sufficient data for calibrating the model. By calibration we mean adjusting the parameters of the model to give an adequate fit of measured data by an experienced modeller. Over the years since the start of the municipal wastewater project the MOUSE ONLINE model has been recalibrated a number of times.

PERFORMANCE OF THE THREE APPROACHES

The three approaches described above all have the ability to predict the hydraulic load to the treatment plant one hour ahead. For this reason 5 rain events in the period from April, 15th to May, 15th 1997 are selected for further analysis. The results are shown in Table 2. The three approaches are compared by the ability to predict the maximum hydraulic load to the plant, the mean standard error of the deviations from the measured load and total volume of the event. The first four rain events are typical frontal rains which have a long duration and a low rain intensity. The last rain event in the table is a thunderstorm with high intense rain. STAR received predictions from MOUSE ONLINE for two of the five rain events only.

Table 2. Performance of the three model prediction approaches

		Flow monitors		One hour predictions		
Rain event	Runoff characteristics	Measured flow	Software sensor	Simple regression model	Grey-box model	Full dynamical wave
April, 23th 1997 duration=6h40m depth=3.4mm	Max flow Std. error Tot. volume	5756 m^3/h 48270 m^3	5683 m^3/h 45789 m^3	4809 m^3/h 906 m^3/h 51719 m^3	5254 m^3/h 768 m^3/h 43260 m^3	- m^3/h - m^3/h - m^3
April, 24th 1997* duration=9h10m depth=13.4mm	Max flow Std. error Tot. volume	12824 m^3/h 74674 m^3	15754 m^3/h 72588 m^3	12365 m^3/h 1464 m^3/h 68331 m^3	13534 m^3/h 1445 m^3/h 65014 m^3	- m^3/h - m^3/h - m^3
May, 4th 1997 duration=9h20m depth=11.8mm	Max flow Std. error Tot. volume	13123 m^3/h 99961 m^3	13014 m^3/h 93417 m^3	11231 m^3/h 1327 m^3/h 92353 m^3	11388 m^3/h 1384 m^3/h 91066 m^3	11025 m^3/h 3998 m^3/h 96276 m^3
May, 11th 1997* duration=12h10m depth=8.6mm	Max flow Std. error Tot.volume	7362 m^3/h 59518 m^3	9847 m^3/h 60131 m^3	8360 m^3/h 815 m^3/h 66053 m^3	7891 m^3/h 739 m^3/h 56222 m^3	8524 m^3/h 1385 m^3/h 44567 m^3
May, 14th 1997 duration=42m depth=5.6mm	Max flow Std. error Tot. volume	11613 m^3/h 77284 m^3	12684 m^3/h 72804 m^3	14482 m^3/h 931 m^3/h 75907 m^3	12901 m^3/h 761 m^3/h 70951 m^3	- m^3/h - m^3/h - m^3

*The second and fourth events did not include data for the total runoff period.

All the three approaches are able to predict the magnitude of the maximum flow as well as the total volume through the plant. For on-line control of inlet pumping station and initiation of ATS control strategy, the most important feature of a prediction model is whether the model is capable of dynamically predicting the correct load of the plant. Based on the standard error of the predictions relative to the measured flow, both the simple regression model and the grey-box model perform significantly better in dynamically predicting the flow than the full dynamical wave model. However, no significant difference between the simple regression model and the grey-box model is observed except for the first and last rain event where the grey-box model appears to perform better.

The trends of Table 2 are also observed in Figure 2 where the one hour predictions of the three models are compared to the measured flow through the biological treatment and wastewater plant bypass. The left-hand top graph shows the software sensor and measured flow rate. It is also observed that the flow measurement signal shifts between different levels as a function of the inlet pumping station operation, and that the software sensor signal contains spikes caused by starts and stops of the inlet pumps. It should be pointed out from Figure 2 and Table 2 that the software sensor, in general, results in a lower flow rate than the measured flow. The simple regression model performs very well even though it is deterministic and contains no adaptive terms. The grey-box model also performs well, but it is also clear that it has a strong adaptation making it reproduce some of the characteristic features of the software sensor curve. However, the full dynamical wave approach is approximately 2-3 hours late in predicting the peak load and the shape of the prediction time series is very different from the measured flow. The reason for this finding could be lack of model identifiability and/or numerical problems in solving the partial differential equations. It should be stressed that the magnitude of the standard error found for the different approaches is partly due to noise in the flow measurement signal.

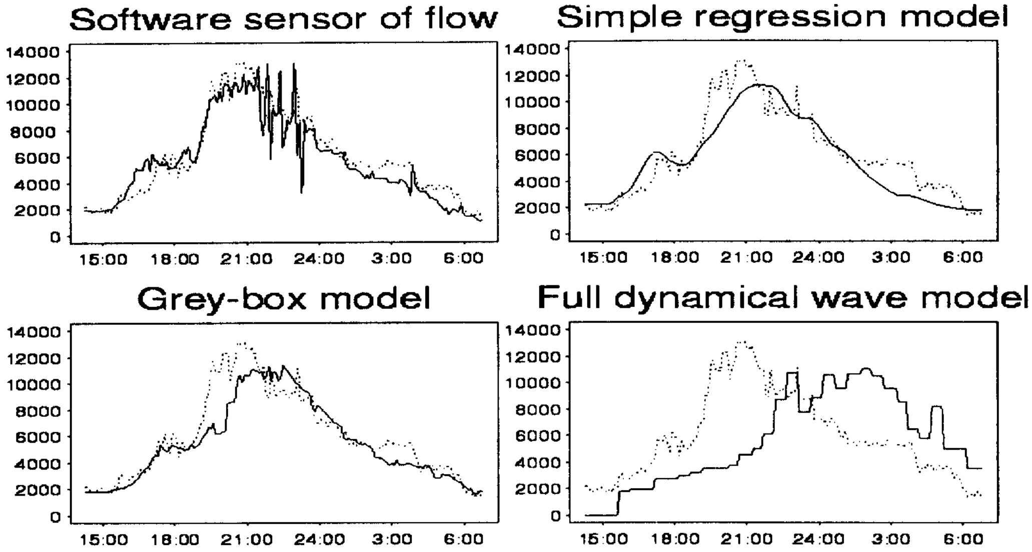

Figure 2. One hour predictions of the three approaches compared to measured flow.

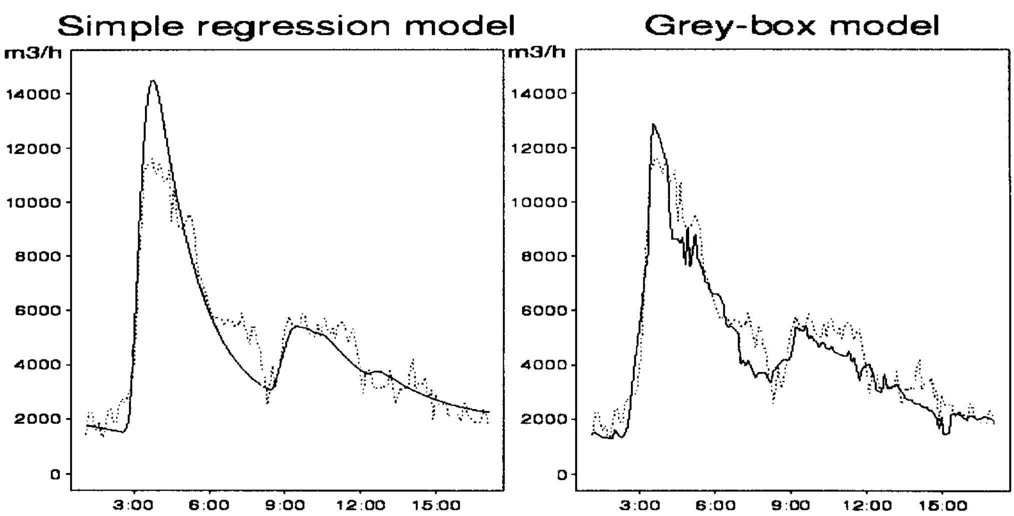

Figure 3. Comparison of the simple regression model and the grey-box model for fifth rain event.

The first four events are typical frontal rains resulting in an almost uniform distribution of rain. Apparently, the rain gauge at the treatment plant is very representative for the total catchment and gives an early measurement for rainfall over the catchment (the catchment is very regular in shape and mainly located to the east of the treatment plant and frontal rains primarily come from the west). Thus, the simple regression model is sufficient for predicting the hydraulic load of the treatment plant during frontal rains. The adaptive grey-box model is more important when rain is not uniformly distributed over the catchment as is often the case with convective rains. Figure 3 compares the simple regression model with the grey-box model. The simple regression model clearly makes an overshoot of the incoming hydraulic load, while the grey-box model performs better. This is due to two reasons: 1) the adaptivity of the grey-box model and 2) a smaller rainfall-runoff transfer function for the grey-box model. For prediction horizons shorter than one hour, the grey-box model will perform even better while the performance of the simple regression model will remain unchanged.

CONCLUSION

The ATS principle is an effective control for increasing the biological processing capacity of wastewater treatment plants. The hydraulic capacity of the plant can be increased by 25-75% during rain storm events without reducing the removal capacity of nutrients and organic carbon. The ATS control is most effective if sludge is moved from the secondary clarifiers to the reaction tanks before the large hydraulic loads occur. Thus, predictions of incoming loads are a valuable source of information for the ATS control.

Three different approaches for predicting the hydraulic load of the plant one hour ahead have been compared. The three approaches are: 1) a simple regression model, 2) an adaptive grey-box model and 3) a detailed model based on hydrological and the full dynamical wave theory. The two first approaches result in good predictions of flow which can be used for initiating the ATS control, while the last approach is not applicable for initiating ATS control. The simple regression approach is sufficient for uniformly distributed rain such as frontal rains, because the majority of the contributing catchment has a relatively small spatial extent and the rain gauge is very representative. If the rain is not uniformly distributed convective, e.g. the grey-box model performs better than the simple regression model.

For on-line control systems used in daily operation, models for predicting future states of the system should be kept simple and robust. Another important aspect is that the models should be identifiable from measured data in order to reflect the characteristics of a real system. A simple model also has the benefit that it takes considerably less time for identification and implementation. The simple regression model and the grey-box model approaches are applicable for control of the sewer system as well.

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