

Proceedings of the 4th International Modelica Conference, Hamburg, March 7-8, 2005, Gerhard Schmitz (editor)

T. Ziehn, G. Reichl, E. Arnold *TU Ilmenau; Fraunhofer Institute Ilmenau, Germany* **Application of the Modelica library WasteWater for optimisation purposes** pp. 351-356

Paper presented at the 4th International Modelica Conference, March 7-8, 2005, Hamburg University of Technology, Hamburg-Harburg, Germany, organized by The Modelica Association and the Department of Thermodynamics, Hamburg University of Technology

All papers of this conference can be downloaded from http://www.Modelica.org/events/Conference2005/

Program Committee

- Prof. Gerhard Schmitz, Hamburg University of Technology, Germany (Program chair).
- Prof. Bernhard Bachmann, University of Applied Sciences Bielefeld, Germany.
- Dr. Francesco Casella, Politecnico di Milano, Italy.
- Dr. Hilding Elmqvist, Dynasim AB, Sweden.
- Prof. Peter Fritzson, University of Linkping, Sweden
- Prof. Martin Otter, DLR, Germany
- Dr. Michael Tiller, Ford Motor Company, USA
- Dr. Hubertus Tummescheit, Scynamics HB, Sweden

Local Organization: Gerhard Schmitz, Katrin Prölß, Wilson Casas, Henning Knigge, Jens Vasel, Stefan Wischhusen, TuTech Innovation GmbH

Application of the Modelica library *WasteWater* for optimization purposes

T. Ziehn*, G. Reichl*, E. Arnold**

 * Technische Universität Ilmenau Department of Automation and Systems Engineering
 P.O. Box 10 05 65, 98684 Ilmenau, Germany tilo.ziehn@stud.tu-ilmenau.de, gerald.reichl@tu-ilmenau.de ** Fraunhofer-IITB
 Application Center Systems Technology
 Am Vogelherd 50, 98693 Ilmenau, Germany
 eckhard.arnold@ast.iitb.fraunhofer.de

Abstract

The following work is a contribution to dynamic optimal control strategies of an activated sludge model. The model is applied to the waste water treatment plant (WWTP) in Jena, Germany. The model is implemented using the Dymola software package with the application of the free available Modelica library *WasteWater*. On the basis of this model open-loop and closed-loop (Model Predictive Control MPC) optimizations are applied and the results are evaluated. The main focus is on the variable operating costs of the WWTP.

Keywords: waste water treatment, dynamic optimization, model predictive control

1 Introduction and problem description

Nowadays new waste water treatment plants are designed for reliability and safety, not for operational cost efficiency. Further more sustainable sewage management, which is subject to increasing legal requirements, plays an important role. Therefore, the application of simulation and optimization methods to the waste water purification process is necessary. The principal purposes are the reduction of the load for the environment (adherence to the limits of the effluent parameters) with simultaneous minimization of the waste water treatment costs.

The free available Modelica library *WasteWater* [1] was developed and is successfully applied to the WWTP Jena. In this plant blowers and pumps are controlled by simple SISO control loops with standard

controllers (usually two-point controllers).

The WWTP Jena is comperatively well equiped with various on-line measurement devices including COD, NH_4^+ -N, NO_3^- -N and PO_4^{3-} -P. Only on the basis of this equipment, investigations concerning dynamic control strategies become possible.

The cleaning achievement of a WWTP can be evaluated with the help of the effluent parameters of the receiving water. Some of these effluent parameters (e.g. NH_4^+ -N) of the WWTP Jena are considerably below legal limits. As a result the operating costs are higher than is necessary. The electrical energy costs of the blowers and pumps, as well as the sludge disposal costs, represent the main part of the variable costs which are required to operate the WWTP Jena. The aim of this work is to find optimal trajectories for blowers and pumps by using dynamic optimization

methods. Mainly dry weather scenarios were chosen from the stored data for simulation and optimization purposes. As a result the minimization of the operation costs of the WWTP, with simultaneous adherence to the limits of the effluent parameters, becomes possible. These results are used as a basis for further investigations concerning closed-loop operation (Model Predictive Control MPC).

2 Modelling of the WWTP Jena

The dynamic model of the WWTP is of crucial importance for the model-based optimization. There is a multiplicity of mathematical models, which describe the waste water purification process. However, these models are almost exclusively applied for simulation purposes. Due to the complexity of the used model an object-oriented approach is worthwhile.



Figure 1: Simplified sytem of the Jena WWTP

The programming language Modelica represents this object-oriented approach. In this context the software package Dymola was used for simulation, since the C++ code, generated automatically by Dymola, is particularly suited for optimization purposes. The free Modelica library *WasteWater* was used for the implementation of the model of the WWTP Jena. The library contains the Activate Sludge Models (ASM) No. 1 to No. 3 [2] and different multi-layer models for secondary clarifier.

The WWTP Jena is characterised by a connection size of 145,000 people equivalent (p.e.), a cascadetype denitrification with pre-clarification, biological and chemical phosphorus removal and sludge digestion. The bio-gas produced by sludge fouling is used in a block-type thermal power station of 2x250 kW. A simplified system of the plant is shown in Figure 1.

Existing control loops (usually two-point controllers) are isolated in and/or removed from the model for the optimization process, with the goal being to find optimal trajectories (e. g. the control of the blowers for the air supply into the nitrification tanks). Both, the physical limits of the control variables (blowers, pumps) and the limits of the effluent parameters (e. g. maximum 1 mg $\rm NH_4^+/l)$ must be kept.

The model of the WWTP Jena is implemented by using the Activated Sludge Model No. 2d of the IWA task group, which is part of the Modelica library *WasteWater*. A summerised description of the model reads:

$$\frac{dS_i}{dt} = (S_{i,in} - S_i) \frac{Q_{in}}{V} - r_i, \qquad (1)$$
$$i \in \{F, A, NH, NO, PO, I, ALK, N\}$$

$$\frac{dS_O}{dt} = (S_{O,in} - S_O)\frac{Q_{in}}{V} + r_O + r_{air},$$
 (2)

$$\frac{dX_i}{dt} = (X_{i,in} - X_i) \frac{Q_{in}}{V} - r_i, \qquad (3)$$

$$i \in \{I, S, H, PAO, PP, PHA, AUT, \\ TSS, MeOH, MeP\}$$

In equation (1) the index i stands for the different dissolved concentrations such as inert organic matter (S_i) , substrate $(S_F + S_A)$, nitrate nitrogen (S_{NO}) , etc., and in equation (3) for the particular concentrations, which are amongst others the heterotrophic (X_H) and autotrophic (X_{AUT}) biomass. Variables subscripted by index 'in', e.g. $S_{i,in}$, indicate concentrations in the flow Q_{in} entering a considered tank. Equation (2) describes the balance of the dissolved oxygen and has an additional term for the oxygen uptake (aeration r_{air}) caused by the blowers. The reaction rates r_i and r_0 in the balance equations (1) - (3) are given by the model matrix of the ASM No. 2d. It models 19 relevant concentrations (state variables) and 21 processes per tank. The WWTP Jena model is described by approximatly 3000 equations and 250 state variables. The complete description and development is available in [2].

The object oriented approach implemented in Modelica combines the advantages of a hierachical model structure and the reusability of model components in a multi-domain modelling environment of complex dynamic systems. The model components such as nitrification tank, secondary clarifier, blower, flow mixer, divider and so on have to be defined for all types of ASM models because of differing variables and the number of variables. The components are characterised by internal variables declared independently of other components, and by connectors linking the components.

3 Optimal control problem

The optimization based control requires the dynamic model of the WWTP (developed in section 2). The whole model and control problem transformation procedure is done automatically by exporting a compiled flat model representation of the WWTP in C++ from Dymola [3], that can be used by the optimization solver Hqp/Omuses [4], [6].

3.1 Open-loop problem

According to the problem described in section 1 different nonlinear optimal control problems can be formulated and solved taking into account different objective functionals. The main aim of the optimization is to reduce operating costs, e.g. the electrical energy cost taking into account the time-dependent electricity tariff, respectively. The objective functional is minimised with respect to the constraints. Restrictions for the state variables results from legal limits of effluent concentrations of the WWTP to the receiving water. The controls are limited due to the maximum installed pump and blower capacity.

Using the multi-stage control parameterisation technique described in [4], the continuous optimal control problem is approximated by a constrained discretetime optimal control problem, that reads:

$$J = F(\mathbf{x}^{K}) + \sum_{k=0}^{K} \left[\rho_{e}^{k} f_{o,e}^{k}(\mathbf{x}^{k}, \mathbf{u}^{k}, \mathbf{z}^{k}) + f_{soft}^{k} + (4) \right]$$
$$\rho_{s}^{k} f_{o,s}^{k}(\mathbf{x}^{k}, \mathbf{u}^{k}, \mathbf{z}^{k}) + \rho_{o}^{k} c_{o} f_{o,c}^{k}(\mathbf{x}^{k}, \mathbf{u}^{k}, \mathbf{z}^{k}) \right]$$

with $f_{o,e}$ - electrical energy costs resulting from timedependent tariff and electrical energy demand for blower and pump operation, $f_{o,s}$ - sludge disposal costs depending on waste sludge flow rate and composition, taking into account profit from bio-gas utilisation, $c_o f_{o,c}$ - chemical dosage costs (negligible), f_{soft}^k - penalty term for soft constraints (slack variables), $\rho_e^k, \rho_s^k, \rho_o^k$ - weighting factors, \mathbf{x}^k - model state variables, \mathbf{u}^k - control inputs and \mathbf{z}^k - non-controllable inputs (e.g. inflow and concentrations).

The electrical energy costs can be formulated as follows:

$$f_{o,e} = \int_{t_0}^{t_e} c(t) \cdot p_{el}(t) dt \tag{5}$$

with c(t) - time dependent tariff and p_{el} - electrical energy depending on the air supply into the nitrification tanks. A linear connection between the electrical

energy and the amount of air flow into the nitrification tanks could be determined. The blowers responsible for the air supply into the nitrification tanks N(III), N/DN(V) and N(VI) (Figure 1) represent the main part of the variable electrical energy costs. The costs resulting from pumps are negligible.

The constrained discrete-time optimal control problem is numerically solved as a large-scale and structured nonlinear programming problem in the state and control variables.

3.2 Closed-loop problem

The Model Predictive Control (MPC) offers the possibility to merge an optimal control problem solution into a closed-loop. One substantial advantage in comparison to simple control loops is in the treatment of constraints for the controls and the state variables. In this work a nonlinear MPC is considered with an economic cost function. There is no setpoint because of external input dynamics. The MPC algorithm can be summerised in the following steps:

- 1. Set: $\hat{k} = 0$
- 2. State estimation: Get the current states $\mathbf{x}^{\hat{k}|\hat{k}}$ using past measurements, e.g. Nonlinear Moving Horizon State Estimator (NMHSE).
- 3. Prediction: Get a prediction of the noncontrollable inputs $\mathbf{z}^{k|\hat{k}}$ (reads: inputs at the time k calculated at the time \hat{k}), $k \in [\hat{k}, \hat{k} + K - 1]$ for a given horizon K (prediction horizon) using the process model (summerised description equations (1) - (3)).
- 4. Optimal control problem: Calculate the future control signal $\mathbf{u}^{k|\hat{k}}, k \in [\hat{k}, \hat{k} + K 1]$ by solving an optimal control problem (reference to section 3.1 and equation (4)) with subject to the process model and the constraints.
- 5. Applying: Send the control signal $\mathbf{u}^{\hat{k}|\hat{k}}$ to the process.
- 6. Shift: $\hat{k} = \hat{k} + 1$ and go back to step 2.

Many linear MPC approaches have found successful applications and important issues such as online computation, robustness and stability are well addressed. Within nonlinear MPC, research is still in progress. Therefore, and since the implemented WWTP Jena model has more than 250 state variables with only 10 measureable outputs, the following application of the



Figure 2: Open-loop optimization results (control signals, electrical energy costs and effluent value for NH⁺₄-N)

MPC to the model of the WWTP Jena is only considered on nominal conditions. It is assumed that an exact model of the existing plant is beeing used without any disturbances and that all state variables are available. Because of these assumptions the state estimation is not considered in this work. However, a succesful approach of the nonlinear moving horizon state estimator to an activated sludge model can be found in [7] and an application of MPC for an ASM No. 1 can be found in [8].

For further investigations on the WWTP Jena model it is advisable to reduce the number of state variables. This can be done for example by using a simple secondary clarifier instead of a multi-layer secondary clarifier.

Another simplification is made by assuming that the non-controllable inputs can be determined exactly and so the prediction (step 3) is not applied. Only on-line measured data of the WWTP Jena is used. When applying the MPC algorithm to the real plant investigations regarding the prediction of the non-controlable inputs (inflow and concentrations) are still necessary. In this context it is also important to examine how prediction errors affect the results of the applied trajectories. The legal limits of the effluent parameters of the WWTP must always be guaranteed.

4 Results

Primarily dry weather scenarios are considered in the open-loop investigations. The main point is the minimization of the electrical energy costs taking into account the effluent parameter limits of the WWTP.

Figure 2 shows the results of an open-loop optimization process. The optimal trajectory of one of the blowers is presented in comparison to the trajectory resulting from the control by the basic control loops (Figure 2 upper left). The different electrical energy tariffs (HT - high tariff and LT - low tariff) are marked by vertical lines. A piecewise constant approximation of the control variables was chosen to support



Figure 3: MPC results (effluent value for ammonium and control signal of the blower for the air supply)

the use of the tariffs more efficiently. In the right lower part of Figure 2 the effluent parameter of ammonium (NH_4^+-N) is represented. It shows that the chosen upper constraint for ammonium $(1 \text{ mg NH}_4^+-N/1)$ becomes active. With optimal trajectories of the blowers the electrical energy costs can be reduced by more than 10 % (Figure 2 lower right). It is even possible to achieve a higher reduction of the electrical energy costs (up to 15 %) by including additional control variables (e.g. the pump for the sludge recirculation, Figure 2 upper right) in the optimization process.

The legal limit for the effluent parameter NH_4^+ -N is about 10 mg/l and therefore much higher than the applied limit of 1 mg/l. However, all investigations are considered with dry weather scenarios. The limit for NH_4^+ -N is reduced in order to guarantee that the legal limit can be kept even under uncertain conditions. With a higher limit for NH_4^+ -N (e.g. 5 mg/l) the electrical energy costs can be reduced by more than 20 %. In addition the sludge costs are taken into account and the control variable responsible for the sludge removal is included in the optimization process. However, it is necessary to limit the total suspended solids (TSS) in the secondary clarifier, otherwise too much sludge would be removed from the whole process. The investigations also consider the bio-gas utilization and the profit obtained. Further results can be found in [5].

The results of the open loop investigations (due to different scenarios) can be merged with the help of the Model Predictive Control (MPC) into a closed-loop. The influence of the prediction horizon and the stepsize on the results is examined. For all further investigations a data record is used, which contains dry weather data and a rain event.

It can be shown that the prediction horizon is of little importance for optimization results, taking into account the electrical energy costs. Different prediction horizons from 0.5 days up to 5 days are examined, with stepsizes from 0.25 days up to 1 day. The results (electrical energy costs) are nearly the same. Figure 3 shows the results with a prediction horizon of 2 days and a stepsize of 1 day. The upper part of Figure 3 represents the control signal of one of the blowers. The resulting effluent parameter NH_4^+ -N is presented in the lower part of Figure 3. With occurrence of the rain event (day 8) the chosen upper constraint can not be kept by using the implemented simple control loops. Only by applying Model Predictive Control strategies can the constraint for NH_4^+ -N be kept.

In the case of dry weather (day 1 to day 5) it is possible to save approxamately 11 % on electrical energy costs. During the entire investigation period of 10 days it is even possible to save more than 12 % with the optimal trajectories. The following control variables are taken into account: the control of the blowers, the control of the recirculation of the sludge and the control of the return sludge. With the control of the return sludge and the recirculation it becomes possible to shift activated sludge at short notice (from the biology into the secondary clarification and in reverse). However, altogether no TSS is extracted from the process.

Also investigations concerning all costs (electric energy costs and sludge costs) are examined. In this case the optimization horizon has substantial influence on the results. The control for the sludge removal is of substantial importance. In the case that the rain event is not predicted early enough too much sludge is extracted from the process and with the occurrence of the rain event it is not possible to keep the necessary cleaning achievements (constraints, e.g. 1 mgNH_4^+ -N/l) of the water since insufficient biomass is available in the tanks. Only prediction horizons smaller than 6 days could be investigated since the computer capacity was exhausted at this point.

5 Summery and conclusion

In this work the dynamic optimization method was applied to a WWTP model. With the help of the library WasteWater an ASM No. 2d model of the WWTP Jena was examined and evaluated. Different scenarios were provided and mainly dry weather data were used for simulation and optimization. The influence of different control variables was investigated by using openloop optimizations. These results could be used in a closed-loop by applying Model Predictive Control strategies. It could be shown that regarding the electrical energy costs more than 10% can be saved in comparision to existing simple control loops. However, to apply the results and the MPC strategy to the real plant further investigations are still necessary. The prediction of the non-controllable inputs is not implemented yet or the state estimation for the state variables.

References

- G. Reichl. *WasteWater* a Library for Modeling and Simulation of Wastewater treatment plants. In: Proceedings of the 3rd Modelica Conference, Linköping, Sweden, Modelica Association, 3-4 November 2003.
- [2] M. Henze, W. Gujer, T. Mino and M. v. Loosdrecht. Activated sludge models ASM1, ASM2, ASM2d and ASM3. Technical report, IWA task group, 2000.
- [3] H. Elmquist et al. Dymola dynamic modeling laboratory. User's manual. Dynasim AB. Sweden, 2001.
- [4] R. Franke and E. Arnold. The solver **Omuses/HOP** for structured large-scale constrained optimization: algorithm, implementation, and example application, Sixth SIAM Conference on Optimization, Atlanta, 1999.
- [5] T. Ziehn. Untersuchungen zur optimalen Steuerung der KA Jena mit Hilfe der Modelica-Bibliothek WasteWater. Ilmenau, Germany: Unpublished report, Dept. of Automation and Systems Engineering, Technische Universität Ilmenau, 2004.
- [6] R. Franke. Formulation of dynamic optimization problems using Modelica and their efficient solution. Proceedings of the 2nd International Modelica Conference, Oberpfaffenhofen, 2002.
- [7] E. Arnold and S. Dietze. Nonlinear moving horizon state estimation of an activated sludge model. In F. G. Filip, I. Dumitrache, and S. S. Iliescu, editors, Large Scale Systems: Theory and Applications. 9th IFAC/IFORS/IMACS/IFIP Symposium, pages 554-559, Bucharest, Romania, 2001.
- [8] E. Arnold, S. Dietze, and G. Reichl. Application of model-predictive control for long-term operation of a municipal wastewater treatment plant. In K. Konarczak and D. Trawicki, editors, Technology, Automation and Control of Wastewater and Drinking Water Systems, TiASWiK'02, pages 211-216, Gdansk-Sobieszewo, Poland, 2002.