Influent load prediction using low order adaptive modelling

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Abstract: This paper presents the use of models for predicting influent flow to the Rya wastewater treatment plant. Momentaneous influent flow is calculated using physical modelling and is then used to identify prediction models using ARX filters. Dry weather and stormwater runoff flows are modelled separately with the dry weather model predicting the flow as the average of past dry weather days and the stormwater model also using past flow data but with rainfall predictions as an extra input signal. The results indicate that accurate 24 hour predictions can be made during dry weather. With the addition of a stormwater runoff model with a shorter prediction horizon the combined models is believed to be useful for improving pump control performance for all weather conditions.

INTRODUCTION

In continuously operated wastewater treatment plants (WWTP) it is often desirable that the flow through the plant should vary as little as possible for optimal performance. Available buffer capacity in wastewater transport systems can be used to achieve minimum variance. Influent flow predictions would therefore be helpful in making maximum use of the buffer capacity with no or little changes in pumping rate during the predicted time horizon.

Several studies have been made concerning modelling and prediction of wastewater flow using mechanistic and black-box type models. It has been shown useful to combine model types in a hybrid model with both deterministic and stochastic components (Vojinovic *et al*, 2003). In another work with an approach similar to this study (Tan *et al*, 1991) dry and wet weather are described separately, with the dry weather flow modelled as an average of previous dry weather days and wet weather modelled as a recursively adaptive parametric system.

In this case study a separation of the influent flow into a dry weather flow and an additional stormwater runoff is applied. Both types of flow depend dynamically on ground conditions. Dry weather flow has an obvious daily variation, but also a slow seasonal bias change as ground water levels and industrial loads vary. Stormwater runoff depends on precipitation as well as saturation in the upper ground layers. Two different models are used to describe the two kinds of influent flows. The dry weather flow is formed as an average of previous dry weather days, while the stormwater runoff is modelled as a recursive ARX (autoregressive, with exogenous input) system. The combined models will be used to predict the influent flow to the Rya WWTP in Göteborg, Sweden. This is a different approach than earlier attempts with deterministic conceptual modelling (MOUSE) of the Rya WWTP system (Gustafsson *et al*, 1993, Lumley *et al*, 1995).

METHODS

The Rya WWTP treats wastewater from the Göteborg region with a connected area of approximately 200 km^2 and a dry weather load of about 210 000 m^3/d and peaks up to 1 425 000 m^3/d (Äijälä and Lumley, 2005). Wastewater is transported to the Rya WWTP through a large tunnel system comprised of two main branches of about the same size, separated by the Göta River (Figure 1). The input flow to the north and south tunnel system is calculated with a physical model describing the relation between the output and input flow and the rate of change of water levels. Based on these input flows the dry weather and rainfall models used for prediction are identified.

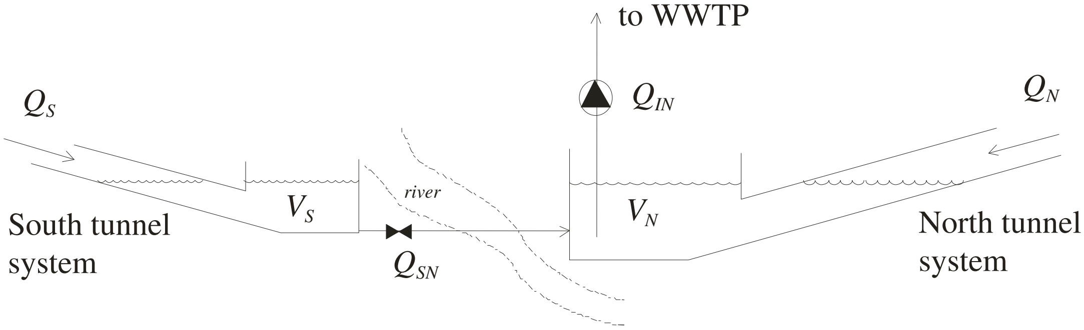

Figure 1 Overview of the tunnel system. The north and south tunnel systems are connected through inverted siphons under the Göta River, with valves controlling the Q_{SN} flow. The tunnel sections can be used as buffers and have a total storage capacity of approximately 250 000 m^3.

Flow model

A model is used to calculate the momentaneous flows to the two tunnel sections that give the most flow attenuation in the tunnel system. Measurable flows are Q_{SN}, connecting the south tunnel system through an inverted siphon under the Göta River, and Q_{IN}, influent pumping rate to the Rya WWTP. If the rate of volume change (*dV/dt*) is known for the two sections, input flows can be calculated as

$$Q_N = \frac{dV_N}{dt} + Q_{IN} - Q_{SN}$$
$$Q_S = \frac{dV_S}{dt} + Q_{SN}$$

with Q_N and Q_S being the flow in the north and south tunnel systems respectively. The rate of change of the volume in the tunnel sections is estimated from measurements of the water level h using a mathematical function $A(h)$ to translate the rate of level change to rate of volume change. The value $A(h)$ can be interpreted as the effective water area in the tunnel system at the current level and depends on the geometrical properties of the non-prismatic tunnels.

During dry weather the influent flow to the attenuation sections can be considered as almost constant for short time periods. If during that period of time a large change is made in the outgoing flow Q, for example a step in the input pump rate, a clear difference will be seen in the rate of change of the water level as illustrated in Figure 2. This gives information about the relationship between rates of change of water level (*dh/dt*) and rate of change of volume (*dV/dt*) which can be expressed mathematically as

$$A(h) = \frac{Q_1 - Q_2}{\frac{dh_2}{dt} - \frac{dh_1}{dt}}$$

by which an estimate of the value of the function *A(h)* at the present level *h* can be made. By repeating this for a large number of different levels, as seen in Figure 3, a complete function describing the tunnel's volume properties can be approximated using curve fitting methods. The rate of volume change in the tunnel sections can then be calculated as

$$\frac{dV}{dt} = A(h)\frac{dh}{dt}$$

and thereby making it possible to determine the tunnel system influent flows Q_N and Q_S.

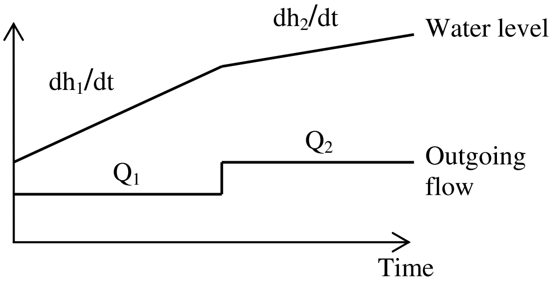

Figure 2 Illustration of how a step change in outgoing flow affects the rate of change of water level in the tunnel section.

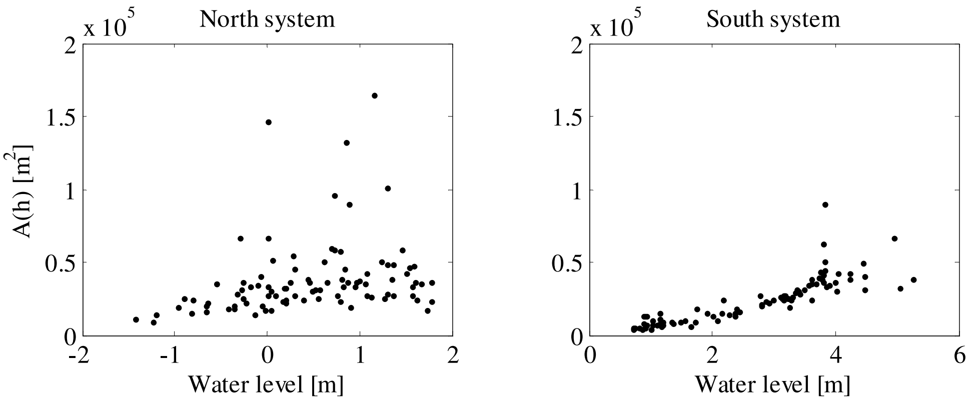

Figure 3 Calculations of the relationship between rate of level change and rate of volume change at different water levels in the tunnel systems. The assumption that incoming flows are constant during the measurement period is not always valid, which probably is the cause of outliers since they were recorded at times with high flows in the tunnel system. The level - volume relationship is in agreement with results from an earlier study using MOUSE.

Prediction

The purpose of prediction is to be able to make a good estimation of future values of the flow input in the tunnel system. The flow during dry weather is very different from rainfall runoff flow, as seen in Figure 4, and therefore has to be modelled separately.

Dry weather model. The dry weather flow depends mainly on the time of day as the activities of industries and households vary. The flow pattern is more or less similar from day to day, although it is different in appearance between the north and south tunnel systems. The dry weather flow is described by two components, a mean flow value and a flow pattern, similar to Tan *et al*, 1991. The flow pattern is a vector whose elements are weighted mean values of the flow shape, sampled with certain time intervals, e.g. every half hour. The mean value of the flow pattern is zero, i.e. it is centred around the *x*-axis. To describe the complete dry weather flow the mean value parameter is added to the flow pattern.

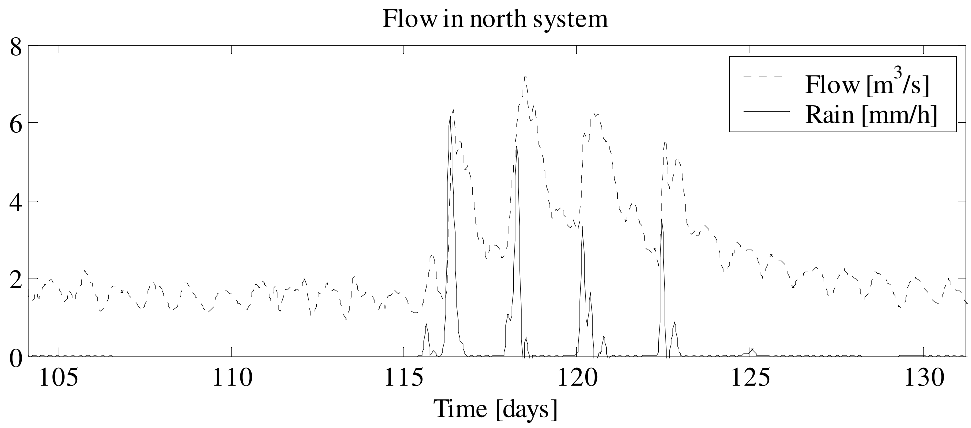

Figure 4 Influent flow to the north tunnel section. The different nature of dry weather flow and stormwater runoff necessitates separate models.

When a new flow value is sampled it adapts the flow pattern using an ARX filter, with a filter parameter deciding the weight placed on new and old values respectively. The mean flow value which is based on the average flow over 24 h is filtered in the same way but optionally using a different weight parameter. The ARX filter uses the previous output $y_d(t-1)$ and current input value $u_d(t)$ to calculate the new output value according to

$$y_d(t) = wy_d(t-1) + (1-w)u_d(t)$$

where the coefficient w is the weight factor with $0 \le w \le 1$. A higher value of w gives a stronger weight to old values and thereby a slower adaptation to changes. To avoid disturbances in the flow pattern and mean flow caused by rainfall runoff, a limit is set and if exceeded no change is made to the output values. Since the variation of the flow is small, the current values for flow pattern and mean value can be used to predict future dry weather flow (Figure 5).

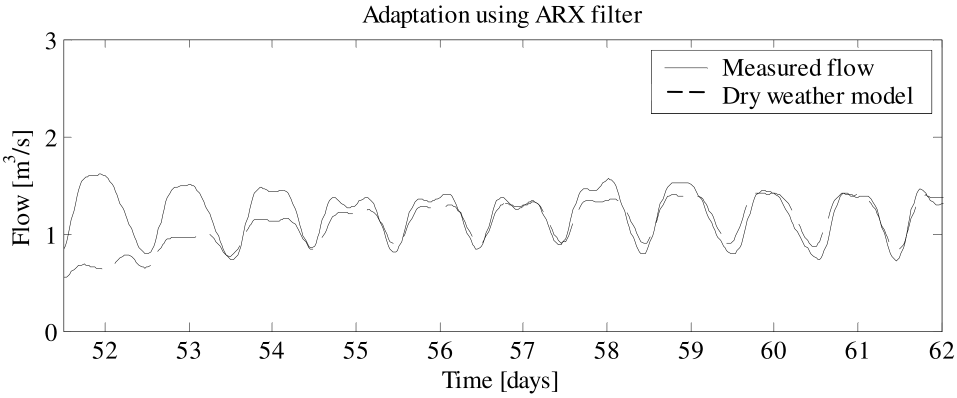

Figure 5 A dry weather model is adapted to measured flow in the south tunnel system using an ARX filter. The daily flow pattern and the mean value are filtered separately and can have different rates of adaptation by setting appropriate values for *w*. After the first learning stage a slower adaptation rate can be set.

Stormwater runoff model. The dry weather model is used to remove the periodic base from the incoming flow, giving a clearer view of the correlation between rainfall and runoff and also helping the identification of a correct model (Figure 6).

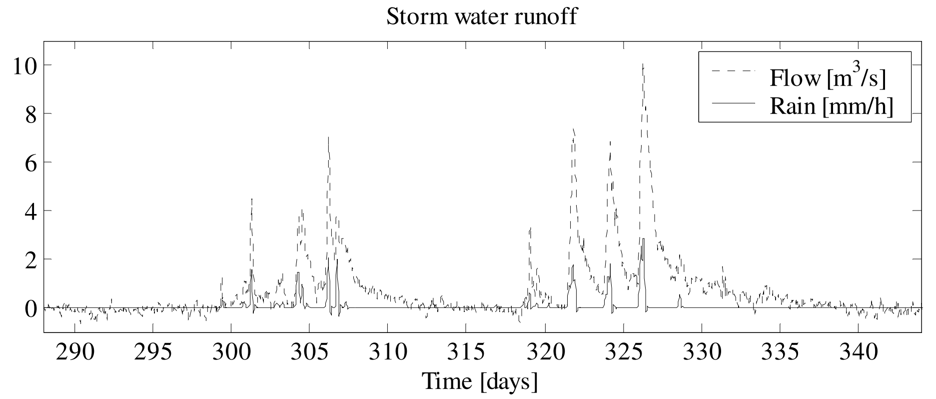

Figure 6 Using the dry weather model the daily periodic component is subtracted from the influent flow to calculate of the runoff flow. Then a model is identified to describe the correlation between rainfall and runoff flow.

An adaptive ARX model was found sufficient to describe how the two flows (y) from the tunnel systems dynamically depend on the measured rainfall (u). The reason for using adaptation of the model parameters is to better describe the changing time constants of the runoff, which vary depending on season and past weather. The ARX model consists of a regression vector φ, in which previous input and output values are stored, and a parameter vector θ with the corresponding model coefficients. With the model order parameters na and nb setting the number of past data samples of input and output, the model can be written as

$$\varphi(t-1) = [-y(t-1) \quad \dots \quad -y(t-na) \quad u(t-nk) \quad \dots \quad u(t-nk-nb+1)]^T$$

$$\theta = [a_1 \quad \dots \quad a_{na} \quad b_1 \quad \dots \quad b_{nb}]^T$$

where the dead time *nk* sets the response delay from input to output. The prediction of future output values can now be written as:

$$\hat{y}(t+1) = \varphi^T(t)\theta$$

Using a recursive algorithm the constant parameter vector can be replaced with a time varying variant $\hat{\theta}(t)$ which is continuously updated to fit the present system conditions by minimizing the prediction error:

$$\varepsilon(t) = y(t) - \varphi^T(t-1)\hat{\theta}(t-1)$$

The parameter vector estimation algorithm (Åström and Wittenmark, 1989) is

$$\begin{aligned}
&\hat{\theta}(t) = \hat{\theta}(t-1) + K(t)\varepsilon(t) \\
&K(t) = P(t)\varphi(t-1) = P(t-1)\varphi(t-1)\left(\lambda + \varphi^T(t-1)P(t-1)\varphi(t-1)\right)^{-1} \\
&P(t) = \left(I - K(t)\varphi^T(t)\right)P(t-1)/\lambda
\end{aligned}$$

where λ is a parameter that determines the rate of adaptation of the model parameters $\hat{\theta}(t)$. The initial value of *P* sets the early rate of adaptation. The *P* matrix will then be updated in every iteration of the algorithm and is together with λ used to calculate the vector *K*, which determines how the prediction error $\varepsilon(t)$ is used to update the model parameters $\hat{\theta}(t)$. (*I* is the identity matrix).

RESULTS AND DISCUSSION

In Figure 7a a prediction is used which says that future values will be the same as current. This very simple method results in a prediction time lag which is very noticeable, compared to the ARX model prediction in Figure 7b, when flow changes are significant. Since the model uses a prognosis of future rainfall as an extra input it is possible to get a more accurate prediction at the start of the stormwater runoff. The autoregressive part of the model describes the dynamics of the flow, i.e. the time constant that determines how quickly the runoff flow will diminish after a storm, thus making it possible to also predict decreasing flow.

With the recursive algorithm the model parameters that describe system properties such as flow dynamics (time constants) and rain influence can be adapted in real-time. As seen in Figure 4 and Figure 6 the rain impulse response of the runoff flow decrease rapidly at first, but after a certain point it declines more slowly, lasting for several days or weeks. The adaptation of model parameters helps predict the flow during such circumstances.

Two parameters that affect the adaptive ARX prediction are the forgetting factor λ and the initial value of the *P* matrix. For $P_{init} = aI$ a smaller value of *a* results initially in a slower adaptation of the θ vector. A smaller value for λ means that recent data is more significant and results in a higher variation in the θ values. The increased adaptation comes at the price of a lower stability, with measurement errors having a larger impact on the model parameters.

In Figure 8 plots of typical flows for dry weather and storm are shown. By using the adaptive flow pattern estimation it is possible to make good predictions for periods up to 24 hours in dry weather conditions. With the addition of the parametric stormwater model predictions can also be made of the runoff component, but with a 24 hour prediction time the results are rather inaccurate, as seen in Figure 8b. During such periods a much shorter prediction horizon has to be used (Figure 8a), where the prediction time is two hours.

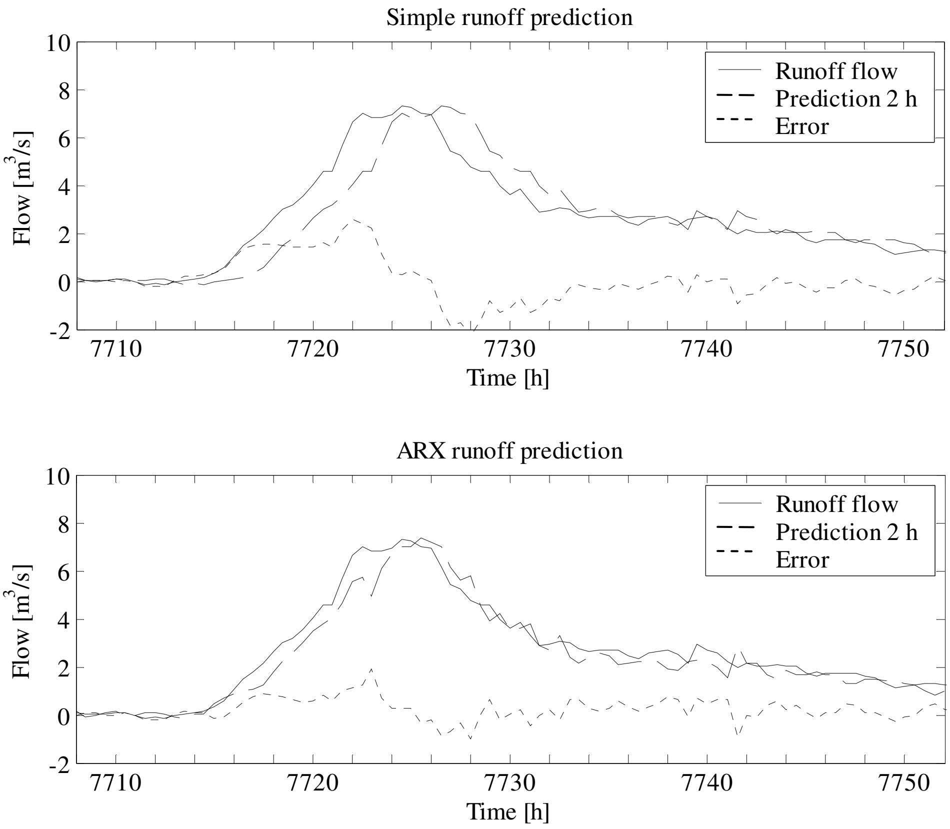

Figure 7 (a) Simple flow prediction "same as now". (b) ARX model prediction. The ARX model has two advantages over the simple prediction. The use of predictions of future rain as an external input gives a more rapid response to stormwater runoff. As the dynamics of the runoff component is modelled it can also make an estimation of how fast the flow will decrease after the rain.

CONCLUSIONS

By using the flow pattern estimation for dry weather flow it is possible to make quite good predictions for periods up to 24 hours. By adding runoff flow prediction using an adaptive ARX filter, the model can also handle rainy conditions with a prediction time of a few hours. To achieve a good prediction of the initial runoff flow rain response, a prognosis of future rain levels should be used as an extra input to the ARX model.

The recursive update of parameters means that the model will adapt itself to changes in the system and eliminates the need for historic data for model identification. This makes it possible to implement in a newly constructed system and can at the same time provide better results than a model with constant parameters identified from a large set of historical data, depending on how much the modelled system varies over time.

The results indicate that useful predictions of future influent flow can be made using these models. The calculation of momentaneous flow has been implemented in the Rya WWTP's SCADA system, and the operator can view the dry weather and stormwater runoff flows and storage volumes and use this information for planning pumping strategies during rain events. During the spring of 2005 the prediction of future flows will be implemented together with new control algorithms for the inlet pumping station.

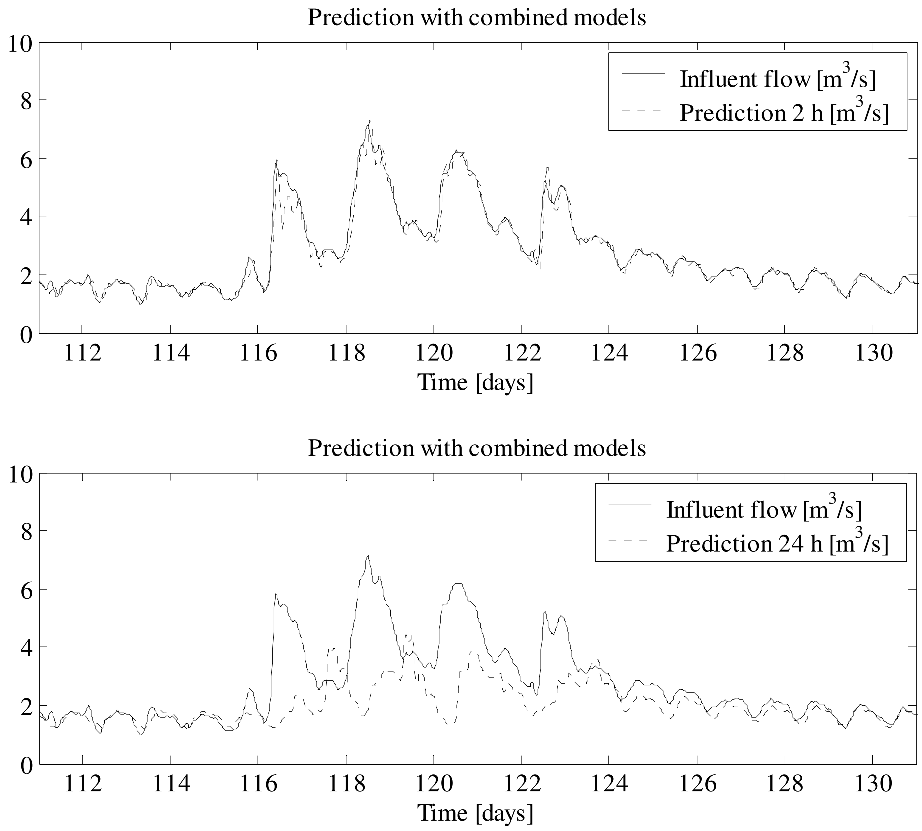

Figure 8 Influent flow prediction with (a) 2 and (b) 24 hour prediction horizon. It is possible to use the model for 24 hour predictions with good results as long as there is no stormwater runoff in which case the prediction time has to be significantly shorter.

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