Comparison of Two Nonlinear Predictive Control Algorithms for Dissolved Oxygen Tracking Problem at WWTP

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Abstract:
The wastewater treatment plant is classified as a complex system due to its nonlinear dynamics, large uncertainty in the disturbance inputs, multiple time scales in the internal process dynamics and multivariable structure. Aeration is an important and expensive activity that is carried out during wastewater treatment plant operation. A precise aeration control in biological processes for all the operating conditions is necessary in order to guarantee adequate biological conditions for microorganisms. Therefore, the most important is to operate the biological processes so that a minimal energy was consumed and minimal DO concentration demand was applied. The paper proposes a two advanced control systems to track the dissolved oxygen reference trajectory. A decentralized and multivariable nonlinear predictive control algorithms are designed and compared. Simulation tests for the case study wastewater treatment plant are presented.

Keywords: *aeration, dissolved oxygen, wastewater treatment, mathematical modelling, nonlinear system, predictive control*

1. Introduction
1.1. General information

Progressive development of technology and human population growth caused the amount of produced sewage to increase. Years of experience and scientific research, gave rise to the idea about wastewater treatment plant (WWTP). It is a complex, nonlinear biological-chemical-physical system with strong interactions between processes. Processes are difficult to control due to large disturbances such as inflow and load, nonlinearity, time-varying and complexity with strong coupling of the process variables.

The popular treatment technology used in the field of WWTPs is the biological. Most of the municipal WWTPs use activated sludge processes. Activated sludge refers to a mass of microorganisms where help clean up wastewater. This is a process in which air or oxygen is forced into sewage liquor to develop a biological floc which reduces the organic content of the sewage. Activated sludge is used where high removal of organic pollution is required. For effective wastewater treatment, an activated sludge requires a continuous supply of oxygen/air. Aeration is used in different parts of a WWTP, especially is applied to biological processes (e.g. nitrification, denitrification and phosphorus removal). Additionally, energy consumption of aeration processes has the major share in energy bill at a WWTP.

Dissolved oxygen (DO) concentration is the most important control parameter in the biological WWTP. Unfortunately, in industrial practice, the control of DO is usually carried out using a simple feedback loop (e.g. linear PI algorithm with constant parameters) that does not aim at all at combining the tracking functions with the energy cost optimization. Good control performance for all the operating conditions cannot be achieved. Furthermore, the lack of on-line measurements at the WWTP, may result in limited use of advanced control systems.

1.2. Survey of related works

As mentioned earlier, control of DO is very important and difficult activity in the activated sludge processes. As the DO dynamics is nonlinear and typically WWTP operates under high variability of the influent quality and pollutant parameters.

Works related to control of DO have a long history. Different control technologies have been researched over the last years, e.g. adaptive controller [2], on/off controller with genetic algorithms [11], multivariable PID controller [22], nonlinear multiregional PI controller [23], fuzzy controller [2].

The second group of DO control strategies are algorithms, where beside DO measurement, additionally ammonia nitrogen (NH_4), nitrate (NO_3) and phosphate (PO_4) measurements are included for control system design [21,17].

An interesting and comprehensive review of DO control can be found in [1].

The model predictive control (MPC) technology is an attractive method for dynamic optimizing control. The MPC optimizer enables for direct incorporation of the constraints in the control problem into the optimization task at each time step, what is a great advantage of this technology. During the last years, many industrial applications of control systems have utilized the MPC technology [20].

The MPC algorithm was also applied for DO control at the WWTP. The linear MPC algorithm was proposed in [12] and its application to benchmark simulation WWTP. In [5] the hybrid nonlinear predictive controller was applied. The binary control signals were reformulated to nonlinear programming task at every sampling time. Interesting control results were obtained. In [7] the MPC system of DO control based on self-organizing radial basis function neural

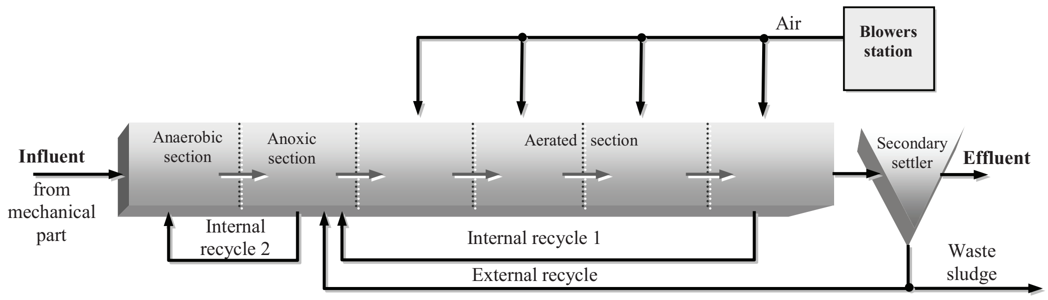

Fig. 1. Scheme of biological WWTP at Kartuzy

network model was designed and examined for the benchmark simulation WWTP.

In [16] a decentralized nonlinear hierarchical predictive control system was proposed. Biological reactor to be coupled with an aeration system and in order to track prescribed DO trajectories. The upper level controller (UCL) prescribes trajectories for airflows desired to be delivered into the aerobic biological reactor zones. The lower level controller (LLC) forces the aeration system to follow those set point trajectories. This controller was synthesized as a hybrid (discrete and continuous manipulated variables) nonlinear MPC.

Authors of the paper [6] derived a nonlinear hybrid predictive control algorithm for the LLC. Dedicated operators were used to derive genetic algorithms, thus allowing for efficient handling of the switching constraints and nonlinear hybrid system dynamics.

In [15] a nonlinear multivariable hierarchical MPC was applied to design the ULC. This controller extends to plants with several aerobic zones supplied by an aeration system of limited capacity. This controller handles the airflow distribution between the zones. The constraint on the airflow that can be delivered by the aeration system is then active. The ULC produces the airflow demands as set points for the LLC.

In summary, the aim of the paper is the design of the hybrid nonlinear control system to perform an efficient control quality of DO concentration for different operating conditions. This paper further develops the results presented in [16,15]. Two advanced hierarchical nonlinear predictive control systems are designed and compared. Only DO and airflow measurements are applied for control systems design. In this paper, as opposite for previous research works [16,15] dynamic of aeration system is omitted and treated as a static system, which provides the amount of air required by the control system. Simulation tests for case study plant are presented.

2. Description of the WWTP

Kartuzy WWTP is typical system with a continuous flow throughout the plant. This system consists of two parts. One is the mechanical where solids, mineral and insoluble organic pollutants are removed. The second is the biological part that is composed of the activated sludge process. The activated sludge method is applied for biological wastewater treatment processes. Only a biological part is considered in the paper. The structure of biological part for the case study plant is shown in Fig. 1.

The advanced biological treatment with nutrient removal is accomplished in the activated sludge reactor designed and operated according the University of Cape Town (UCT) process. The first zone where the phosphorus is released is anaerobic. The second zone where the denitrification process is conducted is anoxic. The internal recirculation 2 of mixed liquor originates from the anoxic zone. The returned activated sludge from the bottom of the clarifiers and the internal recirculation 1 from the end of the aerobic zone (containing nitrates) are directed to the anoxic zone. The last part of the reactor (aerobic) is aerated by a diffused aeration system. This zone is divided into four compartments of various intensity of aeration. The anaerobic, anoxic, and four aerobic tanks have volumes of 800, 800, 700, 1760, 860, and 1150 m^3, respectively. Oxygen is supplied to aerated tanks by the aeration system (blowers, pipes, throttling valves and diffusers). Wastewater is mixed with activated sludge, which helps during the process of wastewater treatment. Different aeration methods are applied: high-purity oxygen aeration, mechanical aeration, and diffused aeration [13]. The last technique is used at the Kartuzy WWTP. The aeration system delivers air to each of the aeration tanks. The wastewater and activated sludge are separated into two parallel secondary settlers. The volume of each secondary settler is approximately 1600 m^3. The activated sludge is internally recirculated from the anoxic tank to the anaerobic zone and from the last aerobic zone to the anoxic tank. These recirculations are typically set to 45 to 100% and 210% of influent waste. Additionally, the wastewater is recirculated from the secondary settlers to the anoxic tank (45 to 100% of influent waste). The excess waste sludge is removed, chemically stabilized, and stored.

3. Control structures

It is industry practice that simple technology is used to control of DO: manual control, rule-based control and PI controller with fixed parameters. High quality of control cannot be obtained by conventional and linear control methods.

MPC technology is an attractive optimizing method for advanced control of dynamic nonlinear systems. The nonlinear MPC algorithm uses the DO model for prediction. The predictive control adjusts its operation in advance, before there are changes in the output of the control system. The two structures of the new control systems are illustrated in Figs. 2–3.

The controller's objective is to force the $S_{o,j}$ (controlled variable) into zones indicated by prescribed references $S_{o,j}^{ref}$ and, at the same time, to minimize the associated electricity cost by blowing air. The controller's objective is to force the $S_{o,j}$ (controlled variable) into zones indicated by prescribed references $S_{o,j}^{ref}$ and, at the same time, to minimize the associated electricity cost by blowing air. The manipulated variables in the control systems are airflows to the each of the aerobic tanks. Decentralized control system (Fig. 2, control system 1), based on information about DO concentration calculates control trajectories of the airflows, taking into account its constraints on minimum and maximum value as well as the rate of change in one step prediction. Respiration R is the disturbing variable that affects DO concentration.

All aeration tanks are connected to a single aeration system. Hence, four independently operating controllers may have a problem with distributing required amounts of air correctly (e.g., for large inflow to the WWTP and/or a sudden increase in concentration of pollutants in wastewater flow). Therefore, a multivariable, nonlinear MPC is also designed (Fig. 3, control system 2).

4. Mathematical models

4.1. Model of biological WWTP

The most popular mathematical description of biological processes at WWTP is a series defined by Activated Sludge Models (ASMs) proposed by International Water Association (IWA). The models (ASM1, ASM2, ASM2d, ASM3) were presented and summarized in [10]. A critical reviews of activated sludge modelling for seven most commonly used models were presented in [8]. In the paper the biological processes are modelled by ASM2d model. ASM2d consists of 21 state variables and 20 kinetic and stoichiometric parameters. Values of those parameters are equal to their default values at 20°C [9]. ASM2d model was calibrated based on real data sets from the Kartuzy WWTP. Additionally, data from the plant permitted to define the quality of load: chemical oxygen demand (COD), total nitrogen concentration (TN) and total phosphorous concentration (TP). Verification of the modelling results was satisfactory and so they were used for control purposes.

4.2. Model of DO concentration

A dynamics of dissolved oxygen for the j-th aeration tank is described by the following nonlinear differential equation:

$$\frac{dS_{o,j}(t)}{dt} = k_{La}\left(Q_{air}(t)\right)\cdot\left(S_{o,sat} - S_o(t)\right) - \frac{S_{o,j}(t)}{K_o + S_{o,j}(t)}\cdot R_j(t) \quad (1)$$

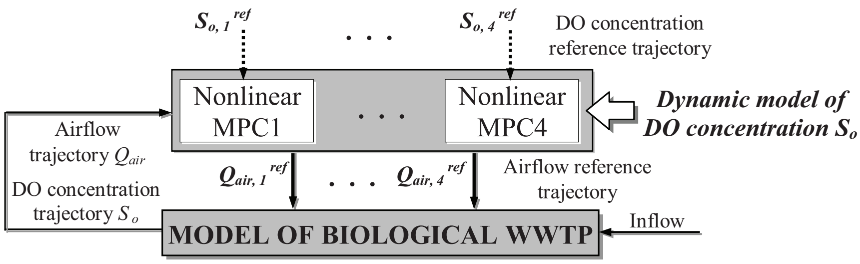

Fig. 2. Structure of the control system 1

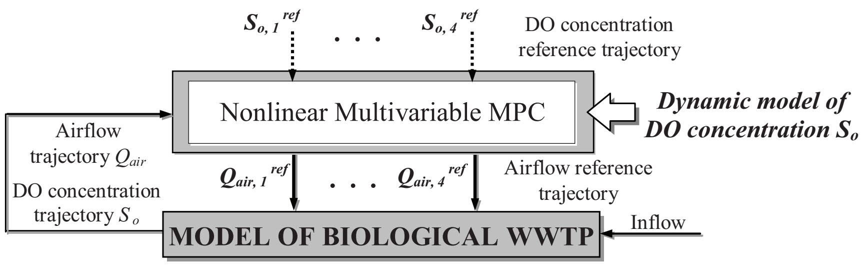

Fig. 3. Structure of the control system 2

where S_o – dissolved oxygen concentration, k_{La} – oxygen transfer function, Q_{air} – airflow, R - respiration, $S_{o,sat} = 8.637$ g O_2 /m^3 – dissolved oxygen saturation concentration, $K_o = 0.2$ g/m^3 – Monod's constant.

The function, $k_{La}(Q_{air})$, describes the oxygen transfer and depends on the aeration actuating system and sludge conditions. Different approaches to modelling this function are presented in literature. In this paper, the linear model is applied:

$$k_{La}\left(Q_{air,j}\right)=\alpha\cdot Q_{air,j}\left(t\right) \tag{2}$$

where $\alpha = 0.208$ 1/m^3 [18].

The respiration R is an important parameter to biological processes taking place in aerobic zones. The respiration varies with time, depends on the biomass concentration, and describes oxygen consumption by the microorganism. This variable can be calculated using the ASM2d model [9]; however, to determine R, another 18 nonlinear differential equations in the ASM2d model are required. Because of the complexity of the ASM2d model, respiration R is treated as an external disturbance signal.

Respiration can be measured by a respirometer. In some research, respiration was assumed to measure and be used for monitoring and control of biological processes. However, dedicated measuring equipment is very expensive; hence, this variable is rarely being measured. Therefore, respiration has to be estimated to be used for control. Different approaches based on the augmented Kalman filter were taken for joint estimation of respiration and oxygen transfer functions [14]. Another approach was presented in literature [19]. A sequential algorithm with the Kalman filter was proposed and investigated. The approach presented in [4] is used in this paper. It is based on point estimation of respiration at the appropriate time instant valid for a particular prediction horizon sufficient to be taken as constant.

5. Predictive controllers design

A model of DO concentration is needed to design an MPC (see (1)). For the j-th aeration tank, the following discrete model can be formulated:

$$\begin{aligned}&\frac{S_{o,j}\left(k+i\right)-S_{o,j}\left(k+i-1\right)}{T}=\\&=k_La\left(Q_{air,j}\left(k+i-1\right)\right)\cdot\left(S_{o,sat}-S_{o,j}\left(k+i-1\right)\right)+\\&-\frac{S_{o,j}\left(k+i-1\right)}{K_o+S_{o,j}\left(k+i-1\right)}\cdot R_j\left(k+i-1\right)\end{aligned} \tag{3}$$

where k and T are the discrete time instant and dissolved oxygen sampling interval.

At the time instant $(k+1)T$, the estimate $\hat{R}_j(k)$ of $R_j(kT)$ can be obtained by discretizing (3), solving the resulting discrete time equation for the unknown respiration value $R_j(k)\overset{\Delta}{=}R_j(kT)$, and substituting the expression $S_{o,j}(k), S_{o,j}(k+1)$ with the measurements $S^m_{o,j}(k), S^m_{o,j}(k+1)$ where $S_{o,j}(k)\overset{\Delta}{=}S_{o,j}(kT)$. Hence:

$$\begin{aligned}\hat{R}_j\left(k\right)=&-\frac{S^m_{o,j}\left(k+1\right)-S^m_{o,j}\left(k\right)}{T}\cdot\frac{K_o+S^m_{o,j}\left(k\right)}{S^m_{o,j}\left(k\right)}+\\&-k_La\left(Q_{air,j}\left(k\right)\right)\cdot\left(S_{o,sat}-S^m_{o,j}\left(k\right)\right)\cdot\frac{K_o+S^m_{o,j}\left(k\right)}{S^m_{o,j}\left(k\right)}\end{aligned} \tag{4}$$

where $Q_{air,j}(t)\overset{\Delta}{=}Q_{air,j}(k),\ t\in\left[kT,(k+1)T\right]$.

In (4), it is important to note that there is a one-step delay. This has no practical significance because of the variability of the aforementioned slow respiration in relation to the rate dissolved oxygen concentration changes. Moreover, it is possible to treat the temporary estimate as a constant prediction of respiration over a suitably selected length of prediction horizon. Because (4) contains measurements, respiration (i.e., differentiation of the measurement noise present in the measurement of dissolved oxygen) occurs during estimation. Results of previous studies [4] indicate that, provided a typical signal is within acceptable noise levels, its effect on the quality of estimates can be omitted (see Figs. 4–7). In Figs. 4–7 the examples trajectories of the DO concentration and respiration R are presented, with (Fig. 4 and 6) and without (Fig. 5 and 7) measuring noise. Knowing the measurement errors characteristic of devices for measuring the DO concentration, the standard deviation of measurement equal 0.1 g O_2/m^3 was assumed.

Results confirm the assumption of low impact of measurement noise in the measurement of DO concentration on the quality of estimate of respiration R. In addition, simplification of the model and the resulting inaccuracies are eliminated by feedback mechanism which is an integral part of the control system.

5.1. Control system 1

The nonlinear MPC performance function for j-th aeration tank is defined as:

$$J=\begin{aligned}&\sum_{i=1}^{Hp}\left(S_{o,j}\left(k+i|k\right)-S^{ref}_{o,j}\left(k+i|k\right)\right)^2+\\&+\sum_{i=1}^{Hp}\alpha\left(Q_{air,j}\left(k+i|k\right)-Q_{air,j}\left(k+i-1|k\right)\right)^2+\\&+\beta\left(Q_{air,j}\left(k-1|k-1\right)-Q_{air,j}\left(k|k\right)\right)^2+\\&+\sum_{i=1}^{Hp}\chi\left(Q_{air,j}\left(k+i-1|k\right)\right)^2\end{aligned}\quad ;j\in\{1,2,3,4\} \tag{5}$$

The first term in (5) represents the tracking error. The second and third terms describe rates of changes of the control input over H_p (prediction horizon) while the fourth term represents the control cost. The weights α, β and χ are tuning knobs used to achieve a desired compromise between the tracking error, the intensity of switching the blowers, and the cost of the energy used for pumping air.

Let $Q^{\min}_{air,j}$ and $Q^{\max}_{air,j}$ be the minimum and maximum value of the airflow, respectively. The constraints

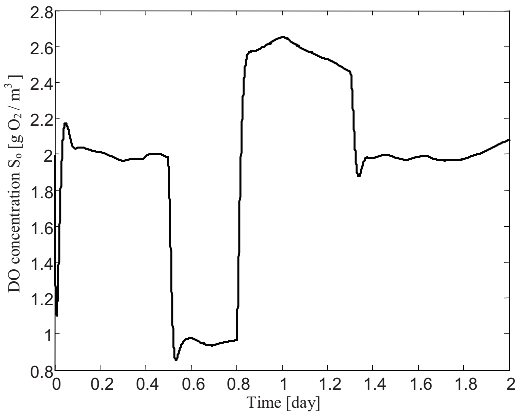

Fig. 4. DO concentration in aeration tank – without measurement noise

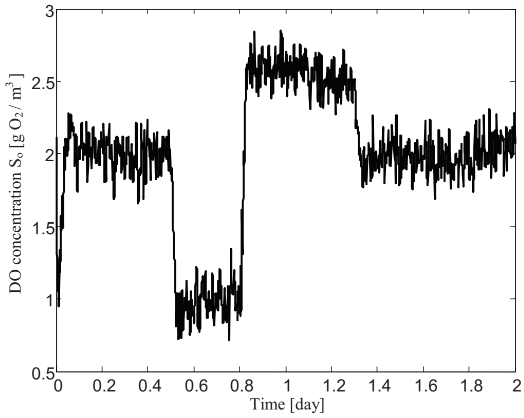

Fig. 5. DO concentration in aeration tank – with measurement noise

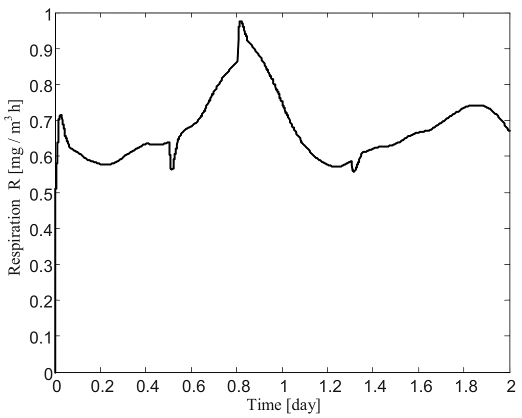

Fig. 6. Respiration in aeration tank – without measurement noise

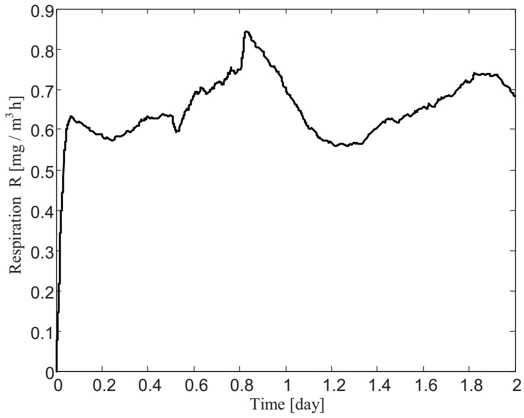

Fig. 7. Respiration in aeration tank – with measurement noise

on minimum and maximum values of control action at each prediction step are defined as follows:

$$Q_{air,j}^{\min} \le Q_{air,j}(k+i-1\,|\,k) \le Q_{air,j}^{\max}; \quad \begin{matrix} j \in \{1,2,3,4\} \\ i = 1,\dots,H_p \end{matrix} \tag{6}$$

where $Q_{air,j}^{\min} = 0\ \mathrm{m^3/h}$ and $Q_{air,j}^{\max} = 1800\ \mathrm{m^3/h}$.

Moreover, $\Delta Q_{air,j}^{\max}$ is the maximum value of the rate of change. The constraints are given by:

$$\begin{cases} \left|Q_{air,j}(k+i\,|\,k) - Q_{air,j}(k+i-1\,|\,k)\right| \le \Delta Q_{air,j}^{\max} \\ \left|Q_{air,j}(k-1\,|\,k-1) - Q_{air,j}(k\,|\,k)\right| \le \Delta Q_{air,j}^{\max} \end{cases}; \quad \begin{matrix} j \in \{1,2,3,4\} \\ i = 1,\dots,H_p \end{matrix} \tag{7}$$

where $\Delta Q_{air,j}^{\max} = 1800\ \mathrm{m^3/h}$.

At the time instants kT the nonlinear MPC solves its optimisation task by minimising the performance function (5) with respect to the aeration flows subject to the constraints (6) and (7). The DO concentrations $S_{o,j}(k+i|k)$ at the aerobic zones predicted over H_p are calculated by using the discretized models (3). The respirations $R_j(k+i-1)$ in these models are replaced by their predictions $R_j(k+i-1|k)$ that are calculated according to (4) based on the DO measurements at the aerobic zones. The initial conditions $S_{o,j}(k|k)$ are taken from the measurements. This results in the optimised $Q_{air,j}(k|k), \dots, Q_{air,j}(k+H_p=1|k)$ DO trajectories over the prediction horizon.

5.2. Control system 2

The MPC performance function is written as:

$$J = \sum_{j\in\{1,2,3,4\}} \left[\begin{matrix} \sum_{i=1}^{H_p} \left(S_{o,j}(k+i|k) - S_{o,j}^{ref}(k+i|k)\right)^2 + \\ + \sum_{i=1}^{H_p} \delta\left(Q_{air,j}(k+i|k) - Q_{air,j}(k+i-1|k)\right)^2 + \\ + \varphi\left(Q_{air,j}(k-1|k-1) - Q_{air,j}(k|k)\right)^2 + \\ + \sum_{i=1}^{H_p} \gamma\left(Q_{air,j}(k+i-1|k)\right)^2 \end{matrix} \right] \tag{8}$$

The first term in (8) represents the tracking error. The second and the third term describe the rate of change of the control input over H_p, while the fourth term represents the control cost. The weights δ, φ, and γ were calculated based on simulation tests.

The constraints on $Q_{air,j}^{\min}$ and $Q_{air,j}^{\max}$ are given by:

$$Q_{air,j}^{\min} \le \sum_{j\in\{1,2,3,4\}} Q_{air,j}(k+i-1\,|\,k) \le Q_{air,j}^{\max}; \quad i = 1,\dots,H_p \tag{9}$$

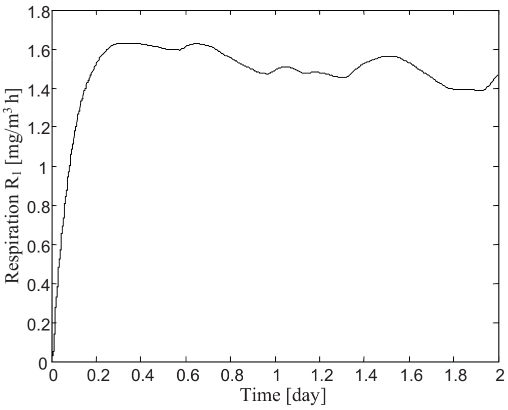

Fig. 8. Respiration in aeration tank 1

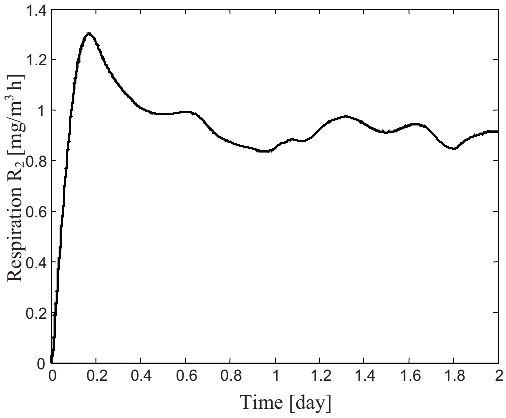

Fig. 9. Respiration in aeration tank 2

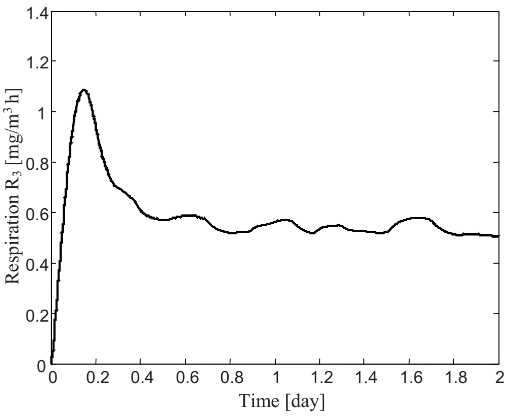

Fig. 10. Respiration in aeration tank 3

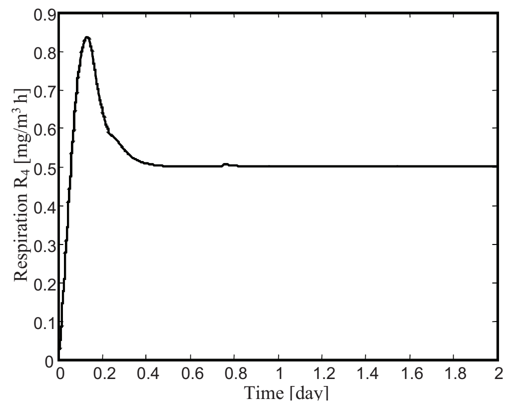

Fig. 11. Respiration in aeration tank 4

where
$$Q_{air,j}^{\min} = 0 m^3/h \text{ and } Q_{air,j}^{\max} = 5000 m^3/h.$$

The constraints on $\Delta Q_{air,j}^{\max}$ are defined as follows:

$$\begin{cases} \left| Q_{air,j}(k+i|k) - Q_{air,j}(k+i-1|k) \right| \le \Delta Q_{air,j}^{\max} \\ \left| Q_{air,j}(k-1|k-1) - Q_{air,j}(k|k) \right| \le \Delta Q_{air,j}^{\max} \end{cases}; \quad \begin{matrix} j \in \{1,2,3,4\} \\ i = 1,\dots,H_p \end{matrix} \tag{10}$$

where $\Delta Q_{air,j}^{\max} = 5000 m^3/h$.

The nonlinear MPC generates at time instant *k*, the control sequence, $\left\{ Q_{air,j}^{ref}(k),\dots,Q_{air,j}^{ref}(k+H_p-1) \right\}_{j=1}^{4}$, based on a discretised nonlinear model (3) with the predicted trajectory of $R_j(k)$ over $k \in [k, k+H_p-1]$ (4) by minimizing the performance function (8) with respect to $\{Q_{air,j}(k),\dots,Q_{air,j}(k+H_p-1)\}_{j=1}^{4}$ subject to the constraints (9)-(10).

6. Simulation tests and comparative analysis

In this section the proposed two novel control systems (see section 5) were tested by simulation, based on real data records from the case study Kartuzy WWTP. The commercial simulation package Simba [18] was applied to modelling biological processes at a WWTP (ASM2d model). Matlab environment was applied to implementing two advanced control strategies. The Sequential Quadratic Programming (SQP) solver was applied to solve the nonlinear MPC optimisation task.

The amount and composition of the influent wastewater to WWTP is varied during the day. Their variability is modelled by four parameters (disturbances): inflow Q_{in}, *COD*, *TN* and *TP*. The input disturbances were as follows: Q_{in} (between 2200-3500 m^3/h) and *COD* (between 700-1200 mg/dm^3) were time-varying; *TN* (equal 90 mg/dm^3) and *TP* (equal 10 mg/dm^3) were constants over time. Their values and variability correspond to the real values of the influent wastewater for case study WWTP.

First, it examined the effect of the length of the prediction horizon H_p and the length of the prediction step *T*, on control quality and computation time. Control errors were increase by shortening H_p and lengthening *T*. As a result of numerical analysis, simulation parameters of predictive controllers were as follows: H_p *=10* steps and *T=5* min.

Simulation results are shown for four aeration tanks. Most important parameter disturbing the process of aeration is the respiration *R* (Figs. 8-11). It refers to the rate of oxygen consumption by bacteria as a result of biochemical reactions. These results show that the respiration disturbance is time-varying, reflecting the varying load of the WWTP (inflow and load).

Control results for DO tracking at Kartuzy WWTP are illustrated. The different range of DO changes are set, which corresponds to the optimal conditions of aeration wastewater. In Figs. 12, 14, 16 and 18 the set

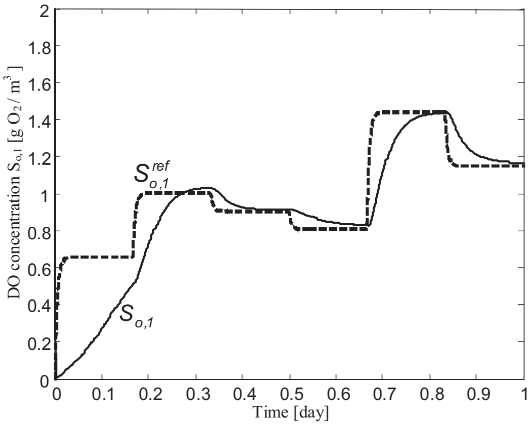

Fig. 12. DO concentration in aeration tank 1 – control system 1

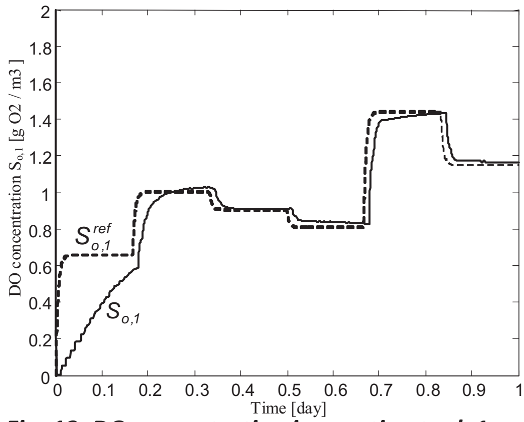

Fig. 13. DO concentration in aeration tank 1 – control system 2

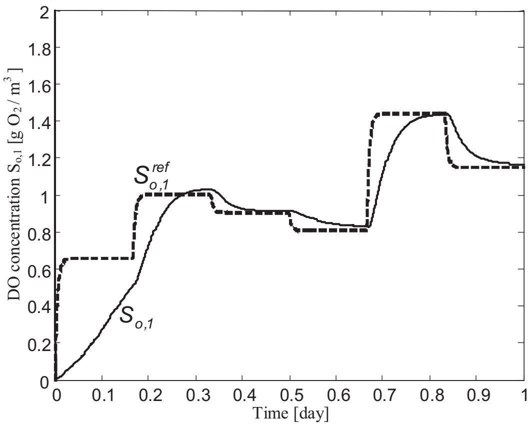

Fig. 14. DO concentration in aeration tank 2 – control system 1

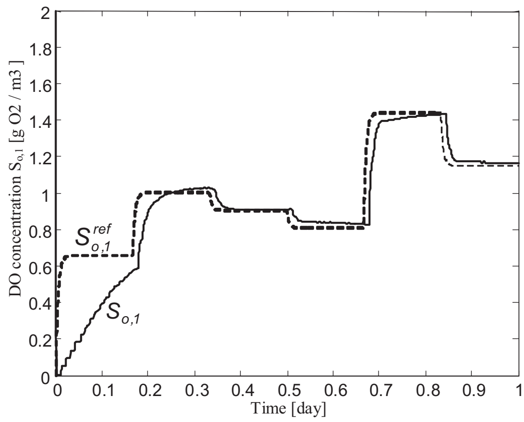

Fig. 15. DO concentration in aeration tank 2 – control system 2

point S_o^{ref} and DO tracking S_o for control system 1 are presented. In Figs. 13, 15, 17 and 19 the results for control system 2 are illustrated.

For both control algorithms was calculated Root Mean Square (RMS) error, given by:

$$RMS = \sqrt{\frac{\left(S_o - S_o^{ref}\right)^2}{n}} \tag{11}$$

where n denotes the number of samples.

The control results of RMS error are summarized in Table 1.

Table 1. DO tracking error

Control system	RMS error – aeration tank			
	1	2	3	4
Control system 1	0.143	0.110	0.128	0.134
Control system 2	0.044	0.041	0.028	0.049

The control results, for two control systems, show on a good tracking performance by using nonlinear advanced control strategies. It can be seen to follow the DO trajectory with good accuracy. The control system 2 demonstrates better quality control, but takes longer to complete required calculations. The control system 2 is characterized by a larger RMS error. For this system, RMS error does not exceed 0.05 in value (see Table 1). Control results could be even better, but not for constraints included in the predictive control systems (see [6]–[7] and [9]–[10]).

The average time to solve one predictive optimization task for control system 2 is longer (much larger number of decision variables). However, this time is small enough to carry out the calculation on-line with appropriate prediction horizon, required by the dynamics of the plant and the disturbances rate of change.

The main advantage of control system 1 is less computations effort. In addition, in case of failure of one of the controllers the other three controllers can still control the supply of oxygen the individual aerated tanks.

In some cases, for example increased inflows of sewage with a high concentration of pollutants, set points trajectories of DO concentration can vary significantly and control system 1 may have a problem with the proper distribution of the required amount of air (it is connected with the fulfillment of constraints, see [6]–[7]). This situation can cause a deviation of the control trajectories.

Better quality control for control system 2 takes into account the needs of all aerobic tanks and the possibility of aeration system and therefore is able to find a compromise in the air the division.

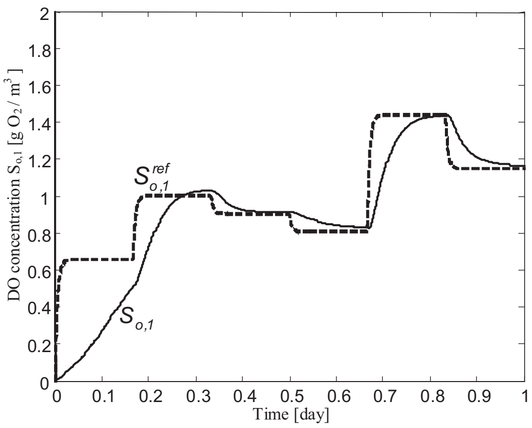

Fig. 12. DO concentration in aeration tank 1 – control system 1

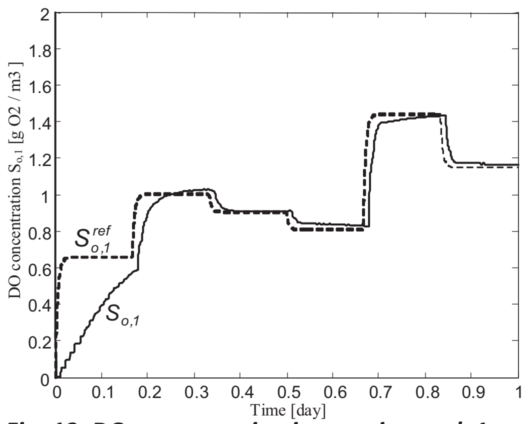

Fig. 13. DO concentration in aeration tank 1 – control system 2

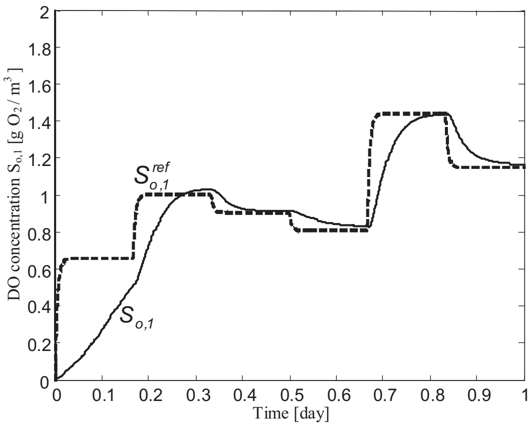

Fig. 14. DO concentration in aeration tank 2 – control system 1

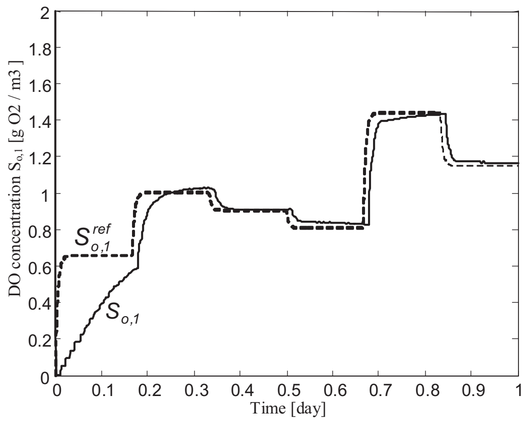

Fig. 15. DO concentration in aeration tank 2 – control system 2

7. Conclusions

Control of dissolved oxygen at a WWTP is important for economic and process reasons. The paper has addressed an important and difficult control problem. A novel approach to the dissolved oxygen concentration tracking has been presented. Two nonlinear predictive control systems have been designed and compared. Its properties and tracking performance have been investigated by simulation based on real data sets from Kartuzy case study plant. Promising results have been observed.

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