The application of model predictive control of ammonia nitrogen in an activated sludge process

D. Vrečko, N. Hvala and M. Stražar

ABSTRACT

In this paper a model predictive controller (MPC) for ammonia nitrogen is presented and evaluated in a real activated sludge process. A reduced nonlinear mathematical model based on mass balances is used to model the ammonia nitrogen in the activated sludge plant. An MPC algorithm that minimises only the control error at the end of the prediction interval is applied. The results of the ammonia MPC were compared with the results of the ammonia feedforward-PI and ammonia PI controllers from our previous study. The ammonia MPC and ammonia feedforward-PI controller give better results in terms of ammonia removal and aeration energy consumption than the ammonia PI controller because of the measurable disturbances used. On the other hand, with the ammonia MPC, comparable or even slightly poorer results than with the ammonia feedforward-PI controller are obtained. Further improvements to the MPC could be possible with an improved accuracy of the nonlinear reduced model of the ammonia nitrogen, more sophisticated control criteria used inside the controller and the extension of the problem from univariable ammonia to multivariable total nitrogen control.

Key words | activated sludge process, aeration control, ammonia control, model predictive control, oxygen control

D. Vrečko (corresponding author)
N. Hvala
Department of Systems and Control,
Jožef Stefan Institute,
Jamova 39, SI-1000 Ljubljana,
Slovenia
E-mail: *darko.vrecko@ijs.si*

M. Stražar
Domžale-Kamnik Wastewater Treatment Plant,
Študljanska 91,
SI-1230 Domžale,
Slovenia

INTRODUCTION

The aim of a wastewater treatment plant (WWTP) is to treat wastewater and to provide effluent concentrations below the defined limits, irrespective of the influent and the weather changes. At the same time it is desirable that the operating costs relating to the electrical energy and the chemical dosing are as low as possible. Unfortunately, these goals are difficult to achieve in practice, but one possible solution is to apply more advanced control strategies.

One of the most promising advanced control algorithms with the potential to control wastewater treatment processes is a model predictive controller (MPC). An MPC uses a process model and optimisation to calculate the optimal control signal. It can be applied within the existing control loops in WWTPs, e.g., for DO control, ammonia control, nitrate control, total nitrogen control, etc., thereby replacing the traditionally used PID controllers. The main advantage of an MPC is that it allows the control of the processes with many manipulated and controlled variables with strong cross interactions and handles the various process constraints in a systematic way (Maciejowski 2002). It also offers optimisation of the various objective functions that can include different quality criteria and operational costs. However, so far, MPCs have been mainly tested on simulated WWTPs. In Hoen *et al.* (1996), Steffens & Lant (1999), Alex *et al.* (2002), Brdys & Díaz Maíquez (2002), Rosen *et al.* (2002) and Stare *et al.* (2007), predictive controllers with complex or reduced nonlinear mathematical models were proposed for ammonia, nitrate or oxygen control, while in Steffens & Lant (1999), Sotomayor & Garcia (2002), Vrečko *et al.* (2004) and Holenda *et al.* (2008), predictive controllers with linear mathematical models were evaluated. The optimal values of the manipulated variables, such as airflow rates, recycle flow rates, oxygen concentrations, etc., were in most cases calculated by using different optimization techniques. However, validation of an MPC on real WWTPs is still required. Therefore, the main purpose of this paper is to report our experience of applying an MPC in a real activated sludge process.

doi: 10.2166/wst.2011.477

The paper is organised as follows. In the following section the wastewater pilot plant where the testing of the MPC was carried out is described. Next, a reduced nonlinear mathematical model of the ammonia nitrogen in the pilot plant is presented. Afterwards, an ammonia MPC is described. In the next section the results of the MPC applied in the pilot plant are shown and discussed. Finally, the most important conclusions are drawn.

PILOT PLANT

An ammonia MPC was tested on a moving bed biofilm reactor (MBBR) pilot plant located at Domžale-Kamnik WWTP. A scheme of the MBBR pilot plant together with the sensors used for its control is shown in Figure 1.

The technology of an MBBR differs from the conventional suspended-biomass activated sludge process in that the biomass is attached to the small, free-floating plastic carriers that are added to the reactors (Ødegaard *et al.* 1994). Besides there being some advantages to this technology, e.g., better control over the biomass in the case of rain events and toxic spills, the drawback of this technology is that higher oxygen concentrations are needed in the aerobic reactors since oxygen has to diffuse into the biofilm. The pilot plant consists of two anoxic reactors, two aerobic reactors and an additional reactor where the water is collected before returning as an internal recycle or passing down to the settler. Mixers are installed in the anoxic reactors to maintain mixing, while the aerobic reactors are mixed by the airflow. Only the total airflow into the aerobic reactors can be manipulated. Around half of the total airflow goes in the first aerobic reactor and the other half in the second aerobic reactor. The influent to the pilot plant is wastewater after a mechanical primary treatment. The influent flow rate was kept constant to fix the hydraulic retention time of the pilot plant. The pilot plant was equipped with the following sensors: a flow rate sensor and an ammonia sensor at the influent, an airflow rate sensor in the aeration system, oxygen sensors in the first and second aerobic reactors, an ammonia sensor in the second aerobic reactor and a wastewater temperature sensor at the effluent.

MATHEMATICAL MODEL OF THE AMMONIA NITROGEN IN THE PILOT PLANT

Predictive control requires a mathematical model of the process. However, various types of mathematical models can be used, such as linear models, reduced nonlinear models, neural networks, etc. In our study a reduced nonlinear model of the ammonia nitrogen is used since we proved in our previous study that it has a better prediction capability than a linear black-box model (Stare *et al.* 2006). The reduced nonlinear model is based on the mass balances for ammonia nitrogen in the reactors of the pilot plant. The nitrification reaction rate is modelled on the basis of expressions used in the ASM models (Henze *et al.* 2000). The model equations were additionally simplified by combining the first and second anoxic reactors into one anoxic reactor, and the first and second aerobic reactors into one aerobic reactor. The obtained reduced nonlinear model for ammonia nitrogen in the pilot plant consists of three nonlinear differential equations:

$$\frac{dS_{NH2}}{dt} = \frac{1}{V_{12}} Q_{in} S_{NHin} + \frac{1}{V_{12}} Q_{int} S_{NH5} - \frac{1}{V_{12}} (Q_{in} + Q_{int}) S_{NH2}, \quad (1)$$

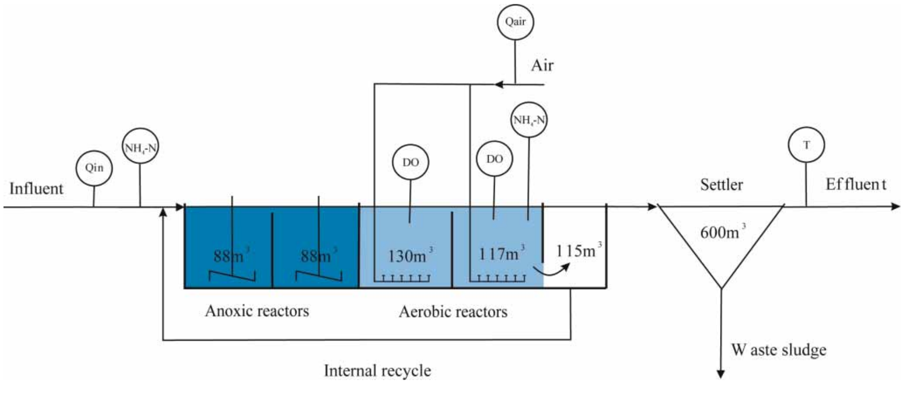

Figure 1 | Scheme of the MBBR pilot plant.

$$\frac{dS_{NH4}}{dt} = \frac{1}{V_{34}}(Q_{in} + Q_{int})(S_{NH2} - S_{NH4}) - r_{NH} \times \left(\frac{S_{NH4}}{K_{NH} + S_{NH4}}\right)\left(\frac{1}{1 + e^{-K_{OA1}S_{O4} + K_{OA2}}}\right)\Theta^{(T-20^{\circ})}, \quad (2)$$

$$\frac{dS_{NH5}}{dt} = \frac{1}{V_5}(Q_{in} + Q_{int})(S_{NH4} - S_{NH5}). \quad (3)$$

The model variable S_{NH2} represents the ammonia concentration at the outlet of the second anoxic reactor, Q_{in} is the influent flow rate, Q_{int} is the internal recycle flow rate, S_{NHin} is the influent ammonia concentration, S_{NH4} is the ammonia concentration at the outlet of the second aerobic reactor, S_{NH5} is the ammonia concentration at the outlet of the fifth reactor, S_{O4} is the oxygen concentration in the second aerobic reactor and T is the wastewater temperature. The model parameter V_{12} is the volume of the combined anoxic reactors, V_{34} is the volume of the combined aerobic reactors, V_5 is the volume of the fifth reactor, r_{NH} is the nitrification reaction rate parameter, K_{NH} is the ammonia half-saturation coefficient, K_{OA1} and K_{OA2} are the parameters of the exponential switching function and Θ is the temperature coefficient. As can be seen from the model, the anoxic reactors and the fifth reactor are not aerated and were modelled by only considering the hydraulic processes. In aerobic reactors, an exponential switching function is used to model the nitrification reaction rate instead of the Monod switching function to get a better description of the nitrification limitation at lower oxygen concentrations in the biofilm (Stare *et al*. 2006).

The continuous differential equations of the reduced mathematical model were discretised using the Euler method before they were applied in the MPC algorithm. A sampling time of 5 min was chosen so as to be small enough to accurately model the nitrification and hydraulic processes. An additional time delay of 120 min was introduced to the model (3) in order to compensate for the time delay between the peaks of the measured and modelled ammonia concentrations. This delay can be attributed to the ammonia sensor, which was not located in situ but in a laboratory building close to the pilot plant reactors, as well as to inaccurate modelling. Ammonia nitrogen usually changes over a time frame of hours, so this time delay significantly reduces the performance of the ammonia control.

The values of the flow rates and the volumes that were used in the model were taken directly from the pilot plant project scheme and are given in Table 1.

Table 1 | Values of the flow rates and volumes used in the reduced nonlinear model

Model parameters	Q_{in}	Q_{int}	V_{12}	V_{34}	V_5
Values	1,296 $m^3 d^{-1}$	3,158 $m^3 d^{-1}$	176 m^3	247 m^3	115 m^3

The kinetic model parameters were estimated from the measurements. Since our mathematical model is nonlinear in terms of the kinetic parameters, their values can be estimated from measurements only by applying some optimization techniques. Since not all the model parameters are uniquely identifiable from the plant measurements, the kinetic parameter Θ has to be tuned manually, whereas the parameters r_{NH}, K_{NH}, K_{OA1} and K_{OA2} can be optimised by using the fmincon function in the Matlab Optimization Toolbox so that the best fit in the least-square sense is achieved between the model and the measurements. The values of the estimated kinetic parameters are given in Table 2.

The kinetic model parameters were estimated using the data from 8 days of pilot plant operation. The mean relative squared error of the obtained model was similar to that achieved in (Stare *et al*. 2006), i.e., around 50%. The mathematical model so obtained was then used in the MPC of the real plant. The comparison between the modelled and measured ammonia concentrations in the last aerobic reactor during the testing period of the MPC is shown in Figure 2. It can be seen that the dynamics of the modelled ammonia concentration is appropriate, but an offset between the modelled and measured ammonia in the last aerobic reactor was obtained. When calibrating the model, the offset was not outstanding as the ammonia concentration in this period was not controlled and varied over a wide range. However, this offset is normally not a problem because it can be compensated inside the MPC algorithm, as explained in the next section. At approximately 1.5 day of the validation period a large peak in the measured ammonia occurs, which can not be seen in the modelled ammonia. The reason for this difference was the failure of the influent ammonia sensor, which caused the ammonia model to be

Table 2 | Values of the kinetic parameters of the reduced nonlinear model

Model parameters	r_{NH}	K_{NH}	K_{OA1}	K_{OA2}	Θ
Optimisation range	[0, 2000]	[0, 5]	[0, 2]	[0, 10]	–
Values	1,200 g $m^{-3} d^{-1}$	0.56 g m^{-3}	0.46 $m^3 g^{-1}$	3.93	1.1

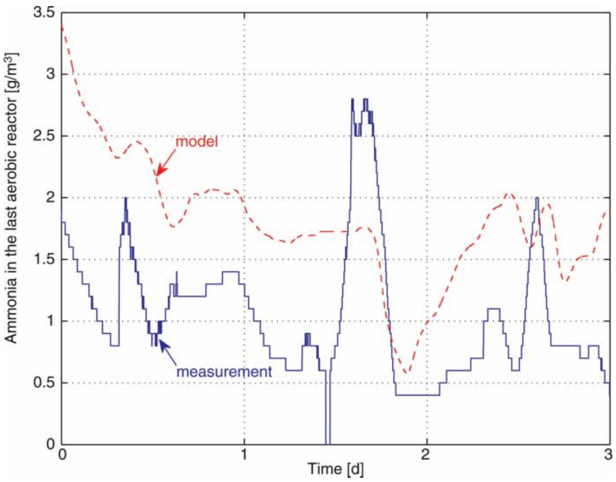

Figure 2 | Comparison between the modelled and measured ammonia concentrations in the last aerobic reactor.

fed with a different, constant and probably lower influent ammonia than the pilot plant.

MODEL PREDICTIVE CONTROL OF AMMONIA NITROGEN

An ammonia control scheme with the MPC is shown in Figure 3. It consists of an ammonia MPC and two PI controllers. The ammonia MPC works in the outer loop of the control scheme, whereas the PI controllers work in the inner loops. The MPC controls the ammonia nitrogen in the last aerobic reactor by changing the oxygen set-point in the same reactor. The oxygen concentration is then controlled with the oxygen PI controller that manipulates the total airflow set-point. Finally, the airflow set-point is controlled with the airflow PI controller that changes the air valve. The PI controllers used in the inner loops are the same as those applied in our previous study at the same pilot plant (Vrečko *et al*. 2006). An advantage of the cascade control is that the disturbances inside the inner loops can be removed much more quickly. In addition, the inner control loops significantly linearize the nonlinearity inside the loops.

A description of the behaviour of the ammonia MPC is shown in Figure 4. In the MPC at every sampling instance the process outputs are predicted for the finite prediction interval by using the process model. Manipulated variables in the prediction interval are calculated in such a way to minimise selected objective function. MPCs use a receding horizon control law where at a certain sampling instance only the first manipulated value is applied to the process while all further values are rejected. The objective function used in the ammonia MPC was the minimization of the difference between the predicted and set-point ammonia concentrations. Normally, the objective function is calculated over a certain prediction interval, but in our case the algorithm was simplified by considering only the difference between the predicted and set-point ammonia concentrations at the end of the prediction interval. The prediction of the ammonia nitrogen is made with the reduced nonlinear model described above. Furthermore, only a single oxygen set-point move is calculated inside the prediction interval, i.e., a constant oxygen set-point within the prediction interval is considered. Its value is constrained within a limited range. These two presumptions

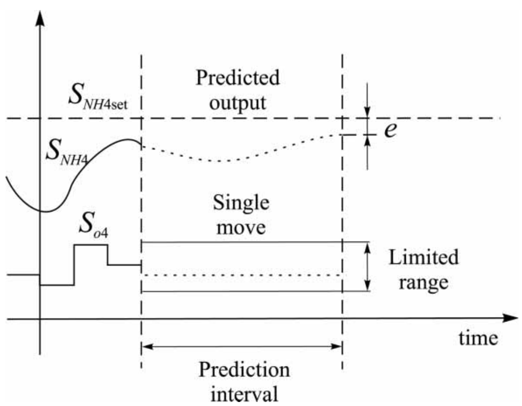

Figure 4 | Description of the ammonia MPC behaviour.

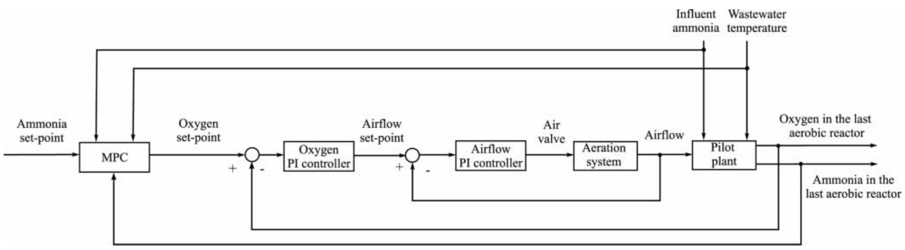

Figure 3 | An ammonia control scheme with an MPC.

very much simplify the optimisation problem. By taking a long enough prediction interval, the relation between the oxygen set-point and the ammonia concentration is a monotonically decreasing function, so that a simple bisection method can be applied to solve the optimisation problem. The bisection optimisation ends when a change of the manipulated variable in the last iteration is smaller than 0.01. Normally, less than 10 iterations are required to reach this tolerance. It should be pointed out that the measurable disturbances, such as the concentration of the influent ammonia and the temperature of the wastewater, are assumed to be constant for the whole prediction interval.

A mathematical model used for a prediction is never completely accurate. However, a model error can be compensated, to some extent, by considering the output model error d(k), which can be estimated at every MPC sampling instance k as:

$$\mathrm{d}(k) = S_{\mathrm{NH4,meas}}(k) - S_{\mathrm{NH4}}(k), \tag{4}$$

where $S_{\mathrm{NH4,meas}}(k)$ is the measured and $S_{\mathrm{NH4}}(k)$ is the modelled ammonia concentration in the last aerobic reactor, both taken at the current sample instance k. To calculate the ammonia concentration during the prediction interval, d(k) is added to the ammonia concentration as predicted by the model (3) for the entire prediction interval. In this way the control error in the steady-state is compensated and feedback control is incorporated into the predictive controller. However, by compensating the model output a feedback gain that is too high can be obtained, especially when the model is not accurate, which can lead to unstable behaviour of the controller. Thus, in our case the feedback gain was reduced by filtering the output model error:

$$\mathrm{d_f}(k) = K_\mathrm{f} \cdot \mathrm{d_f}(k-1) + (1 - K_\mathrm{f}) \cdot \mathrm{d}(k-1), \tag{5}$$

where $\mathrm{d_f}(k-1)$ is the filtered output model error from the previous sampling instance, K_f is the constant of the filter and $\mathrm{d}(k-1)$ is the output model error from the previous sampling instance. The filtered output model error was then used to correct the model output in the MPC algorithm.

The ammonia MPC includes several control parameters that have to be properly tuned. These parameters are as follows: the MPC sampling time T_s, the prediction interval P, the constant of the output model error filter K_f, the maximum oxygen set-point change at sampling time instance ΔS_{Omax} and the minimum and the maximum values of the oxygen set-point, S_{Omin} and S_{Omax}, respectively. Besides that, the parameters of the oxygen and the airflow PI controller also have to be properly selected. The parameters of the ammonia MPC were manually tuned using a trial-and-error procedure so that acceptable control behaviour was obtained. An important control parameter is the prediction interval P, which was in our case set to a high value of 12 hours (144 samples of 5 min). Such a high prediction interval was chosen to obtain robust behaviour of the ammonia MPC. The model used in the controller is not accurate; therefore, it would be hard to improve the performance of the MPC by only changing the values of the control parameters. On the other hand, the values of the parameters of the PI controllers were taken from our previous study (Vrečko *et al.* 2006). The parameter values of the ammonia MPC, the oxygen PI controller and the airflow PI controller are given in Table 3.

RESULTS AND DISCUSSION

The ammonia MPC was tested on-line at the pilot plant for a couple of weeks. The testing was performed via the internet using a virtual private network (VPN) link between the Jozef Stefan Institute (JSI) and the Domžale-Kamnik WWTP. The ammonia MPC and the oxygen PI controller were implemented in the Matlab environment and connected to the plant via the Matlab – OLE for the process control (OPC) server connection. In contrast, the airflow PI controller was implemented on the programmable logical controller (PLC) at the plant. The sampling time of the

Table 3 | Values of the parameters of the ammonia control scheme

Controller	Parameters					
Ammonia MPC	P 144 samples	T_s 5 min	K_f 0.97	ΔS_{Omax} 0.2 g m^{-3}	S_{Omin} 2 g m^{-3}	S_{Omax} 9 g m^{-3}
Oxygen PI controller	K_{p1} 300 m^6 (g h)$^{-1}$		T_{i1} 400 s	u_{min1} 500 m^3 h^{-1}		u_{max1} 2,200 m^3 h^{-1}
Airflow PI controller	K_{p2} 0.1		T_{i2} 30 s	u_{min2} 0%		u_{max2} 100%

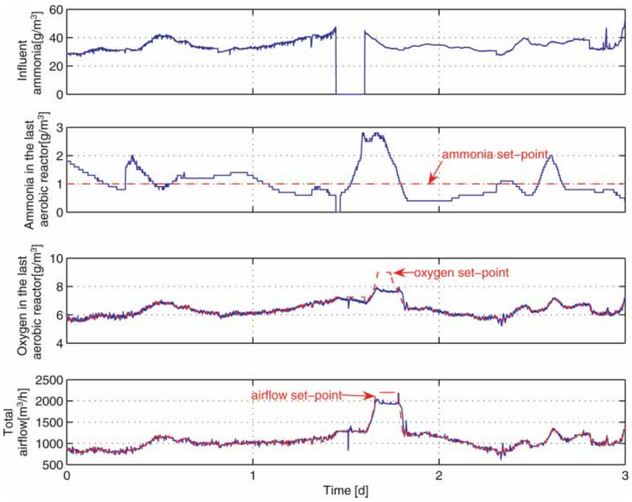

Figure 5 | Results of the ammonia MPC.

Table 4 | Values of the performance criteria calculated for the ammonia MPC, ammonia feedforward-PI and ammonia PI controller

Controller	Ammonia concentration in the last aerobic reactor Average ($g\,m^{-3}$)	min ($g\,m^{-3}$)	max. ($g\,m^{-3}$)	st. dev. ($g\,m^{-3}$)	Airflow per ammonia removed ($m^3\,kg^{-1}$)
Ammonia MPC	1.05	0	2.8	0.52	719
Ammonia feedforward-PI	0.98	0.10	2.20	0.50	602
Ammonia PI control	1.12	0.10	3.70	0.83	849

ammonia MPC was 5 min, and the sampling time of the oxygen PI controller was set to 20 s. The results obtained with the ammonia MPC for 3 days of plant operation are shown in Figure 5.

The MPC successfully controls the ammonia concentration in the last aerobic tank to the preselected set-point of 1 $g\,m^{-3}$, except for the short interval in the middle of the testing period when the influent ammonia sensor failed. During this interval the MPC was out of operation and the dissolved oxygen set-point concentration was kept constant at the last calculated value. Consequently, a peak in the ammonia concentration occurred as the oxygen concentration was too low. When the influent ammonia measurement was restored, the MPC reduced the ammonia peak by rapidly increasing the oxygen-set point to the upper bound of 9 $g\,m^{-3}$.

The performance of the ammonia MPC was compared with the ammonia feedforward-PI and ammonia PI controllers from our previous study (Vrečko *et al.* 2006). Note that all the controllers were tested at the same pilot plant and during similar weather conditions. The feedforward controller from our previous study was realised as a simple, linear first order process. The performance of the controllers was evaluated by calculating some performance criteria, as given in Table 4. It should be mentioned that for the MPC evaluation the period when the influent ammonia sensor failed was not considered.

By comparing the performances of the controllers some interesting observations can be made. The ammonia MPC and the ammonia feedforward-PI controller give better results in terms of ammonia removal and aeration energy consumption than the ammonia PI controller. This is because they use an additional measurable disturbance of the influent ammonia. On the other hand, with the ammonia MPC, comparable or even slightly poorer results than with the ammonia feedforward-PI controller were obtained. One possible reason for this could be the poor accuracy of the reduced nonlinear model of the ammonia nitrogen. An improved model accuracy can, for example, be obtained by extending the mathematical model to five differential equations, one for each reactor. It is also possible to improve our mathematical model by slowly adjusting the model parameters, such as r_{NH}, to compensate for the slow changes in the process (Stare *et al.* 2006). However, the reduced mathematical model is nonlinear in terms of the parameters and the adjustment of its parameters cannot be made easily. Another possibility for improvement is to use linear black-box or gray-box models. By using linear models, optimal values of the manipulated variables can be calculated directly from the control criteria if the process constraints are not considered. Furthermore, the parameters of the linear models can be adjusted in a straightforward way.

Another possible reason for the slightly poorer performance of the MPC could be the univariability of the process, since only the ammonia concentration in the last aerobic reactor is controlled by changing the oxygen concentration in the last aerobic reactor. An advantage of an MPC is normally expected when multivariable processes with multiple inputs and outputs are controlled. However, better results can be obtained when the total nitrogen or the sum of the nitrate and ammonia is optimised. Potential improvements to the ammonia MPC are also to be expected from upgrading the control criteria from the control error at the end of the prediction interval to the sum of all the square control errors inside the prediction interval.

CONCLUSIONS

In this paper a model predictive controller (MPC) for ammonia nitrogen was presented and evaluated on a real activated sludge pilot plant. A reduced nonlinear mathematical model based on mass balances was used to model the ammonia nitrogen in the pilot plant. An MPC algorithm that minimises only the control error at the end of the prediction interval was applied. The results of the ammonia MPC were compared with the results of the ammonia feedforward-PI and ammonia PI controllers from our previous study. The ammonia MPC and the ammonia feedforward-PI controller give better results in terms of ammonia removal and aeration energy consumption than the ammonia PI controller because they use an additional measurable disturbance of the influent ammonia. On the other hand, with the ammonia MPC, comparable or even slightly poorer results than with the ammonia feedforward-PI controller were obtained. Further improvements to the MPC could be possible with an improved accuracy of the nonlinear reduced model of the ammonia nitrogen, more sophisticated control criteria used inside the controller and an extension of the problem from univariable ammonia to multivariable total nitrogen control. In the future an MPC with a linear mathematical model for the optimisation of the total nitrogen removal will be tested on a real activated sludge process.

ACKNOWLEDGEMENT

The financial support of the European Commission (SMAC project, contract EVK1-CT-2000-00056) and of the Ministry of Higher Education, Science and Technology of the Republic of Slovenia are gratefully acknowledged.

REFERENCES

Alex, J., Tschepetzki, R. & Jumar, U. 2002 Predictive control of nitrogen removal in WWTP using parsimonious models. In *15th IFAC World Congress on Automatic Control, Barcelona*.

Brdys, M. A. & Díaz Maíquez, J. 2002 Application of fuzzy model predictive control to the dissolved oxygen concentration tracking in an activated sludge process. In *15th IFAC World Congress on Automatic Control, Barcelona*.

Henze, M., Gujer, W., Mino, T. & van Loosdrecht, M. 2000 *Activated Sludge Models ASM1, ASM2, ASM2d and ASM3*. IWA Publishing, London, England.

Hoen, K., Shuhen, M. & Köhne, M. 1996 Control of Nitrogen Removal in Wastewater Treatment Plants with Predenitrification, Depending on the Actual Purification Capacity. *Water Science & Technology* **33** (1), 223–236.

Holenda, B., Domokos, E., Redey, A. & Fazakas, J. 2008 Dissolved oxygen control of the activated sludge wastewater treatment process using model predictive control. *Computers and Chemical Engineering* **32**, 1270–1278.

Maciejowski, J. M. 2002 *Predictive Control with Constraints*. Prentice-Hall, Harlowe.

Ødegaard, H., Rusten, B. & Westrum, T. 1994 A new moving bed biofilm reactor–applications and results. *Water Science & Technology* **29** (10–11), 157–165.

Rosen, C., Larsson, M., Jeppsson, U. & Yuan, Z. 2002 A Framework for extreme-event control in wastewater treatment. *Water Science & Technology* **45** (4–5), 299–308.

Sotomayor, O. A. Z. & Garcia, C. 2002 Model-based predictive control of a pre-denitrification plant: linear state-space model approach. In *15th IFAC World Congress on Automatic Control, Barcelona*.

Stare, A., Vrečko, D. & Hvala, N. 2006 Modeling, identification, and validation of models for predictive ammonia control in a wastewater treatment plant – a case study. *ISA Transactions* **45**, 159–174.

Stare, A., Vrečko, D., Hvala, N. & Strmčnik, S. 2007 Comparison of control strategies for nitrogen removal in an activated sludge process in terms of operating costs. *Water Research* **41** (9), 2004–2014.

Steffens, M. A. & Lant, P. A. 1999 Multivariable Control of Nutrient-Removing Activated Sludge Systems. *Water Research* **33** (12), 2864–2878.

Vrečko, D., Hvala, N. & Gerkšič, S. 2004 Multivariable predictive control of an activated sludge process with nitrogen removal. In *CAB 9, Computer Applications in Biotechnology, 9th International Symposium, 28–31 March 2004, Nancy, France*.

Vrečko, D., Hvala, N., Stare, A., Burica, O., Stražar, M., Levstek, M., Cerar, P. & Podbevšek, S. 2006 Improvement of ammonia removal in activated sludge process with feedforward-feedback aeration controllers. *Water Science & Technology* **53** (4–5), 125–132.

First received 28 June 2010; accepted in revised form 18 November 2010