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TWO - LEVEL DISSOLVED OXYGEN CONTROL FOR ACTIVATED SLUDGE PROCESSES

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Abstract:
Two-level controllers for dissolved oxygen reference trajectory tracking for activated sludge processes is proposed and investigated. Both the nutrient and the phosphorous removal from a wastewater by its biological treatment using an activated sludge technology are considered. Typically, an aeration system itself is a complicated hybrid nonlinear dynamical system with faster dynamics compared to internal dynamics of the dissolved oxygen at a biological reactor. It is common approach to neglect this dynamics and also important operational limitations of this system such as a limited frequency of allowed switching of the blowers. The paper proposes a two level controller to track prescribed dissolved oxygen trajectory. The upper level control unit produces desired aeration flow set points. For this unit the aeration system is an actuator. The nonlinear model predictive control algorithm is applied to design this controller unit. Also, the predictive control is used to design the lower level control unit based on a linearised hybrid dynamics of the aeration process. The overall controller is validated by simulation using real data sets and ASM2d model of the biological reactor.

Keywords: bio-technical processes, nonlinear systems, set-point control, predictive control, hierarchical control.

1. INTRODUCTION

An activated sludge wastewater treatment plant can be classified as a complex system due to its nonlinear dynamics, large uncertainty in uncontrolled inputs and in the model parameters and structure, multiple time scale of the dynamics, and multi input-output structure. In addition, rather scarce measurements are available during plant operation; hence using the mathematical models is essential in designing the controller. However, there is significant uncertainty in these models and their identification is still an open problem. Hence, until recently an intensive work on physical modelling wastewater plant was rather separated from using these models for a controller design. Recent developments in control technology and particular in model predictive control, handling an uncertainty, estimation, trajectory tracking in nonlinear systems and intelligent control triggered out new research and applications in this field. A hierarchical three level control structure that utilises multiple time scale in the plant dynamics for robust optimised control of the biological wastewater treatment was proposed in (Brdys and Zhang, 1999, 2001). In this paper a design of the lower level controller that allows tracking the robustly optimised dissolved oxygen concentration (DOC) trajectory prescribed by the higher control level is considered. The DO control design was considered in (e.g., Haarsma and Keesman, 1995; Olsson and Newell, 1989; Lindberg and Carlsson, 1966 and Brdys and Konarczak, 2001). A model predictive control based on linearised model of the DO dynamics was first considered by Haarsma and Keesman (1995). Nonlinear model reference adaptive control and nonlinear predictive control was investigated by Brdys and Konarczak (2001) for the nitrogen and phosphorus removal showing an excellent performance of the predictive controllers. A fuzzy model predictive controller that is based on piecewise linearisation is proposed in the accompanying paper (Brdys and Díaz-Maíquez, 2002). A superior performance of nonlinear predictive controller over the linear one was demonstrated. The controller output is an airflow this is a set point for an aeration systems, the actuator. Typically, an aeration system itself is a complicated hybrid nonlinear dynamical system with faster dynamics compared to internal dynamics of the dissolved oxygen at a biological reactor. It is common approach to neglect this dynamics and also important operational limitations of this system imposed by the blower station. A blower once has been switched off cannot be switched on immediately, but after some time period, due to thermal capacity of the motor. If the time period is long comparing to rate of change of the airflow then this needs to be taken into account by a controller scheduling operation of the blowers. Otherwise, the desired airflow demand may not be met as the needed blower is disabled and cannot be activated. The paper proposes a two level controller that is illustrated in Fig.1, to track prescribed dissolved oxygen trajectory. The upper level control unit produces desired set points of the aeration flow. The nonlinear model predictive algorithm proposed by Brdys and Konarczak (2001) is applied to design this controller unit. Also, the predictive control algorithm is used to design the lower level control unit based on a linearised hybrid dynamics of the aeration process. The overall controller is validated by simulation using real data sets and ASM2d model of the biological reactor.

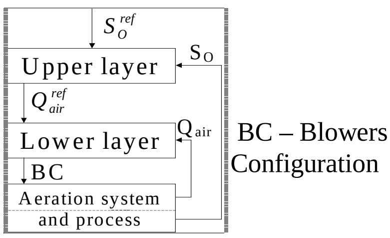

Fig. 1. The controller structure

2. UPPER LEVEL CONTROLLER: AERATION FLOW GENERATION

2.1 An approach to controller design

Considering the dissolved oxygen (DO) control problem the aerobic zone can be separated from other parts of the WWTP (Waste Water Treatment Plant), with the inputs and outputs depicted in Fig. 2:

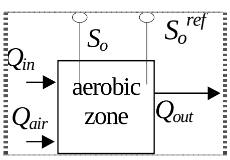

Fig. 2. Inputs and outputs of an aerobic zone

A dynamics of S_o is described by the nonlinear differential equation (Olsson and Newell, 1999):

$$\frac{dS_o(t)}{dt} = \frac{Q_{in}(t) \cdot S_{o,in}(t) - Q_{out}(t) \cdot S_o(t)}{V(t)} + k_{La}(Q_{air}(t))(S_{o,sat} - S_o(t)) - \frac{S_o(t)}{K_o + S_o(t)} R_r(t) \qquad (1)$$

where V, $S_{o,sat}$=9.23gm^{-3},K_o=0.3gm^{-3} denote volume of aeration tank, dissolved oxygen saturation concentration and Monod constant DO limit, respectively and $R_r(t)$ is the theoretical respiration level.

The function $k_{La}(Q_{air})$ describes the oxygen transfer and it is in general nonlinear and depends on the aeration actuating system and sludge conditions. It is assumed linear in the paper (Olsson and Newell, 1999) and

$$k_{la}(Q_{air}) = \alpha Q_{air} + \beta \qquad (2)$$

where the constants α, β are plant dependent and during simulations α=3.5m^{-3}, β=0h^{-1}.

The third term in (1) denotes the respiration rate in the reactor. Although the respiration rate may rapidly change responding to fast changes of the influence or returned sludge flow the quantity R_r(t) changes much slower than S_o(t) (Brdys and Konarczak, 2001). There are another twelve nonlinear differential equations in the ASM1 model and eighteen in the ASM2d model needed to determine R_r(t). Structure of ASM models is presented in Fig. 3. It means that the state-space model of the dissolved oxygen concentration is described by very high order nonlinear dynamics. Moreover, with phosphorus reactions taken into account, the ASM2d model (Henze, 1999) needs to be used that involves more than sixty parameters. Most of these parameters cannot be identified (they are not identifiable). Hence, the control problem is also under heavy uncertainty and adaptive or robust control technology is needed in order to handle the uncertainty. Regardless on obvious difficulties in developing good dynamic performance control algorithm, a dimension of the resulting controller would not allow its efficient implementation as the S_o dynamics is fast. The uncertainty as it follows from (1) has an impact on S_o only through R_r. Clearly, S_o influences R_r. This cause-effect loop can be broken by considering R_r(t) as an external signal. Indeed, assuming R_r(t) is the disturbance input the overall dynamic model reduces to (1) and becomes the SISO nonlinear model. The control design problem becomes vastly simplified. Moreover, usually the first element in (1) is relatively small in relation to the other elements and can be neglected. Hence, the dynamics described by (1) can be reduced to:

$$\frac{dS_o(t)}{dt} = k_{La}(Q_{air}(t)) \cdot (S_{o,sat} - S_o(t)) - \frac{S_o(t)}{K_o + S_o(t)} \cdot R_r(t) \qquad (3)$$

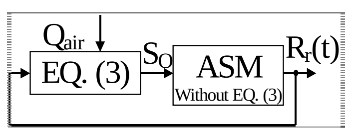

Fig. 3. ASM Structure

2.2 Nonlinear model predictive controller (NMPC)

A fundamental prerequisite to be successful in the controller design that is based entirely on (1) is an ability to obtain on-line good enough estimates of R_r(t) (Lukasse 1997) over required periods. Lindberg and Carlsson (1996) have developed Kalman filter for the respiration rate estimation (the third term in (1)) together with parameters of the exponentially nonlinear function $k_{La}(Q_{air})$. The estimates were used to feed their nonlinear controller designed based on a feedback linearisation. As there exist practically active constraints on the magnitude and rate of change of Q_{air} the paper applies model predictive control technology (Maciejowski, 2002) for the DO controller design. Hence, a predictor of R_r is needed. As the problem has at least two-time scale structure, that is R_r changes much slower than S_o, (Brdys and Konarczak (2001) have shown that (1) can be used to design the predictor that is suitable for the model predictive controller (MPC) design. Namely, discretising in time (3), the respiration value at t=kT, where T denotes the DO sampling rate, can be obtained in terms of the measured values of S_o at the time instants kT and $(k+1)T$ and the control input applied at the k-th time step as:

$$R_r(k) = -\frac{S_o(k+1) - S_o(k)}{T} \cdot \frac{K_o + S_o(k)}{S_o(k)} - \left(k_{La}(Q_{air}(k))(S_{o,sat} - S_o(k))\right) \cdot \frac{K_o + S_o(k)}{S_o(k)} \quad (4)$$

As R_r(t) changes slowly this value is taken as the prediction $\hat{R}_{r,[k+1,k+1+H_p]}(k)$ of $R_r(k)$ over the horizon $[k+1, k+1+H_p]$ in the model based optimisation problem that is solved by the MPC at $(k+1)T$. If clean measurements of R_r(t) are available the formula (4) is used to interpolate the values between the measurement time instants. The control input $Q_{air}(k)$ is a set point to the reactor actuator that is to an aeration system and therefore, the following constraints must be satisfied:

$$Q_{air}(kT) \le Q_{air}^{\max} \text{ and}$$

$$\left| Q_{air}((k+1)T) - Q_{air}(kT) \right| \le \Delta Q_{air}^{\max} \quad (5)$$

where $Q_{air}^{\max} = 3\text{m}^3\text{h}^{-1}\text{m}^{-3}$ and $\Delta Q_{air}^{\max} = 3\text{m}^3\text{h}^{-1}\text{m}^{-3}$.

The NMPC generates at time instant $k+1$ the control sequence $\{Q_{air}(k+i)\}_{i=1}^{H_p-1}$, where H_p is the control horizon, based on a discretised nonlinear model (3) with the prediction of trajectory of $R_r(k)$ according to (4), by minimising a standard quadratic function. If necessary, more samples of DO at kT_γ over $[kT,(k+1)\mathrm{T}]$, where $T_\gamma < T$, are also used to estimate $R_\gamma(k)$ by using (4). A linear interpolation is applied for the smoothing purposes. Then the value of $R_\gamma(k)$ obtained for the last T_r interval is taken as the prediction for an optimisation problem that is solved by MPC $(k+1)T$. During simulations H_p = 5, T = 5 min, and T_r = 30s were used.

3. LOWER LEVEL CONTROLLER: AERATION FLOW TRACKING

A typical structure of the WWTP aeration system is depicted in Fig. 4. In practice WWTP include more than one aeration tank and one blower station to supply aeration tanks with the air. The blower station contains several blowers that force air to the collector and then the airflow is divided among diffusers of the aeration tanks.

Two types of the blower motors are used: variable-speed and multiple-speed. Inverters power the variable-speed blowers. Typically, two-speed blowers are used. Both types of the blowers have important operational limitation. A blower once has been switched off cannot be switched on immediately, but after some time period. Required airflow of each diffuser is maintained through throttling valve position. Proportional controller is often used for this purpose, with required Q_{air} as a reference input. Due to the throttle valve features such as dead zone, hystersis, it is in fact a nonlinear system. The airflow should not be throttled too much. This means, that a pressure at the collector node, p_c, should have a value that will allow throttling valves to work at nearly fully opened position. An aeration system itself is a complicated hybrid nonlinear dynamical system with fast dynamics. Due to different pipe parameters the flow dynamics features of different elements of the aeration system are not the same. Some of them can be neglected. Usually in this system the collector-diffuser dynamics can be neglected. Dynamics of the throttling valves positioning can also be neglected.

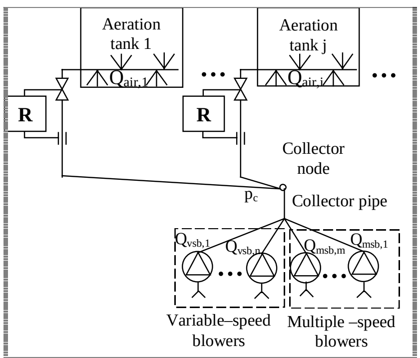

Fig. 4. Typical structure of the WWTP aeration systems

3.1 Modelling the aeration system

The model of the aeration system consists of the following main elements.

Blower station The blower station compresses air assuring appropriate pressure p_c at the collector node. The station consists of blowers with fixed-speed motors, multiple-speed motors and variable-speed motors. The following linear approximated model has been proposed for the blowers:

$$Q_b = a\Delta p_b + bn_b + c \quad (6)$$

where Q_b – blower flow, Δp_b – pressure loss across the blower, n_b – blower speed, c-constant.

Collector pipe: Collector pipe is treated as the fluid capacitance with negligible fluid resistance. The pressure at the collector node is modelled by the equation:

$$\frac{dp_c}{dt} = \frac{1}{C_c}\left(\sum Q_b - Q_c\right) \tag{7}$$

where
$$C_c = \frac{p_c}{V_c} \tag{8}$$

$$p_c = p_{od} + \Delta p_d + p_h \tag{9}$$

where C_c – collector capacitance, Q_c – collector flow, V_c – collector volume, p_c – pressure at the collector node, p_{od} - opening pressure of a diffuser, Δp_d – pressure loss across a diffuser, p_h – hydrostatic pressure at an aeration tank

Pipe connecting the collector node and the diffuser The collector-diffuser pipe is modelled as a fluid capacitance with two resistances. The first resistance is nonlinear and its value depends upon the throttling valve angular position. The second one represents the diffuser resistance. The model equation reads:

$$\frac{dQ_{air}}{dt} = \frac{1}{C_d}\cdot\frac{1}{R_d}\cdot\frac{1}{R_v}\cdot\Delta p_d - \left(\frac{1}{C_d}\cdot\frac{1}{R_v} + \frac{1}{C_d}\cdot\frac{1}{R_d}\right)\cdot Q_{air} \tag{10}$$

where Q_{air} – air flow to aeration tank, C_d – diffuser capacitance, R_d – diffuser resistance, R_v – throttling valve resistance and

$$R_d = \frac{\Delta p_d}{Q_{air}} \tag{11}$$

$$R_v = \frac{\left(\frac{a\cdot Q_{air}}{\varphi^b}\right)^c}{Q_{air}} \tag{12}$$

where φ - angular valve position

Airflow regulator: A proportional regulator model is used. In the control loop nonlinear elements are added: dead zone and hysteresis.

3.2 Design of hybrid model predictive controller (HMPC)

The problem that is to be solved at the lower level is to schedule over time horizon H_p with the sampling rate T_l, the blower motor operation and to determine which blowers are to be *on* and the speed for the variable speed motors in such a manner that total air flow demand is satisfied and at the same time all limitations resulting from the dynamical and static properties of the blower units as well as limit on a high pressure at the collector node are meet. The aeration system model described above is used to for designing the model predictive controller at the lower level. The corresponding optimisation problem is nonlinear and mixed integer, hence difficult to be solved. A sparse structure of nonlinearities is utilised and a piecewise linearisation is efficiently applied to obtain an accurate enough approximation of the original problem in a form of a mixed integer linear programming problem (MILP). The controller minimises a cost of energy consumed by the blower station over prediction time horizon:

$$\min \sum_l \left[\sum_m Q_{msb}(m,l) + \sum_n Q_{vsb}(n,l) + p_c(l)\right] \tag{13}$$

where l – l-th prediction time step, $Q_{msb}(i,l)$ – air flow of *m-th* blower with fixed speed (multi-speed) motor at time step l, $Q_{vsb}(n,l)$ – air flow of *n-th* blower with variable speed motor at time step l, $p_c(l)$ – collector pressure at at the step l.

Let us notice that in fact the repetitive optimising control technology is used. In general, at the lower level the prediction horizon and sampling interval are shorter than at the upper level.
The main constraints to be met at each time step l are as follows:

$$Q_{air,tot}(l) = \sum_j Q_{air,ref}(j,l) \tag{14}$$

where j – j-th aeration tank, $Q_{air,tot}(l)$ – total air demand at step l,
$Q_{air,ref}(n,l)$ – the *j-th* aeration tank airflow that is prescribed at *l-th* time step by the *upper level* MPC. Hence,

$$Q_{air}(j,l) = Q_{air,ref}(j,l) \tag{15}$$

where $Q_{air}(j,l)$ – air flow blown to *j-th* aeration tank at step l;

$$\sum_m Q_{msb}(m,l) + \sum_n Q_{vsb}(n,l) = Q_{air,tot}(l) \tag{16}$$

$$p_c(l) \le p_{c,max} \tag{17}$$

where $p_{c,max}$ – upper limit on collector pressure;

$$p_c(l) = \Delta p_d(j,l) + p_{od}(j,l) + p_h(j,l) \tag{17}$$

where $\Delta p_d(j,l)$ – pressure drop across *j-th* diffuser and throttling valve at time step l, $p_{od}(j,l)$ – opening pressure of the *j-th* diffuser at time step l. $p_h(j,l)$ – hydrostatic pressure of the sewer at j-th aerobic tank at time step l

Models of the diffuser profile $\Delta p_{od}(Q_{air})$ have been included in constraints.

For each blower a constraint on a minimum time interval between the consecutive blower motor shut down and start up instants is formulated as:

$$X_b(k) = X_b(k-1) + X_{b,on}(k-l) - X_{b,off}(k) \tag{18}$$

$$X_{b,on}(k) + X_b(k) \le 1 \tag{19}$$

$$X_b(k) = X_{s1}(k) + X_{s2}(k) \tag{20}$$

$$X_{s1}(k) + X_{s2}(k) \le 1 \tag{21}$$

where: $X_b(k)$ – operational state index at time interval k, $X_{b,on}(k)$ – start up index at time interval l, $X_{b,off}(k)$ – shut down index of the at time interval l, $X_{s1}(k)$, $X_{s2}(k)$– speed state index corresponding to its the speed at time interval k, and l is a time steps when cant turn on blower. All indices are binary variables.
Notice, that the Esq. 18-21 constitutes discrete dynamics. This dynamics added to the continuous dynamics yields overall a hybrid dynamical system.

During simulations, H_p =10 and T_l = 5min or 2.5min, were assumed for the lower level controller. Because it was assumed at the upper control level that H_p = 5, the last value of the airflow predicted by the upper level controller was extended to cover the remaining time steps at the lower level prediction horizon.

4. CASE STUDY SIMULATION RESULTS

In this paper, the WWTP at Kartuzy is considered. The WWTP aeration zone consists of three aeration tanks. Two blowers supply the overall aeration system. The first one can run with two fixed speeds while the second is variable speed, thus it is controlled by an inverter. After a blower motor has been shut down it cannot be started again earlier than in 15 minutes. The control system operation over 24 hours was simulated. Two sets of sampling rates were investigated at the upper and lower control levels: T=T_l = 5min, and T = 5min and T_l = 2.5min, respectively. The prediction horizons at the upper and lower levels were 5 and 10, respectively. For the first sampling rate, the last reference value produced by the upper level controller was used at the lower control lever to produce the needed reference values over last five time steps. The control schedules of fixed speed blower 1 for T_l = 5min is presented in Fig. 5.

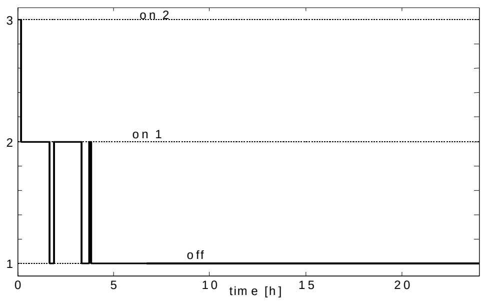

Fig. 5. Schedule of the blower 1, T_l = 5min

The blower 2 speed trajectory for T_l = 5min is illustrated in Fig. 6.

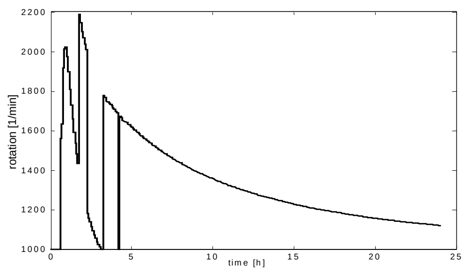

Fig. 6. Speed of the blower 2, T_l = 5min

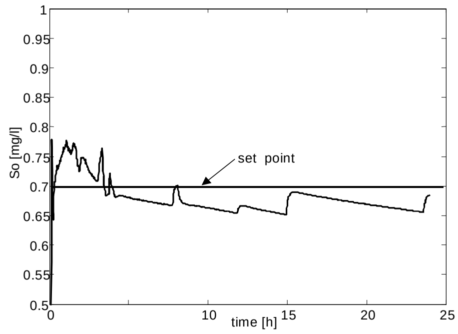

Fig. 7. S_o concentration in aeration tank 1, T_l = 5min

Fig. 7 illustrates the dissolved oxygen concentration S_o in the aeration tank 1 for T_l = 5min. The results show on a good tracking performance of the hierarchical controller. The longer sampling period at the lower level is acceptable.

The biological operating conditions for the controller are determined by biomass concentration in aeration tank and by wastewater quality at inlet to WWTP. The inflow to the first aerobic tank was Q_{in}=2500 [m^3/h], the volumes of the aerobic tanks were 1760 m^3 860 m^3 and 1150 m^3 respectively. Variations of the biomass concentration in the first aeration tank over 24 hours are depicted in Fig. 9.

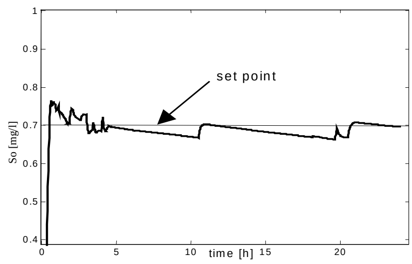

Fig. 8. S_o concentration in tank 1, T_l = 2.5min

Comparisons of the air flow demanded by upper level MPC and air flow supplied to aeration tanks are presented in Fig. 10, for T_l = 5min and in Fig. 11 for T_l = 2.5min. A nonlinear model of the aeration system was used in this experiment for simulation of the system responses.

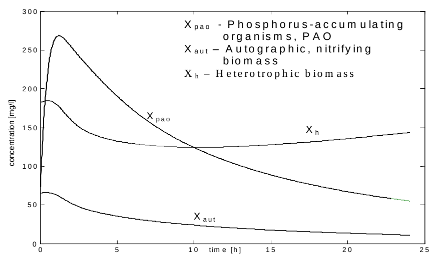

Fig. 9. Most important biomass concentration in aerobic tank 1

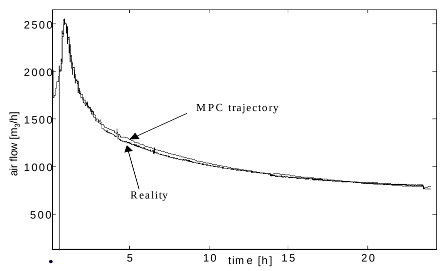

Fig. 10. Air flow comparison: upper level MPC desired and supplied, T_l = 5min

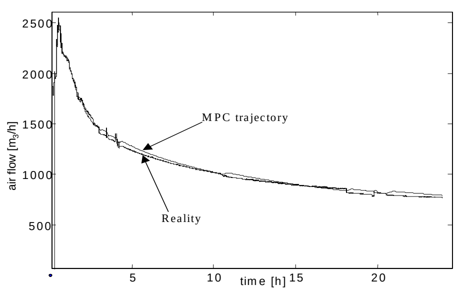

Fig. 11. Air flow comparison: upper level MPC desired and supplied, T_l = 2.5min

Comparison of the air flow demanded by upper MPC level and air flow calculated by lower HMPC is presented in Fig. 12 for T_l = 5min. The simplified piecewise linear model of the aeration system was used be the HMPC and in calculating the system responses.

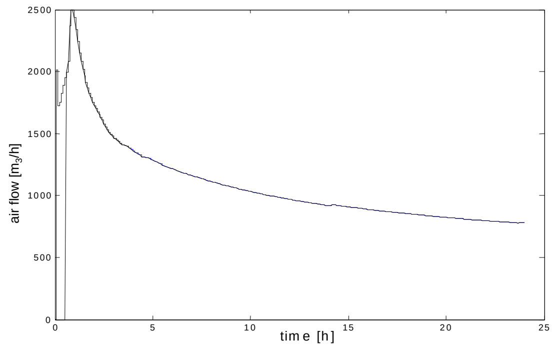

Fig. 12. Air flow comparison: upper level MPC and lower level HMPC, T_l = 5min

In typical operational practice pressure at the collector node p_c is kept at sufficiently high constant level, which guarantees that required airflows will be supplied to the aeration tank over a range of normal operational conditions. This causes that the valves must throttle airflows provided by the blowers. Clearly, it is not good approach from the economical point of view. In Fig. 13 the optimal pressure p_c that is generated by the proposed controller is shown.

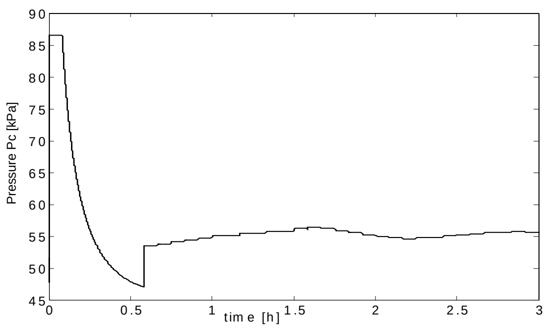

Fig. 13. Optimal pressure p_c

Total calculation time at each step was smaller than 10s (MPC – 1s for each tank, HMPC – 5s). This case study is representative for many WWTP in Poland e.g. Kartuzy, Tczew. Simulation was carried out in Matlab environment. The blowers schedule was determined by using CPLEX solver on PC standard computer with Pentium III 933Mz processor.

5. CONCLUSIONS

The paper has considered a dissolved oxygen reference trajectory tracking for activated sludge processes. Both the nutrient and the phosphorous removal from a wastewater by its biological treatment using an activated sludge technology have been considered. A two-level model predictive controller has been proposed and investigated. As opposed to the previous work the aeration system control has also been included into the overall controller design. This integrated approach has allowed catering for essential operational constraints of the aeration system in a predictive manner. This in turn, has led to the robust least energy and robust operation of the biological process. The properties and tracking performance of the controller have been investigated by simulation based on data records from Kartuzy case study plant and very promising results have been obtained.

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