Model-Based Dosing Control of a Pellet Softening Reactor

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Abstract: The control of a drinking-water treatment plant aims to produce the correct quantity of water, with a constant quality. Achieving constant water quality is not an obvious task, since the online water-quality measurements and possible control actions are limited. Applying model-based control improves disturbance rejection and online process optimisation. For the softening process step, the integral control scheme is shown with multiple controllers for different time scales and process detail. The dosing control is elaborated and verified using simulation experiments. The control is implemented and tested in the pilot plant of Weesperkarspel (Amsterdam). It shows that in the case of accurate state estimation, quick changes in setpoint can be tracked.

Keywords: multivariable control; MPC; crystallisation

INTRODUCTION

In the last decades, most drinking-water treatment plants have been automated. During these first automation realisations, the goal was to operate the treatment plant in the same way as the operators did before. Therefore the control configurations consisted of a heuristic control strategy, based on historical operator knowledge. The controls are designed for the static situation, including extra safety margins to take operator response into account. This was a logical and practical solution. However, this heuristic solution does not optimise the control of a treatment plant.

The heuristic control is based on static local control objectives, without taking the current state of the treatment plant into account. Therefore it is necessary to adopt a new control strategy, which can take into account quality-related and economic criteria and optimise the overall performance of the plant, based on the current state of the processes.

Since the treatment steps are coupled, local changes affect other treatment steps and therefore local optimisations should be considered in a global context. It is necessary that operational actions do not introduce new disturbances to other processes. This must be considered in all levels of control, from basic valve controllers to plant-wide quantity control. At the same time, the control should consider the actual state of the process and optimise plant operations.

The information density in the online measured data of water treatment plants is limited and multiple measurements have to be used to obtain a good view of the actual treatment performance (van Schagen et al., 2006b). By using white or grey models, the process knowledge is no longer stored as historical heuristic rules of thumb or static local control objectives. The local control objectives evolve from applying the new criteria to the existing models in the case of changes to the process, such as boundary conditions, influent properties and desired treated water quality.

The model-based dosing control is part of the new model-based control configuration for the pellet-softening treatment step, consisting of a number of pellet reactors and a bypass. The pellet softening process step at the Weesperkarspel treatment plant is described in the first section. The model-based control configuration is elaborated in the second section. Finally the model-based dosing control scheme is validated in simulation experiments and finally validated in the pilot plant of Weesperkarspel (Amsterdam).

PROCESS DESCRIPTION

In the Netherlands, softening of drinking water in treatment plants is mainly carried out with fluidised pellet reactors. The pellet reactor consists of a cylindrical vessel that is partly filled with seeding material (figure 1). The diameter of the seeding grain is small, between 0.2 and 0.4 mm and consequently the crystallisation surface is large. The water is pumped through the reactor in an upward direction at high velocities, maintaining the seeding material in a fluidised condition. In the bottom of the reactor, chemicals are dosed (caustic soda, soda ash or lime). Calcium carbonate then becomes super-saturated and crystallises on the seeding material, resulting in the formation of pellets. At regular intervals, pellets at the bottom of the reactor are removed. These pellets can be re-used in industry (van Dijk and Wilms, 1991).

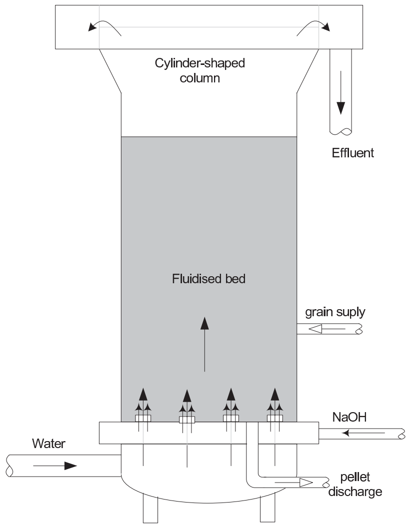

Fig. 1. Fluidised bed reactor for water softening.

Softening in a reactor is normally deeper than the required levels. Therefore, part of the water can be bypassed and mixed with the effluent of the reactors. In general, several identical parallel reactors are installed to increase the reliability of the system and the flexibility in operation. Reactors can be switched on and off in case of flow changes, maintaining water velocities between 60 and 100 m/h.

The mixture of the effluent of the reactors and the bypass water must be chemically stable to avoid crystallisation in the filters after the softening step.

At Weesperkarspel caustic soda (NaOH) is dosed for softening. The seeding material is garnet sand. The dosing of caustic soda in the pellet reactor is adjusted to realise the mixed effluent hardness of 1.5 mmol/l. The pellet removal is based on the hydraulic resistance of the fluidised bed (head loss) and the goal was to keep the hydraulic resistance constant. The garnet sand dosage was a manually set percentage of the mass of discharged pellets. The pH, flow, water temperature and hydraulic resistance were measured every minute, while hardness, calcium, bicarbonate, super saturation, pellet diameter and bed height were measured at longer intervals (Rietveld, 2005).

The characteristics of the softening process at Weespekarspel are given in table 1.

Table 1. Characteristics of softening reactors at Weesperkarspel.

Number of reactors	8	-
Surface area of reactor	5.3	m^2
Maximum bed height	5	m
Typical water velocity	60-100	m/h
Grain size of seeding material	$0.25\ 10^{-3}$	m
Density of the seeding material	4114	kg/m^3

CONTROL CONFIGURATION

The aim of the control of the softening process is to achieve a desired calcium concentration and, at the same time, minimise the use of dosage material (caustic soda, seeding grains and acid). The available control inputs are the water flow through the bypass and for each reactor the water flow through the reactor, the grain supply rate, the pellet discharge rate, the caustic soda dosage and the acid dosage.

To control the complete treatment step, a modular control setup is chosen. In this way, the controller complexity is minimised, maximising operator understanding of the control structure. Due to the diverse time constants in the process, these controllers are implemented on different platforms, with appropriate performance for the controllers. Figure 2 shows the control modules that are related to the softening process step. On the vertical axis represents the typical time constant of the controller and the horizontal axis shows the process level of the controller.

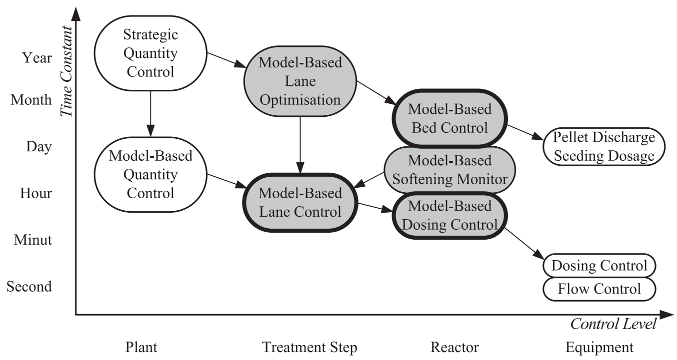

Fig. 2. Control setup for the pellet-softening treatment step. Modular controllers for different time constants and control levels.

The *Strategic Quantity Control* determines the amount of water, which has to be produced at the treatment plant. This is based on yearly consumption patterns, available resources at this plant and, in a multiple plants setup, the other treatment plants. The amount of water to be treated, is then passed to the Model-Based Quantity controller and the Model-Based Lane Optimisation.

The *Model-Based Quantity Control* determines the actual production rate of the entire plant, based on expected daily consumption pattern and the available water in the storage tanks. Restrictions in production rate, due to short-term maintenance, are taken into account and fluctuations of production rate are minimised (DHV, 2008).

The *Model-Based Lane Optimisation* determines the ideal pellet size, bypass ratio and the optimal number of reactors in operation, based on the expected production rate from the Stategic Quantity Control and the expected temperature variations. Changing bed configurations is a long term optimisation, due to the retention time of seeding material in the reactor of approximately 100 days. An extensive description of this optimisation scheme can be found in (van Schagen et al., 2008c).

The *Model-Based Bed Control* achieves the optimal bed composition as found with the Model-Based Lane Optimisation by determining the required pellet discharge and seeding material rates (van Schagen et al., 2008c). It uses the estimation of the current bed composition, determined by the Model-Based Monitor. This can be the model-based monitor of the complete reactor as shown in van Schagen et al. (2006b).

The *Model-Based Monitor* estimates the accuracy of the measurement devices and determines the actual state of the softening process. This monitor is used to verify the measurements that are used by the other controllers. In the case of unexpected differences between measurement and model outcome, operators are notified to take appropriate action. If measurement accuracy is sufficient, the model can be used to estimate unmeasured quality parameters using online measurements and historical laboratory results. Finally the actual state of the process can be estimated, such as the diameters of the pellets in the softening reactor at different heights. An extensive description of this monitoring scheme can be found in van Schagen et al. (2006b).

The *Model-Based Lane Control* determines the current flow and quality setpoints for each lane. It uses the estimated bed composition from the Model-Based Monitor and the actual production rate from the Model-Based Quantity Control. This controller is introduced, since the fluidised bed has limited control possibilities and it is expected that the actual bed composition is different for each reactor. The Model-Based Bed Control strives for the optimal bed composition, while the Model-Based Lane Control adapts to the current bed composition. The Model-Based Lane Control is elaborated in van Schagen et al. (2006a).

The *Model-Based Dosing Control* determines the actual dosing of caustic soda in the reactor to achieve the desired calcium concentration after the reactor, while respecting the constraints of the reactor. The objective of this controller is to follow the setpoint for the Model-Based Lane Control smoothly. The Model-Based Dosing control is shown in this article.

The *Pellet Discharge*, *Seeding Dosage*, *Dosing Control* and *Flow Control* follow the setpoints from the model-based controllers, by adjusting the physical devices such as valves and pumps. These local controllers are implemented in the process automation system of the plant.

MODEL-BASED DOSING CONTROL

The control of water flow and base dosage in the softening reactor is not straightforward. The dosing control and flow control are strongly interrelated. The retention time in the reactor is at least five minutes and response to control actions can only be detected after this time, since water quality can only be measured in the effluent of the reactor. The measurement of the total hardness (the main controlled variable), is a semi-online measurement and has a delay of at least ten minutes. The online pH measurement is inaccurate and has a tendency to drift. Changes in flow and dosing must be gentle, to prevent introduction of process disturbances and fast-changing water quality parameters, which cannot be compensated in consecutive treatment steps. Since the water production rate is predicted, setpoint changes can be predicted as well. Ideally the control should take these predicted changes into account. Finally, the constraints of the reactor, such as maximal height and maximal dosing must never be violated.

Controller Configuration

A model-based multivariable controller is used to meet all requirements. A linear Model Predictive Controller (linear MPC) is used, since in this case calculation time is limited and valid solutions must be guaranteed. The information density in the process is insufficient to use a data-based model. The controller model is therefore obtained through numerical lineralisation of the white nonlinear model described in van Schagen et al. (2008a). The nonlinear model is linearised using the current bed composition found by the Model-Based Lane Control for the given reactor, and the current influent water quality parameters, water flow and caustic soda dosage.

Model predictive control is an online model-based optimal control technique based on the receding horizon principle. An online optimisation algorithm (normally a linear or quadratic programming algorithm) is applied to compute a series of control actions that minimizes a pre-defined cost function or 'performance index', subject to certain constraints. Applying the receding horizon principle means that only the first control sample is implemented and the horizon is shifted one time-step. Then the optimisation starts all over again. Figure 3 shows the principle of receding horizons graphically: $r(k)$, $y(k)$ and $u(k)$ are the reference, output and control (or manipulated) signals, N_m is the 'Minimum cost horizon', N_c is the 'Control horizon' and N the 'Prediction horizon'.

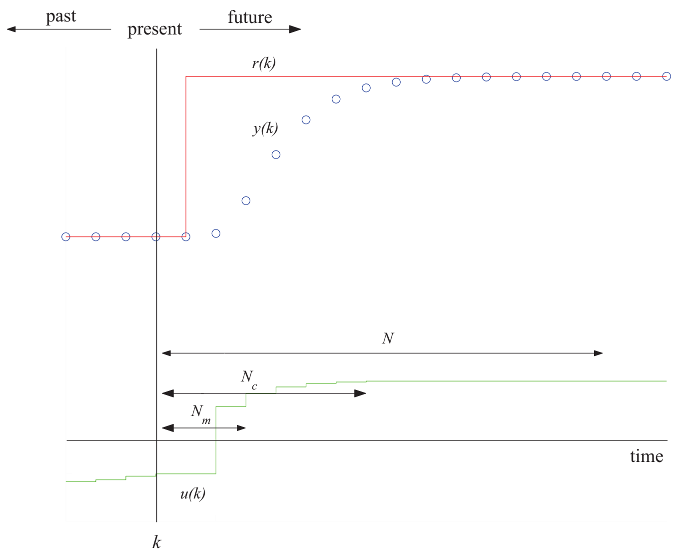

Fig. 3. The principle of linear model predictive control

At time instant k the system output is predicted from time step k until $k+N$ as a function of the control actions. Then the performance index is minimized resulting in an optimal control trajectory $\{u(k|k), ..., u(k+N_c-1|k)\}$.The outputs from k until $k + N_m - 1$ are left out of the optimisation (to ignore minimum-phase and dead-time behaviour of the system) and the control actions are not allowed to change after time step $k + N_c - 1$.

Many different varieties of model predictive control configurations exist. The one chosen to implement for the pellet reactor controller is the so called 'Standard Predictive Control' (SPC) configuration (van den Boom and Backx, 2001). The advantage of this configuration is its flexibility and its state-space formulation.

The control objectives are to follow the current and future setpoints of the Model-Based Lane Control under smooth variation of the manipulated inputs, as formulated in the following cost function:

$$\begin{aligned} J = & \sum_{j=N_m}^{N} \|\mathbf{y}(k+j|k) - \mathbf{r}_y(k+j)\|_P^2 \\ & + \sum_{j=1}^{N} \|\Delta\mathbf{u}(k+j|k)\|_{Q_{\Delta u}}^2 \\ & + \sum_{j=1}^{N} \|\mathbf{u}(k+j|k) - \mathbf{r}_u(k+j)\|_{Q_u}^2 \end{aligned} \tag{1}$$

where N and N_m are the prediction horizon and the minimum costing horizon, and $\mathbf{r}_u$ and $\mathbf{r}_y$ are the references for the inputs and the outputs. In this way the control can use the setpoint predictions from the Model-Based Lane Control, due to predicted production rate changes.

The inputs are the caustic soda dosage and the water flow through the reactor. The outputs are the fluidised bed height in the reactor and the following water quality parameters in the effluent of the reactor: calcium concentration, pH, M-alkalinity and conductivity.

To meet the physical constraints in the process the linear MPC takes these constraints into account:

$$\begin{aligned} \mathbf{u}_{min} &< \mathbf{u}_k < \mathbf{u}_{max} \\ \mathbf{y}_{min} &< \mathbf{y}_k < \mathbf{y}_{max} \end{aligned} \tag{2}$$

To introduce extra integration action in the MPC controller, the model is modified to an IIO model. The new state vector consists of the previous output and the difference of the sate vector of the linearised model. The state update equation is now given by:

$$\begin{aligned} \begin{bmatrix} \mathbf{y}_k \\ \mathbf{x}_{k+1} - \mathbf{x}_k \end{bmatrix} = & \begin{bmatrix} \mathbf{I} & \mathbf{C} \\ \mathbf{0} & \mathbf{A} \end{bmatrix} \begin{bmatrix} \mathbf{y}_{k-1} \\ \mathbf{x}_k - \mathbf{x}_{k-1} \end{bmatrix} + \\ & \begin{bmatrix} D \\ B \end{bmatrix} (\mathbf{u}_k - \mathbf{u}_{k-1}) \end{aligned} \tag{3}$$

with the corresponding output function:

$$\mathbf{y}_k = [\,\mathbf{I}\ \mathbf{C}\,] \begin{bmatrix} \mathbf{y}_{k-1} \\ \mathbf{x}_k - \mathbf{x}_{k-1} \end{bmatrix} + D\,(\mathbf{u}_k - \mathbf{u}_{k-1}) \tag{4}$$

where $\mathbf{A}$, $\mathbf{B}$, $\mathbf{C}$ and $\mathbf{D}$ are the system matrices of the linearised model.

To compensate for plant-model mismatch an observer is used, to estimate the offset in $\hat{\mathbf{y}}_k$. The state update in the MPC controller is therefore given by:

$$\begin{aligned} \begin{bmatrix} \hat{\mathbf{y}}_k \\ \hat{\mathbf{x}}_{k+1} - \hat{\mathbf{x}}_k \end{bmatrix} = & \begin{bmatrix} \mathbf{I} & \mathbf{C} \\ \mathbf{0} & \mathbf{A} \end{bmatrix} \begin{bmatrix} \hat{\mathbf{y}}_{k-1} \\ \hat{\mathbf{x}}_k - \hat{\mathbf{x}}_{k-1} \end{bmatrix} + \\ & \begin{bmatrix} D \\ B \end{bmatrix} (\mathbf{u}_k - \mathbf{u}_{k-1}) + \\ & \begin{bmatrix} \mathbf{L} \\ \mathbf{0} \end{bmatrix} (\mathbf{y}_{k-m} - \hat{\mathbf{y}}_{k-m}) \end{aligned} \tag{5}$$

where $\mathbf{y}_{k-m}$ is the measurement result of m samples ago, due to the measurement delay.

A detailed explanation of the linear MPC algorithm is given in van den Boom and Backx (2001).

Simulation Results

To evaluate the performance of the controller, simulations were performed for the full-scale plant. The sample time for the controller was chosen to be 1 minute. The minimum cost horizon N_m, the control horizon N_c and the prediction horizon N are chosen to be 3,10,20 respectively, since the hydraulic retention time of the reactor is about 3 to 5 minutes. The setpoint for reactor flow and calcium concentration were taken from the lane controller. The simulation is started with a lane flow of 400 m^3/h, increasing the lane flow to 570 m^3/h, due to a production rate change after 1 hour. The reactor flow is kept constant and the bypass flow is increased. As a result from this flow change, the calcium concentration has to change from 50 to 35 mg/l. This is a regular change in calcium setpoint to produce constant water quality in the mixed effluent of reactor and bypass:

$$[\mathrm{Ca}^{2+}]_l = \frac{[\mathrm{Ca}^{2+}]_{in} F_{BP} + [\mathrm{Ca}^{2+}]_r F_{w,r}}{F_{w,l}} \tag{6}$$

Finally, if all lanes are operated at maximum capacity, the lane controller can increase the reactor flow for all reactors that are not yet limited by fluidised bed height. Therefore, in the simulation, the reactor flow is increased to 450 m3/h (the maximum flow for this reactor). The lane flow in this case is 640 m^3/h.

The operating point for the linearised model is the steady-state of the dissolved components in the nonlinear model with current estimated bed composition and the current influent flow and dosage. The states, which describe the bed composition ($\mathbf{m}_g$ and $\mathbf{m}_c$) are kept constant during numerical linearisation. The weighting matrices in equation 1 are diagonal, and the non-zero diagonal elements are given by:

$$\begin{aligned} P(\mathrm{Ca}^{2+}) &= 0.1 \\ Q_u(F_w) &= 1 \\ Q_{\Delta u}(F_w) &= 1 \\ Q_{\Delta u}(F_s) &= 0.1 \end{aligned} \tag{7}$$

The non-zero weights in P and Q_u penalise the deviation of the calcium concentration and water flow from their reference values. Change in the manipulated variables are penalised to achieve a smooth transition between operation points. In addition, level constraints are defined for all outputs and inputs, based on their physical ranges. To make the simulation more realistic, noise was added to the simulated outputs. For the measurements of calcium and M-alkalinity the measurement noise was set at 2%, for bed height, pH and conductivity 1%.

The observer gain was chosen to be diagonal and the same for all measurements, since it is used to estimate model offset. The change in offset is expected to be equal for all measurements.

$$\mathbf{L} = \mathrm{diag}\left([0.2\ 0.2\ 0.2\ 0.2\ 0.2]\right) \tag{8}$$

The simulation results using the nonlinear process model are shown in figures 4 and 5. In figure 4 the dashed-dot line is the setpoint for the calcium concentration, changing from 50 to 35 mg/l, due to a lane flow increase. The solid line is the simulated process values without measurement noise, while the dots are the actual measurement values available for the MPC controller. For calcium, M-alkalinity and conductivity, these measurements are only taken every 10 minutes, with a 10 minute delay. In the graph the measurements are therefore shifted by 10 minutes. The pH measurement and bed height measurements are online measurements and available every minute. The dashed line is output estimation $\hat{\mathbf{y}})_k$ of the MPC controller. In figure 5 the dashed-dot line is the setpoint for the reactor flow from the lane controller and the solid lines are the actual setpoints from the MPC controller.

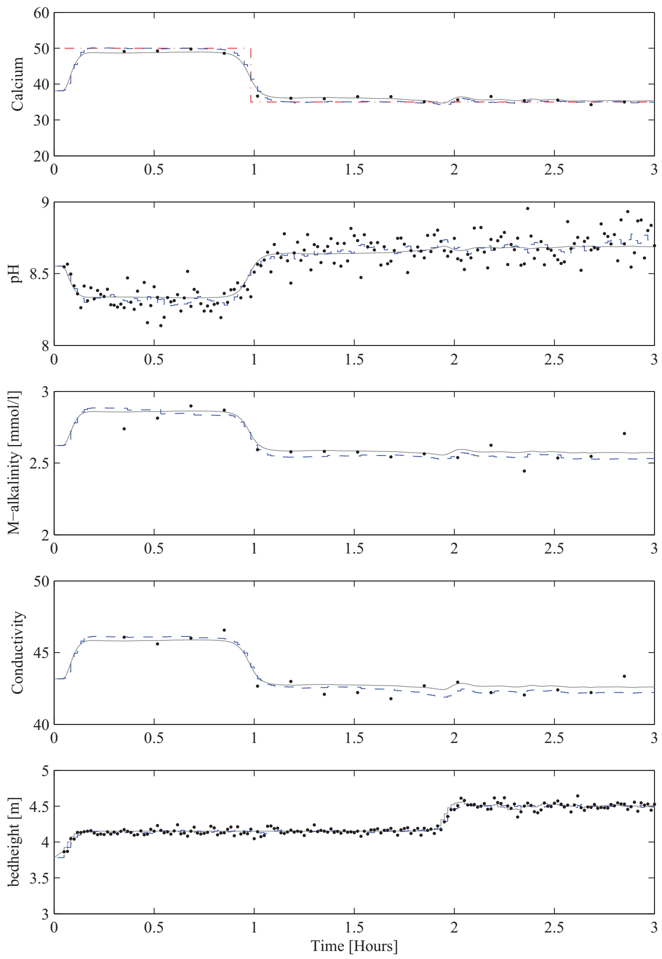

Fig. 4. Simulation results outputs. dashed-dot: Reference, dashed: Estimate, solid: Process, dots: Measurements

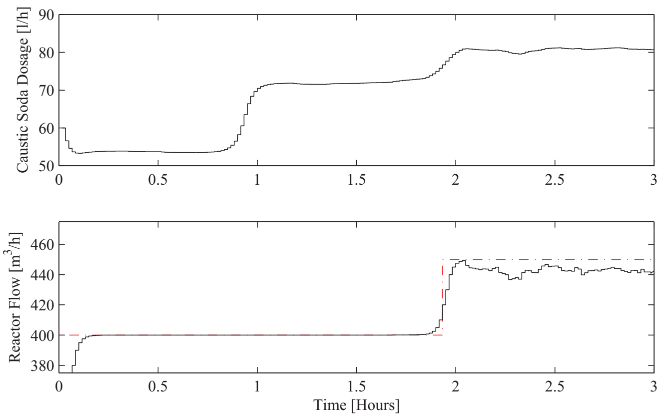

Fig. 5. Simulation results control inputs. dashed-dot: Reference, solid: MPC.

It can be observed, that the tracking of the reference signal is appropriate, including the desired smooth transition. The calcium concentration and the flow change starts before the actual setpoint change, as expected, to get a smooth transition close to the desired setpoint. Another interesting observation is that the water flow through the reactor and the caustic soda dosage are not strictly linked (as opposed to the current heuristic strategy). A flow reference change shows a rapid flow response, but a relatively slow dosage response, which results in a negligible change of the calcium concentration. Finally it can be seen that the MPC controller prevents a flow increase to the setpoint of 450 m^3/h, due to the limitation in bed height.

Pilot plant Results

The MPC controller is also implemented on the pilot plant of Weesperkarspel. The setpoints for the calcium concentration and reactor flow follow a similar pattern as in the full-scale reactor simulation. In this experiment the weighting matrices in equation 1 are diagonal, and the non-zero diagonal elements are given by:

$$\begin{aligned} P(\mathrm{Ca}^{2+}) &= 3 \\ Q_u(F_w) &= 1 \\ Q_{\Delta u}(F_w) &= 0.01 \\ Q_{\Delta u}(F_s) &= 0.01 \end{aligned} \tag{9}$$

The matrices are selected to focus on setpoint achievement and less on smooth transition. The non linear model is the model from a validation experiment. The bed composition in this experiment is determined using the pressure drop measurement with different flows in the reactor. In the pilot-scale plant the pH measurement is not available as online measurement, and is determined semi-online during the M-alkalinity titration. The results from the pilot plant experiments are shown in figures 6 and 7.

The MPC controller in the pilot plant is performing as expected. The relatively small weighting matrix for control variations in equation 10 cause more variation in the caustic soda dosage and flow than for the full-scale simulation experiment.

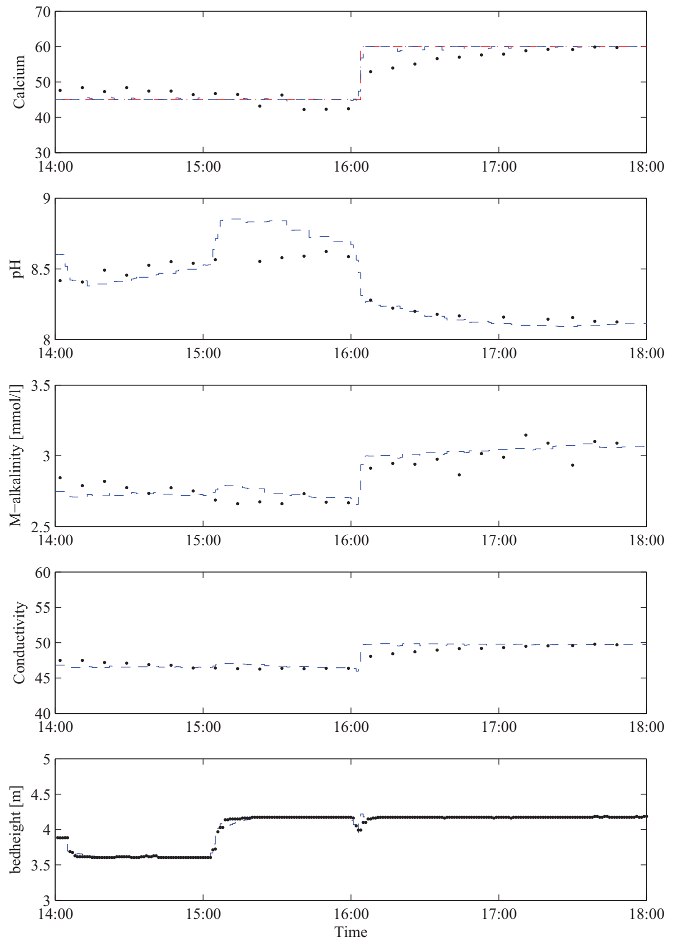

Fig. 6. Pilot plant experiment results outputs. dashed-dot: Reference, dashed: Estimate, dots: Measurements

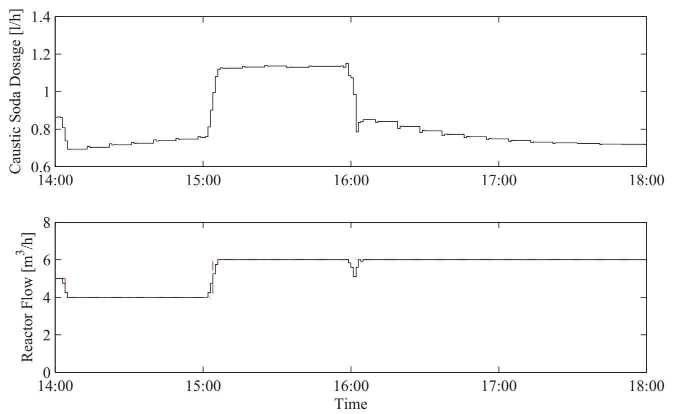

Fig. 7. Pilot plant experiment results control inputs. dashed-dot: Reference, solid: MPC.

CONCLUSIONS

The performance of the softening process step can be improved by applying a model-based control scheme. The control configuration is split in separate controllers for different control levels and time constants. To achieve smooth but quick responses to changing setpoints, a linear MPC is shown to be an effective controller.

A linear MPC controller shows a smooth transition between sudden changes of setpoints, while using a limited number of online and semi-online measurements. The controller is shown to function appropriately in the pilot-scale plant of Weesperkarspel.

REFERENCES

DHV (2008). http://www.aquasuite.com. Internet.

Rietveld, L. (2005). *Improving operation of drinkingwater treatment through modeling*. Ph.D. thesis, Faculty of Civil Engineering and Geosciences, Delft University of Technology.

van den Boom, T.J. and Backx, T.C. (2001). *Model Predictive Control*. TU Delft, Faculty of Information Technology and Systems. Lecture notes.

van Dijk, J. and Wilms, D. (1991). Water treatment without waste material - fundamentals and state of the art of pellet softening. *Journal of Water Supply: Research and Technology-AQUA*, Vol 40(5), 263–280.

van Schagen, K., Rietveld, L., Babuška, R., and E.Baars (2008c). Control of the fluidised bed in pellet softening process. *Chemical Engineering Science*, 63(5), 1390–1400. doi:10.1016/j.ces.2007.07.027.

van Schagen, K., Babuška, R., Rietveld, L., and E.Baars (2006a). Optimal flow distribution over multiple parallel pellet reactors: a model-based approach. *Water Science & Technology*, 53(4-5), 493–501.

van Schagen, K., Bakker, M., Rietveld, L., Veersma, A., and Babuška, R. (2006b). Using on-line quality measurements in drinking water process control. In *AWWA WQTC Conference*. Denver, USA.

van Schagen, K., Rietveld, L., and Babuška, R. (2008a). Dynamic modelling for optimisation of pellet softening. *Journal of Water Supply: Reasearch and Technology-AQUA*, 57(1), 45–56. doi:10.2166/aqua.2008.097.