Predictive control of an activated sludge process for long term operation

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Abstract

The application of a multivariable predictive controller to an activated sludge process is discussed in this work. Emphasis is given to the model identification and the long term assessment of the controller efficiency in terms of economical and environmental performances. A recurrent neural network model is developed for the identification problem and the dynamic matrix control is chosen as suitable predictive control algorithm for controlling the nitrogen compounds in the bioreactor. Using the Benchmark Simulation Model No.1 as virtual platform, different predictive controller configurations are tested and further improvements are achieved by controlling the suspended solids at the end of the bioreactor. Based on the simulation results, this work shows the potentiality of the dynamic matrix control that together with a careful identification of the process, is able to decrease the energy consumption costs and, at the same time, reduce the ammonia peaks and nitrate concentration

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in the effluent.

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1. Introduction

The growing interest of researchers and practitioners in developing and promoting optimisation and control methodologies for wastewater treatment plants (WWTP) responds to the tightened regulations for the improvement of effluent quality while reducing energy consumption, as recently discussed in the comprehensive review of Hreiz et al. (2015). Meeting these objectives mostly depends on real-time automation technologies which would allow an efficient monitoring and supervision of the process units and the implementation of advanced control strategies such as model predictive control (MPC) algorithms (Camacho and Bordons, 1999; Maciejowski, 2002). In such a context, MPC has become an attractive control strategy for a considerable number of WWTP applications over the last years as, for instance, witnessed by the works of Weijers (2000); Rosen et al. (2002); Sotomayor and Garcia (2002); Alex et al. (2002); Corriou and Pons (2004); Ekman (2008); Vrečko et al. (2011) and lately by Mulas et al. (2013, 2015); Vega et al. (2014); Kim et al. (2014); Santìn et al. (2015). This interest is mainly due to the ability of the MPC of dealing with multivariate constrained control problems in an optimal way, using simple and generally linear models.

The main idea behind every MPC algorithms is to use a model of the process to predict the effect of a control action on the plant, by solving on-line and at each time step, an open-loop optimal control problem. The development of a good prediction model is the most critical and time consuming step when developing an industrial MPC project, and it might take up to more than 50% of the total project resources (Darby and Nikolaou, 2012). Generally, the model identification task is accomplished by means of a campaign of open-loop step tests performed during the commissioning stage of the controller implementation (Sotomayor et al., 2009). The nature of WWTP makes the identification procedure more challenging mainly because of the continuous varying process disturbances. In fact, the inlet flow rate and pollutant concentrations are never constant, being subjected to large variations depending of the anthropic and industrial activities. In addition, generally the disturbances are seldom measured on-line and the process is characterised by very slow dynamics (Zhu, 1998).

In the application of MPC to wastewater treatment processes few papers focused on the identification aspects considering the time varying nature of the influent. For studies developed on the Benchmark Simulation Model No. 1 (BSM1, Gernaey et al., 2014), predictive models for MPC have been obtained in ideal situation (Stare et al., 2007), considering step variations at constant input load (Holenda et al., 2008) and assuming that step changes can be also imposed to the measured disturbances in order to design a feed-forward action (Shen et al., 2009). Recently, Han et al. (2014) proposed a nonlinear model predictive control where a self-organising basis function neural network is used to describe the input-output relationships for the two controlled outputs (nitrate in the second anoxic zone and dissolved oxygen (DO) in the last zone of the bioreactor) and two manipulated inputs (internal recycle flow rate and mass transfer coefficient of the fifth bioreactor zone). In this case the identification seems to mimic a real situation where input disturbances are not constant. As full-scale applications, Dellana and West (2009) reported a comparative study on linear and nonlinear black box modelling applied for the prediction of real wastewater treatment plants behaviour. Lately, O'Brien et al. (2011) applied the MPC to a full-scale plant for controlling the DO concentration in the anoxic zones by manipulating the aeration power. In this case, the identification problem is carried out by applying random changes to the manipulated inputs.

The approach proposed in this work mainly addresses two fundamental aspects of the control design. The first one is the obtainment of a process model from plant data, as it is generally the case when dealing with real plants. This step is of paramount importance for the development of a proper controller strategy. The second issue is the process control design, which is addressed by considering a MPC algorithm for removing nitrogen compounds. Simple feedback and ratio controllers are also considered to improve process performances. The study is developed by exploiting the BSM1, with the short and long input data sets (Gernaey et al., 2014) used for conducting the model identification and evaluating the control performance. A Recurrent Neural Network (RNN) model is utilised as appropriate tool to deal with process modelling from data (Tronci et al., 2013), while linear models revealed to be inadequate for capturing the necessary input-output complex behaviour. The Dynamic Matrix Control (DMC) is chosen as suitable MPC algorithm, because of its simplicity, essential to any real WWTP application. In order to maintain a linear MPC controller, the RNN models derived from the simulated plant data are then used to derive the Finite Step Response (FRS) model. As a novelty with respect to previous studies (e.g., Stare et al., 2007; Santìn et al., 2015), aeration of the anoxic zone is considered as manipulated variable in the BSM1 for improving ammonia removal and external carbon addition is not used to improve denitrification. Furthermore, long-term simulations are here exploited to assess the performance of the linear controller strategies, testing their reliability in presence of high variations of the influent and disturbances due to seasonal effects, particularly with respect to the consequences of the temperature lowering.

The paper is organised as follows. After a brief description of the BSM1 model in Section 2, the proposed approach is extensively presented in Section 3, starting with the definition of the control objectives and the adopted performance indexes in Section 3.1. Then, it follows the description of the system identification method in Section 3.2, the selected model predictive control algorithm in Section 3.3 and the definition of basic controllers for the improvement of the process performances in Section 3.4. Next, the results of the predictive controllers are presented and discussed in comparison with basic feedback controllers in Section 4. The most important conclusions are drawn in Section 5.

2. The activated sludge process

To test the potentialities of predictive control strategies on a biological wastewater treatment plant, the Benchmark Simulation Model No.1 (Gernaey et al., 2014) is here exploited. The BSM1 is a fully defined protocol that characterises a common activated sludge process in terms of a typical municipal WWTP influent. The benchmark is based on the two accepted first principle process models: the Activated Sludge Model No.1 proposed by Henze et al. (2000) and the Takàcs model (Takács et al., 1991). The former is used to describe the biological process and the latter is a non-reactive one dimensional layer model that describes the settling process. The models are fully calibrated, meaning that the kinetic and stoichiometric parameters are provided within the benchmark description. The full set of data is available at benchmark group website: `http://www.benchmarkwwtp.org/`.

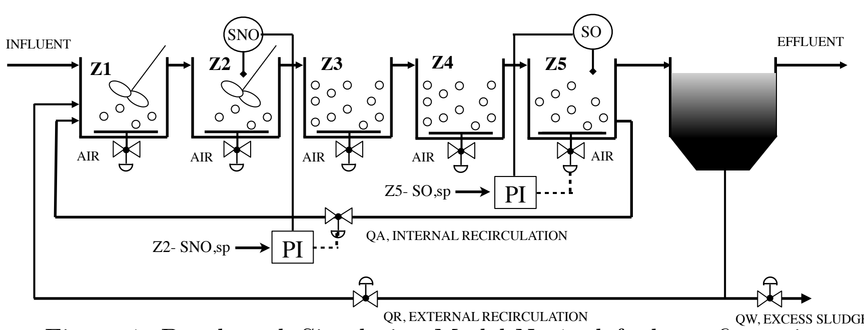
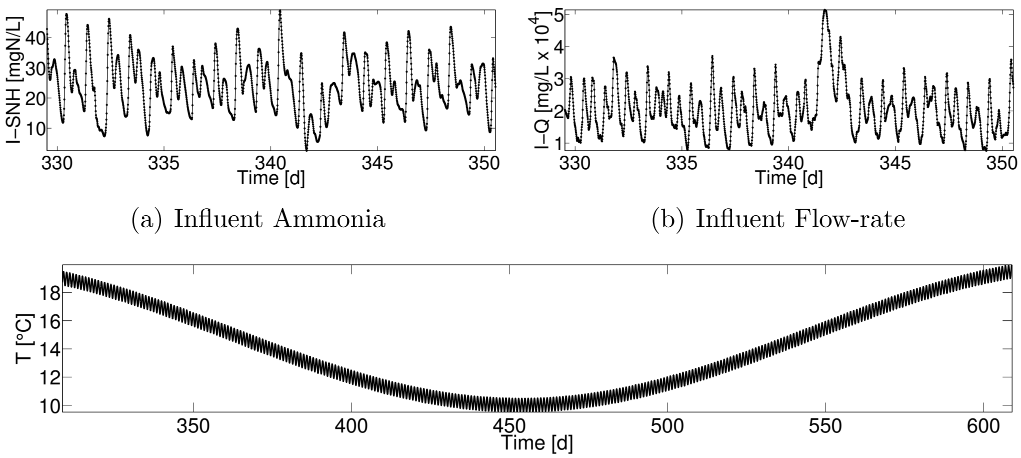


Figure 1: Benchmark Simulation Model No.1: default configuration

The influent data are provided over short (14 days) and long period (609



(a) Influent Ammonia

(b) Influent Flow-rate

(c) Temperature

Figure 2: Long term data: Examples of influent data for ammonia (a) and flow rate (b) during approximately one-month and temperature (c) for approximately one year.

days) with 15 minutes sampling time. The 14 days data files consider three different weather conditions: dry (normal influent variation for a municipal WWTP), storm (same as dry weather with two storm events) and rain (dry weather with a long rain period). The long-term (LT) data set takes into account seasonal effects and temperature variations (Figure 2), allowing a demanding test for the proposed control strategies (Gernaey et al., 2006).

2.1. BSM1 default controllers

The scheme in Figure 1 includes the two feedback loops used in the BSM1. A PI controller regulates the aeration given the DO concentration in Z5 ($Z5$-SO) and the nitrate concentration in zone Z2 ($Z2$-SNO) is controlled by the internal recirculation flow rate given by a PI controller. The default control configuration is used in the following for comparison purposes, in order to show how an advanced control strategy may enhance process performances.

3. Development of the control strategy

The improvement of the activated sludge process performance is addressed by finding a suitable control strategy. This implies the definition of the control objective, including the degree of freedom analysis, the selection of controlled outputs and manipulated variables, together with the determination of the requirements and the performance indexes. As a model predictive control is considered, achieving a good model of the process is essential for the control design.

In order to capture the input-output dynamics of the activated sludge process, output response data are collected from the simulation platform excited by varying the manipulated inputs when considering the long-term influent data (Figure 2). Process identification from plant data is obtained by means of a nonlinear model, which is then exploited to obtain the linear Finite Step Response (FSR) model. Basic controllers are also introduced to saturate the remaining degrees of freedom, leading to an improvement of the plant performances. In the following of this section, the procedure for the development of the proposed strategy is described in details, whereas Figure 3 schematically reports its main steps.

3.1. Problem statement

Main goal of the developed control strategies is to avoid violations of the effluent limits, especially for the nitrogen compounds, while improving the

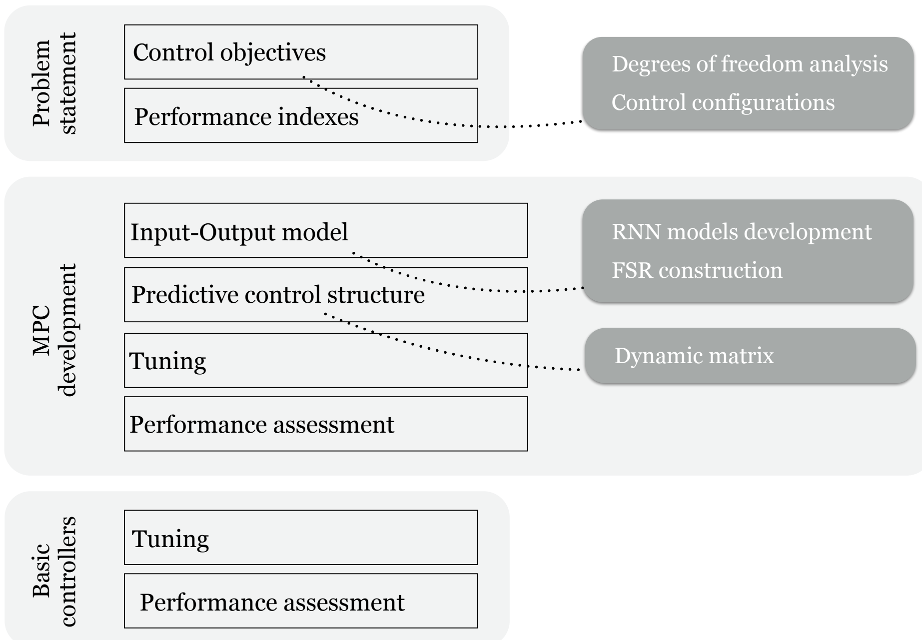


Figure 3: Main steps of the proposed control strategy

process performances and decreasing the operational costs. This has to be achieved in a simple way in order to allow practical and intuitive application on a full-scale plant. It is has been demonstrated that the ammonia-based control of the activated sludge process might imply significant savings in the energy cost and potential improvements in the ammonia removal process (Rieger et al., 2012; Åmand, 2014). On the other hand, it is also mandatory to guarantee that total nitrogen effluent concentration does not exceed the limits imposed by the laws to protect the aquatic environment against eutrophication. For these reasons, the control strategies developed in the present paper aims to: (i) guarantee nitrification and denitrification processes, i.e., an efficient ammonia and nitrate removal; (ii) reduce the energy consumption. Based on the analysis of the available degrees of freedom and on the knowledge on the process, the manipulated and controlled variables are identified and different configurations are investigated (Table 1).

Table 1: Control configurations tested on the BMS1.

			C1	C2	C3	C4	C5	C6
Manipulated Variables	$Z2$-SO-SP	DO set-point in $Z2$	✓	✓	✓	✓	✓	✓
	$Z3$-SO-SP	DO set-point in $Z3$		✓		✓	✓	✓
	$Z4$-SO-SP	DO set-point in $Z4$		✓	✓	✓	✓	✓
	$Z5$-SO-SP	DO set-point in $Z5$	✓		✓	✓	✓	✓
	QA	Internal rec. flow-rate	✓	✓	✓	✓	✓	✓
	QR	External rec.flow-rate					✓	✓
	QW	Waste sludge flow-rate						✓
Controlled Variables	$Z5$-SNH	Ammonia in $Z2$	✓	✓	✓	✓	✓	✓
	$Z2$-SNO	Nitrate in $Z2$	✓	✓	✓	✓	✓	✓
	$Z5$-SS	Suspended Solids in $Z5$						✓
	I-Q	Influent flow-rate					✓	✓

In the configurations from C1 to C4 the nitrate concentration in zone $Z2$ together with the ammonia concentration in zone $Z5$ are the controlled outputs. Dissolved oxygen set-point from $Z2$ to $Z5$ together with the internal recycle flow rate are used as inputs for the model predictive control, to deal with the complex dynamics and constraints of the nitrification-denitrification processes. The manipulation of dissolved oxygen in the second zone, which is always anoxic in the BSM1 layout, is considered in every configuration because it should help to reduce ammonia peaks when the aeration of the three aerated zones is not sufficient and possibly avoid the use of external carbon source for improving denitrification. Also the use of the internal recycle flow rate is maintained in each configuration because it is necessary for the denitrification process. Configuration C5 adds to the predictive controller in C4 a simple ratio control that adapts the external recirculation flow rate to the influent wastewater flow rate. This configuration is further improved by introducing a feedback controller to maintain constant the suspended solids in zone $Z5$ by manipulating the waste sludge flow rate in order to keep an appropriate sludge quality in the system and assure a beneficial sludge age.

The performance of every configuration is evaluated from a quality and economical point of view, using the criteria in Gernaey et al. (2014) for the short and long term scenarios. In particular, for the three weather scenarios (dry, rain and storm) the evaluation is done considering a time interval T of seven days (with $t_1 = 7$ d and $t_2 = 14$ d). For the LT simulation, the time interval consists of 298 days of simulation, with $t_{1,LT} = 311$ d and $t_{2,LT} = 609$ d.

The evaluation of the quality level considers the effluent violations for the main process variables (ammonia (SNH), total nitrogen (TN), total suspended solid (TSS), and chemical oxygen demand (COD)) as percentage of time the plant is violating the limits (Table 2).

Table 2: Effluent limits.

	SNH	TN	TSS	COD	BOD
Limit	4 mgN/L	18 mgN/L	30 $mgSS/L$	100 $mgCOD/L$	10 $mgBOD/L$

The Effluent Quality Index (EQI) in Equation 1 is used for the overall assessment of the pollutant concentrations in the effluent. It relates to the fine to be paid for discharging pollutants in the receiving water bodies and it is a weighted average of the effluent loads of compounds that have a major influence on the receiving water quality.

$$EQI = \frac{1}{T \times 1000} \int_{t_1}^{t_2} \Big((B_{SS}TSS + B_{COD}COD + B_{TKN}TKN + B_{NO}SNO + B_{BOD_5}BOD)E\text{-}Q \Big) dt \tag{1}$$

The weight for the effluent TSS, COD, Total Kjeldahl Nitrogen (TKN), nitrate and Biological Oxygen Demand (BOD_5) are given as in the BSM1: B_{SS}=2, B_{COD}=1, B_{NK}=30, B_{NO}=10 and B_{BOD_5}=2. E-Q represents the effluent flow rate (cf. Figure 1).

The economy of the plant is assessed by calculating the total cost (TC) as a function of the aeration (AE), pumping (PE) and mixing (ME) energy together with the cost due to sludge production (SP) for disposal:

$$TC = k_E \times (AE + PE + ME) + k_D \times SP. \tag{2}$$

where the electricity price k_E is set equal to of 0.09 € per kWh and the sludge disposal price is set equal to 80 € per tonne.

The individual terms in Equation 2 are calculated using the relationships given in the BSM1 description (Alex et al., 2002; Gernaey et al., 2014). Here, AE ($kWhd^{-1}$) is function of the oxygen mass transfer coefficient (K_La_i) in every i-zone of the bioreactor with a given volume V_i. The pumping energy in $kWhd^{-1}$ is calculated as weighted sum of the nitrate recycle flow rate (QA), the external recycle flow rate (QR) and the waste sludge flow rate (QW). The mixing energy ($kWhd^{-1}$) is required in the reactor i when not aerated or if the K_La_i is lower than 20 d^{-1}. The sludge production SP is calculated as function of the solids removed from the process in the waste sludge flow rate and solids accumulated in the system. That is:

$$\begin{aligned}
AE &= \frac{S_O^{sat}}{T \times 1800} \int_{t_1}^{t_2} \sum_{z=2}^{5} V_i K_L a_i dt; \\
PE &= \frac{1}{T} \int_{t_1}^{t_2} \Big(0.004\, QA(t) + 0.008\, QR(t) + 0.05\, QW(t)\Big) dt; \\
ME &= \frac{24}{T} \int_{t_1}^{t_2} \sum_{z=1}^{5} \Big(0.005 \times V_i < 20 \,\text{otherwise}\, 0\Big) dt; \\
SP &= \frac{1}{T \times 1000} \Big(X\text{-}TSS(t_2) - X\text{-}TSS(t_1) + \int_{t_1}^{t_2} (W\text{-}TSS\ QW) dt\Big)
\end{aligned} \tag{3}$$

In Equation 3, S_O^{sat} is the oxygen saturation concentration and X-TSS is the total solid concentration in the activated sludge reactors and in the secondary settler.

3.2. Input-output model

The development of a model is required to predict output trajectories in MPC algorithms. Considering the BSM1 as a virtual plant, input-output data for model development can be collected from an identification test that is designed to make the data maximally informative about the system properties that are of interest to the user. Unlike most chemical processes, WWTPs are subjected to large time-varying disturbances, as the quality of the inlet wastewater changes continuously. This fact implies that it could be difficult to capture the required input-output behaviour because when the manipulated variables are varied during an identification test, the output responses are also affected by disturbances. As further tangle, it is also important to note that typically, most of the input variables (e.g., quality of the influent) is not measured online (lack of proper hardware sensors) and that normally performed laboratory analysis usually does not give a complete characterisation of the influent (Holenda et al., 2008).

For the multivariable control (configurations C1-C4), it is required to model the effects of the five manipulated inputs ($\mathbf{u}$) on the controlled output variables ($\mathbf{y}$=$Z2$-SNO, $Z5$-SNH). The inlet ammonia concentration and flow rate (I-SNH and I-Q) are considered as measured disturbances. The ammonia and nitrate concentration behaviours are affected by the inlet pollutant concentration, flow rate and temperature variations together with the excited manipulated inputs, and it is quite demanding to discern the effect of one variable with respect to the others. Linear autoregressive models with exogenous inputs (ARMAX) are the most used when dealing with MPC (Darby and Nikolaou, 2012) and, as first attempt, they were used to describe the input-output relationships. However, they were not able to capture the relationships between the manipulated inputs and the outputs because of the strong effects of the disturbance variations. A clear evidence of their failure was the frequent wrong evaluation of the process gain sign.

The recurrent neural network (RNN) model, which belongs to the class of nonlinear ARMAX provides a better fitting and it is used to model the process. The recurrent neural network used in this work is sketched in Figure 4. Here, $y(t + T_s)$ represents the output prediction at each sampling time T_s; $\mathbf{y}(t)$ is the lagged network output, $\mathbf{u}(t)$ and $\mathbf{d}(t)$ are the vectors of the manipulated inputs and measured disturbances, which can be constituted by actual and previous values. This implies that the output at time $t + T_s$ is a function of the past values of both the inputs and the output. The neural network is recurrent, in the sense that the output is fed back to the network input nodes, such as dynamics are introduced into the network.

A RNN is developed for each input-output relationship necessary to define the model-based controllers. The sigmoidal activation function is used for the neurons belonging to the hidden layers, and the linear activation function is used for the output neurons, as reported in Equation 4.

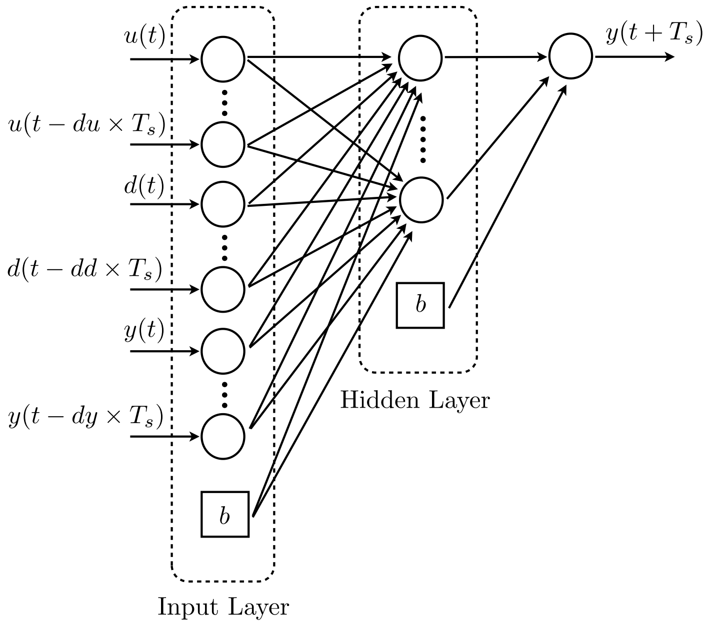


Figure 4: Schematic representation of the recurrent neural network, where $[y(t),\ldots,y(t-dy\times T_s)]$ is the delayed output vector fed back to the input.

$$
\begin{aligned}
y(t+T_s) &= \sum_{i=1}^{n_2} w_2(i,1)z_2(i) + w_2(n_2+1,1)b;\\
z_2(i) &= \frac{1}{1+e^{-(\sum_{j=1}^{n_1} w_1(j,i)z_1(j)+w_1(n_1+1,i)b)}};\\
\mathbf{z}_1(t) &= [\mathbf{y}(t),\mathbf{u}(t),\mathbf{d}(t)];\\
\mathbf{y}(t) &= [y(t),y(t-T_s),\ldots,y(t-dy\times T_s)];\\
\mathbf{u}(t) &= [u(t),u(t-T_s),\ldots,u(t-du\times T_s)];\\
\mathbf{d}(t) &= [d(t),d(t-T_s),\ldots,d(t-dd\times T_s)].
\end{aligned}
\tag{4}
$$

n_1 and n_2 represent the number of input and hidden neurons, respectively.

The model parameter $w_1(j,i)$ represents the weight related to the connection between the jth input and ith hidden neuron and $w_2(i,1)$ is the weight between ith hidden neuron and the unique output neuron. The weights of the neural model are estimated during the training phase. The term b represents the bias and it is set equal to $+1$, $z_1(j)$ is the jth input to the network and $z_2(i)$ is the ith output of the hidden layer. The choice of the delayed output to feed back to the input layer (dy) and delayed inputs (du and dd) along with the number of hidden neurons is addressed using a trial and error approach, aiming to the best compromise between prediction capability and simplicity of the model (parsimonious model). The network training is performed by the Levenberg-Marquardt algorithm, and data for the parameter estimation have been divided into training (70%) and test (30%) sets. Input and output data used to develop the RNN models are scaled such as their variations belong to the interval [-1,+1].

The selection of the best neural model for each input-output relationship is performed using both the Mean Squared Error (MSE) calculated on the test set and evaluating the process gain calculated for each neural network model at different values of the inputs. In more details, the sign of the gain must be coherent with the physics of the process (e.g., ammonia concentration must decrease as oxygen concentration increases in the bioreactor) and it should be the same at different inlet ammonia concentrations.

3.3. Model predictive control development

Nitrification and denitrification processes are strongly correlated and they have a strong impact on aeration energy consumption. A model predictive control provides an integrated solution for controlling such processes because of its ability to deal with interacting variables, complex dynamics, and constraints. MPC also allows the use of more inputs than outputs, and through the solution of the optimisation problem leads to performance improvements. Following the practical requirement of an easy implementation of the controller, the DMC formulation is selected and the input-output models are calculated with finite step response (Ogunnaike and Ray, 1994).

The DMC considers as output controlled variable $\mathbf{y}$, the nitrate concentration in Z2 ($Z2\text{-}SNO$) and ammonia concentration in Z5 ($Z5\text{-}SNH$) of the bioreactor. The configurations C1 to C4 in Table 1 are formulated by combining the available manipulated variables, $\mathbf{u}$: the dissolved oxygen set-points in the bioreactor ($Z_z\text{-}SO\text{-}SP$ with $z = 2, \ldots, 5$) and the internal recirculation flow rate (QA):

$$\mathbf{y} = \begin{bmatrix} Z2\text{-}SNO \\ Z5\text{-}SNH \end{bmatrix}; \mathbf{u} = \begin{bmatrix} Z2\text{-}SO\text{-}SP \\ Z3\text{-}SO\text{-}SP \\ Z4\text{-}SO\text{-}SP \\ Z5\text{-}SO\text{-}SP \\ QA \end{bmatrix} \tag{5}$$

The DMC of the every configuration with m inputs and n outputs finds the vector $\Delta\mathbf{u}(k) \in \mathbb{R}^{mH_u}$ of future control moves that minimises the sum of squared deviations of the predicted control variables from a time-varying reference trajectory, while constraining the magnitude of $\Delta\mathbf{u}(k)$, for a prediction horizon H_p and a control horizon H_u. That is, the DMC optimises the following objective function:

$$\begin{aligned} J[\Delta\mathbf{u}(k)] = & \big[\mathbf{e}(k+1) - \mathbf{A}\Delta\mathbf{u}(k)\big]^T \big[\mathbf{e}(k+1) - \mathbf{A}\Delta\mathbf{u}(k)\big] + \\ & \big[\Delta\mathbf{u}(k)\big]^T \mathbf{W} \big[\Delta\mathbf{u}(k)\big]. \end{aligned} \tag{6}$$

Equation 6 translates the trajectory following problem to a more practical constrained problem on the manipulated variables. Here, k denotes the time index and $\mathbf{e}(k+1)$ is the nH_p-dimensional error vector representing the difference between the desired input trajectory $\mathbf{r}(k+1) \in \mathbb{R}^{nH_p}$ and current output prediction in the absence of further control actions $\mathbf{y}^0(k) \in \mathbb{R}^{nH_p}$.

The prediction error is corrected by the measured outputs $\mathbf{d}_m(k) \in \mathbb{R}^{nH_p}$ available at the sampling instant k and considered constant for the whole prediction horizon. $\mathbf{W} \in \mathbb{R}^{mH_u \times mH_u}$ is a block diagonal weighting matrix that is used to penalise changes in the control signals and avoid excessive effort on the manipulated variables. That is, $\mathbf{W} = \mathtt{bd}[b_1\mathbf{I},\ b_2\mathbf{I},\ ...,\ b_m\mathbf{I}]$ where b_m are the coefficient of the block matrices and $\mathbf{I}$ is the $Hu \times Hu$ identity matrix. It is worth noticing that prediction errors are inevitable, therefore the entire control sequence of Hu control moves is not implemented, but only the first move is applied at every sampling time.

3.3.1. Dynamic matrix

In Equation 6, the simplified model of the process is represented by the dynamic matrix $\mathbf{A} \in \mathbb{R}^{nH_p \times mH_u}$, which is obtained by arranging nm blocks of step-response coefficients between pairs of inputs and outputs, each for a prediction horizon H_p and a control horizon H_u:

$$\mathbf{A} = \begin{pmatrix} a_{11}^{1} & 0 & \dots & 0 & \dots & \dots & a_{m1}^{1} & 0 & \dots & 0 \\ a_{11}^{2} & a_{11}^{1} & \dots & 0 & \dots & \dots & a_{m1}^{2} & a_{m1}^{1} & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ a_{11}^{H_p} & a_{11}^{H_p-1} & \dots & a_{11}^{H_p-H_u+1} & \dots & \dots & a_{m1}^{H_p} & a_{m1}^{H_p-1} & \dots & a_{m1}^{H_p-H_u+1} \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ a_{1n}^{1} & 0 & \dots & 0 & \dots & \dots & a_{mn}^{1} & 0 & \dots & 0 \\ a_{1n}^{2} & a_{1n}^{1} & \dots & 0 & \dots & \dots & a_{mn}^{2} & a_{mn}^{1} & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ a_{1n}^{H_p} & a_{1n}^{H_p-1} & \dots & a_{1n}^{H_p-H_u+1} & \dots & \dots & a_{mn}^{H_p} & a_{mn}^{H_p-1} & \dots & a_{mn}^{H_p-H_u+1} \end{pmatrix} \tag{7}$$

The coefficients a_{ij}^{k} represent the change observed in the output j of a FRS model at different, consecutive, equally space, discrete-time instants k after implementing a unit change in the input variable i. The coefficients in the matrix $\mathbf{A}$ are obtained by performing "off-line" new step tests on the neural model described in Section 3.2, starting from different initial conditions. Even if the activated sludge process exhibits strong nonlinear behaviour, linear controllers are more appealing for real plant operators because they are generally simple to develop and implement if compared to nonlinear controllers. The following assumptions are made: (i) the input of the neural model corresponding to the ammonia inlet flow rate is kept constant, and equal to its mean value calculated considering the same period of the LT dataset used for training the neural model; (ii) the input corresponding to the manipulated variable are changed starting from different initial points. The calculated coefficients vary when changing the initial operating condition, because the system is nonlinear, therefore their mean values are used to obtain the final matrix **A**. This choice is source of uncertainty, but the available output measurements can adjust the model prediction at each sampling time.

3.4. Basic controllers

The DMC configurations do not saturate all the available degrees of freedom, meaning that further control loops might be implemented in order to improve the process performances. The first consideration regards the external recycle flow rate (QR), which has been kept constant in the previous control configurations as in the BSM1. Given the inlet flow rate (I-Q) subjected to large variations, it is reasonable to adapt QR to I-Q, by applying a ratio controller. The combination of DMC with five manipulated variables (C4) and the ratio controller is indicated as configuration C5.

The excess sludge flow rate (QW) is the last remaining degree of freedom and can be used to further improve the efficiency of ammonia and nitrogen removal. A simple PI feedback control is implemented to maintain constant the mixed liquor suspended solid ($Z5$-SS) by manipulating QW. The suspended solids concentration relates to the sludge age, from which depends the efficiency of nitrification. This PI loop aims to preserve the accumulation of solids and keep an appropriate sludge quality in the system. This configuration is referred as configuration C6 in Table 1.

4. Results and discussion

The proposed control strategies relate to the following issues: design of the underlying regulatory controls, design of the MPC, test design for model identification and model development for MPC, improvement of the system performance using PI and ratio controllers. Ideal sensors are considered for the simulations and the different control configurations are assessed in order to find the best one in terms of energy saving and nitrate removal, according to the criteria in Section 3. Considering the BSM1 as a virtual plant, the control strategies are evaluated using the short and long-term input datasets.

4.1. DO regulatory control

The dissolved oxygen set-points in the four zones of the bioreactor are used as manipulated variables for the model predictive control (as given in equation 6). In each zone a PI control is used to drive the dissolved oxygen at the desired set-point, manipulating the oxygen transfer rate, K_La. For each control loop, the values for the constant gain and the integral time are, respectively: $k_c = 100$ d^{-1}g(-COD)$^{-1}$m^3 and $\tau_I = 0.002$ d. The tuning parameters are obtained applying IMC rules to input-output models obtained through step tests. In this case, because the oxygen response to aeration changes is quite fast, the effects of the manipulated K_La are easier identified using the long-term input data set and described through a first order model.

4.2. Recurrent neural network models

The variability of the bioreactor influent characteristics and flow rate did not allow to directly obtain a linear FRS model for DMC from step test data, because it was impossible to estimate the contribution of each input (disturbances or manipulated variables) affecting the process responses. RNN models are therefore exploited to reconstruct the dynamic behaviour of nitrate in the second bioreactor zone and ammonia in the fifth bioreactor zone with respect to the manipulated inputs indicated in Equation 5. This task is addressed by simulating the long-term scenario and obtaining input-output plant data by exiting the plant through step variations of the manipulated inputs. GBN sequences are created for each manipulated input, with a probability of switching equal to 0.6 and a minimum switching time equal to 0.5 d. From the simulation platform, the data are collected within a fixed time interval of *circa* 20 days for each test and sampled every 15 min, for a total of 105 d starting from the 5^{th} day of the long-term inputs data set (Figure 5).

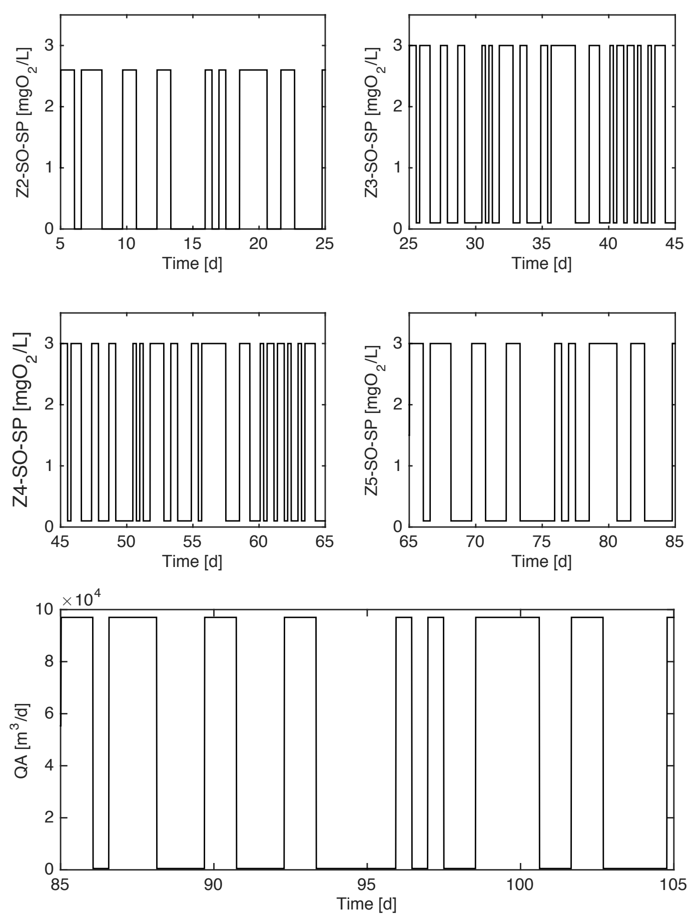


Figure 5: Sequence of input steps for system identification.

For the problem at hand, ten neural network models are obtained to correlate each output to each manipulated input. In order to improve the model capability prediction, the product of inlet ammonia concentration and flow rate is used as input to the neural model. The dynamics of the two measured disturbances (inlet ammonia and flow rate) are those already reported in Figure 2(a) and Figure 2(b).

Table 3: Neural models describing the input-output relationship. The number of hidden units is equal to 8 for each RNN

Input at time t			**Output at time $t + T_s$**
I-$SNH \times I$-Q	$Z2$-SNO	$Z2$-SO-SP $Z3$-SO-SP $Z4$-SO-SP $Z5$-SO-SP QA	$Z2$-SNO
I-$SNH \times I$-Q	$Z5$-SNH	$Z2$-SO-SP $Z3$-SO-SP $Z4$-SO-SP $Z5$-SO-SP QA	$Z5$-SNH

The structures of the obtained neural models in terms of inputs are reported in Table 3; the number of hidden neurons is set equal to 8 for each network configuration. The output prediction at time $(t + T_s)$ is a function of the output and inputs (manipulated and disturbance) at time t, whereas previous values do not improve the prediction capability of the model. It is worth noticing that a one-step ahead prediction is used during the training procedure, and autonomous mode (the lagged output values are always that calculated with the neural model) is used for evaluating the sign of the gain predicted with the neural model.

4.3. Dynamic matrix

A linear predictive model is required to implement the DMC in its traditional form (Ogunnaike and Ray, 1994). This task is addressed using the neural models to carry on “off-line” step response tests from which the dynamic matrix **A** is obtained. Each RNN is excited by varying the input corresponding to the manipulated variables, starting from its mean value and considering step changes of different sizes. The RNN input corresponding to the ammonia inlet flow rate is kept constant and it is set equal to its mean calculated considering the data collected for the previous phase (Section 4.2), that is $I\text{-}SNH \times I\text{-}Q = 4.91{\cdot}10^5\ gNd^{-1}$ in actual dimension. The coefficients of the dynamic matrix **A** are obtained by averaging the responses of the different step changes and they are reported in Figure 6. A scaling procedure is implemented to avoid ill-conditioning, according to the procedure reported in Skogestad and Postlethwaite (2005).

4.4. MPC tuning

The parameters related to the DMC development, such as prediction and control horizon, sampling time and weights, are found by analysing the dynamic response of the process, considering the frequency of the inputs variations and by tuning.

For achieving an acceptable dynamic matrix conditioning while maintaining good controller performances, the dimension of the prediction horizon H_p is set equal to 10 for each configuration. A positive effect on the condition-

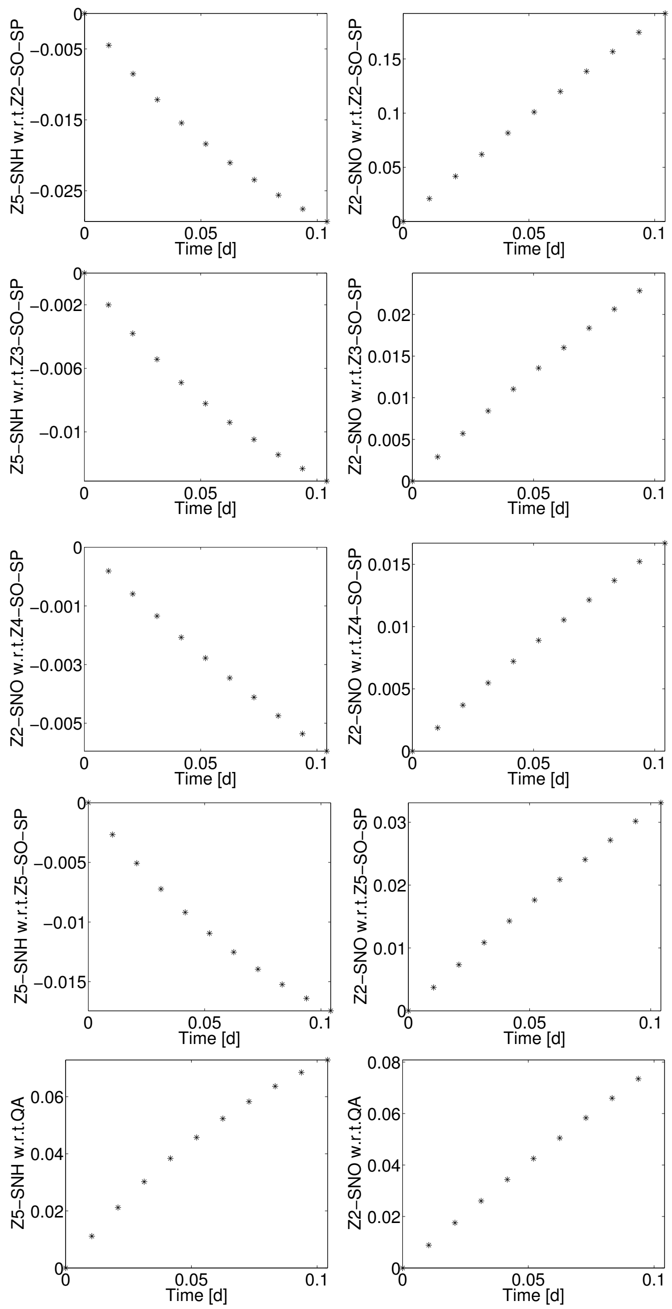


Figure 6: Step response coefficient calculated by the neural model of Z5-SNH (left panel) and Z2-SNO (right panel) with respect to the five manipulated inputs.

ing of the **A** matrix can be obtained using less manipulated variables. On the other hand, increasing the manipulated variables increases the domain space of the possible solutions and the adaptability of the system to different input conditions, as demonstrated in the following of the present work. The control horizon H_u is set equal to 4 for the entire control configuration, as suggested by Ogunnaike and Ray (1994). The control signal remains constant during the prediction horizon and only the first control move is applied at each sampling time.

The weighting matrix $\mathbf{W} \in \mathbb{R}^{m\times m}$ penalises the changes of the manipulated variables, avoiding a too aggressive action of the controllers, reducing possible oscillations and minimising the energy consumption. The elements b_m of the matrix are set as reported in Table 4.

Table 4: Coefficients b_m of the block diagonal matrix $\mathbf{W}$ in Equation 6.

	C1	C2	C3
b_m	[0.01 0.01 0.1]	[0.01 0.01 0.01 0.1]	[0.01 0.01 0.01 0.1]
	C4	C5	C6
b_m	[0.05 0.05 1 0.05 0.5]	[0.05 0.05 1 0.05 0.5]	[0.05 0.05 1 0.05 0.5]

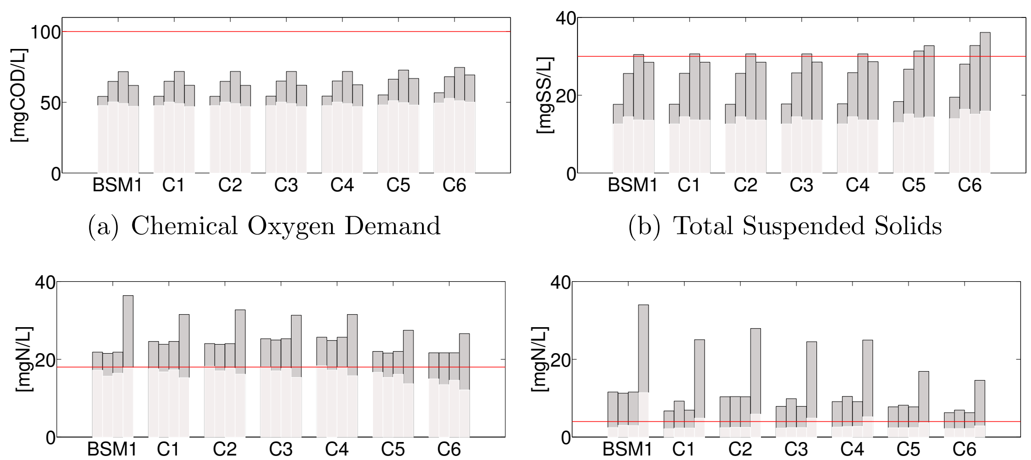
4.5. Basic controllers tuning

The tuning of the basic controllers in configuration C5 and C6 involved the selection of the ratio $QR/I\text{-}Q$ and the PI controller parameters, k_c and τ_I. A sensitivity analysis of the ratio $QR/I\text{-}Q$ led to a value equal to 1.2, which guarantees good performance of the system.

The PI feedback control loop in configuration C6 aims to preserve the accumulation of solids and keep an appropriate sludge quality in the system, being the suspended solids concentration related to the sludge age and, in turns, to the nitrification efficiency. For the purpose, the PI parameters are set equal to k_c = -0.375 m^6 d^{-1} g^{-1} and τ_I = 8 d. The controller tuning was conducted through a trial and error approach, based on $Z5$-TSS step change response with respect to QW. Noticeably, in spite of the influent variations, the slow dynamics of the suspended solids allowed here a simple identification of the excess sludge effects and a linear first-order plus time delay model was used to fit the simulated input-output data. In order to have good performances of the system in every environmental condition, the set-point of $Z5$-TSS needed to be adjusted according to the weather conditions. In fact, during the warmest period, when the temperature is higher than 18°C, the DMC controller was unable to maintain the level of dissolved oxygen in the anoxic tank at the set-point value. This behaviour could be due to high load of $Z5$-TSS, which decreased the sludge age with a consequent loss of the nitrification efficiency in the anoxic zone. Therefore, two different set-points were used for controlling the suspended solids: the set-point was set equal to 4500 mgSS L^{-1} when the temperature was lower then 18°C and equal to 4000 mgSS L^{-1} when the temperature was above 18°C. This strategy led to efficiency improvement of ammonia and nitrogen removal.

4.6. Performance assessment

Given the performance indexes in Section 3.1, the control strategies in Table 1 are tested for an evaluation period of two weeks during the three short scenarios (dry, rainy and storm weather) and for about one year with the LT input conditions. For every configurations, the set-points for the DMC controlled variables are fixed as 1 mgN L^{-1} for the nitrate at the outlet of the anoxic zone, $Z2\text{-}SNO\text{-}SP$, and as 1 mgN L^{-1} for the ammonia at the end of the bioreactor, $Z5\text{-}SNH\text{-}SP$. Comparison results are given in Figure 7. The average and maximum values of the effluent concentrations are reported in terms of COD in Figure 7(a), TSS in Figure 7(b), TN in Figure 7(c) and ammonia in Figure 7(d), evaluated for the short and long term simulations.



(a) Chemical Oxygen Demand

(b) Total Suspended Solids

(c) Total Nitrogen

(d) Ammonia

Figure 7: Maximum (dark grey) and mean (light grey) effluent values: Simulation results comparison during the dry (first column), rain (second column), storm (third column) and long term (fourth column) scenario for the effluent COD (a), TSS (b), TN (c) and SNH (d). The red line gives the effluent limit for the component as in Table 2.

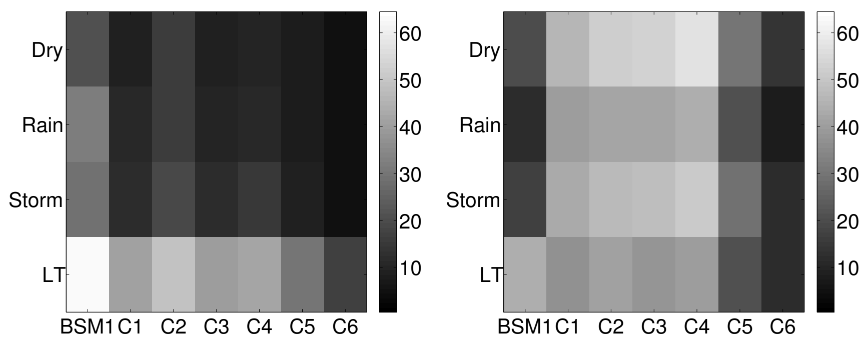
Results show that DMC always outperforms the BMS1 for ammonia removal, for each of the considered situations. Among the configurations with the sole DMC controller (C1 to C4), the C1 shows better performance particularly during normal, dry weather conditions. For the long term simulation, results for ammonia obtained with C1 and C3 are comparable.

On the other hand, the total nitrogen removal does not improve with the mere implementation of the DMC controllers. This is due to the enhancement of nitrification for the removal of ammonia, which produces more nitrates. The effect can be also noticed when considering the averaged total nitrogen, which is generally higher for the DMC configuration when compared to BSM1. Exception being the long-term simulation, where the DMC proved better performances.

It can be further noticed that the proposed configurations do not affect the removal efficiency of COD and its average and maximum values are almost the same of BSM1. This is mostly true also for the effluent TSS concentration which slightly overcomes its limits only during the storm and LT scenario with the last two control configurations. C5 violates the TSS effluent limit for 2.3% of the time during the storm simulation and 0.58% of the time during the yearly simulation. Similarly with the C6 configuration, the TSS limits are violated 2.5% of the time during the short and 0.60% during the long simulations.

The violation of the effluent limits is more evident and severe for the ammonia and total nitrogen, as shown in Figure 8. This is particularly true for the effluent ammonia (Figure 8(a)), which exceeds its limit for over 60%

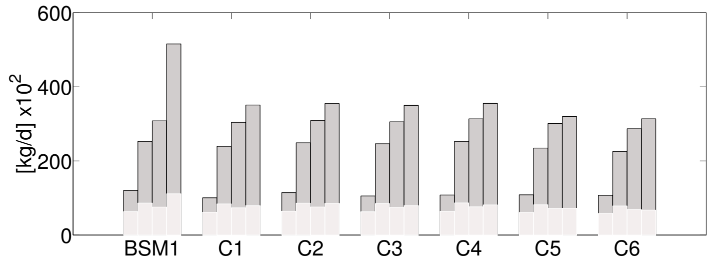
of the time during the one year simulation with the default BSM1 configuration. The violation drops to about 40% if only the DMC controller takes place in the C1 to C4 configurations and to 30% and 17% when the ratio and solid controllers are introduced as in the C5 and C6 configurations. The improvement of the process performances with the C5 and the C6, in particular, is more evident for the total nitrogen removal. In fact, the violation of its effluent limits drops from 44% with the BSM1 default controller to 12% with the C6 control configuration during the long-term simulation.



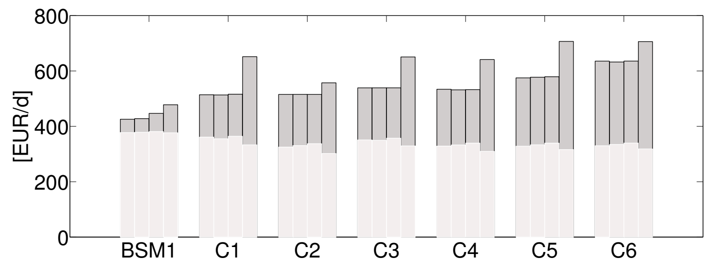
(a) Ammonia (b) Total Nitrogen

Figure 8: Percentage of the limit violations for SNH (a) and TN (b) in the effluent.

The improvement of the process performance in terms of effluent quality can be also noticed from the EQI comparison in Figure 9(a), which considerably decreases with the introduction of the proposed controllers. The same holds for the total average total cost, which is reduced with the DMC controllers. The maximum values though increase remarkably with every configuration, especially due to the higher variations in aeration energy required to reduce the peaks of ammonia.



(a) Effluent Quality Index



(b) Total cost

Figure 9: Maximum (dark grey) and mean (light grey) effluent values: Simulation results comparison during the dry (first column), rain (second column), storm (third column) and long term (fourth column) scenario for the effluent quality index (a) and total costs (b)

Table 5 summarises the results for the configuration C4, C5 and C6 and compare them with the performances of the BSM1 default layout over a simulation period of about ten months (300 days). The results of C5 and C6 evidence a better removal efficiency of ammonia and less total nitrogen in the effluent, coupled with a decrease in the average energy consumptions. On the other hand, C5 and C6, along with C4, lead to higher maxima of energy consumption, which is required to reduce the ammonia peaks. It is worth noticing that the BSM1 configuration has two always anoxic zones ($Z1$ and $Z2$) and maintains a constant aeration in zone $Z3$ and $Z4$, which implies a less efficient ammonia peak reduction.

Table 5: Comparison – Results over 298 days of LT simulation for the quality and economic performance assessment.

	BSM1	C1	C2	C3	C4	C5	C6	
Effluent SNH								
Mean	11.4	4.9	5.9	4.9	5.2	3.7	2.9	mgN/L
Standard deviation	9.9	4.7	5.5	4.4	4.5	2.9	2.0	mgN/L
Effluent TN								
Mean	17.8	15.3	16.2	15.4	15.8	13.7	12.1	mgN/L
Standard deviation	7.4	5.7	5.5	5.7	5.6	4.8	4.8	mgN/L
Effluent Quality								
Mean	11145	7921	8544	7932	8143	7248	6736	kg/d
Standard deviation	6982	4415	4692	4343	4391	3816	3531	kg/d
Aeration Energy								
Mean	3506	3233	2941	3211	3043	3041	3056	kWh/d
Standard deviation	308	933	900	1011	1135	1234	1314	kWh/d
Pumping Energy								
Mean	492	272	246	255	223	287	295	kWh/d
Standard deviation	80	140	117	121	78	103	87	kWh/d
Mixing Energy								
Mean	252	197	168	194	175	187	188	kWh/d
Standard deviation	42	107	83	116	105	110	112	kWh/d
Sludge Production								
Mean	2573	2594	2592	2595	2595	2508	2294	kg/d
Standard deviation	323	335	334	336	336	198	769	kg/d
Total Costs								
Mean	377	333	302	329	310	316	318	EUR/d
Standard deviation	29	82	74	85	95	106	112	EUR/d

Finally, the configuration C6 shows a sensible improvement in the nitrogen compounds removal given by the improved nitrification in the bioreactor, especially during the most demanding cold period of the year. For this reason, it is selected as the most convenient configuration for the task (Figure 10).

The dynamic comparison of the manipulated and controlled variables for C6 and the original BSM1 configurations is reported in Figure 11 and Figure

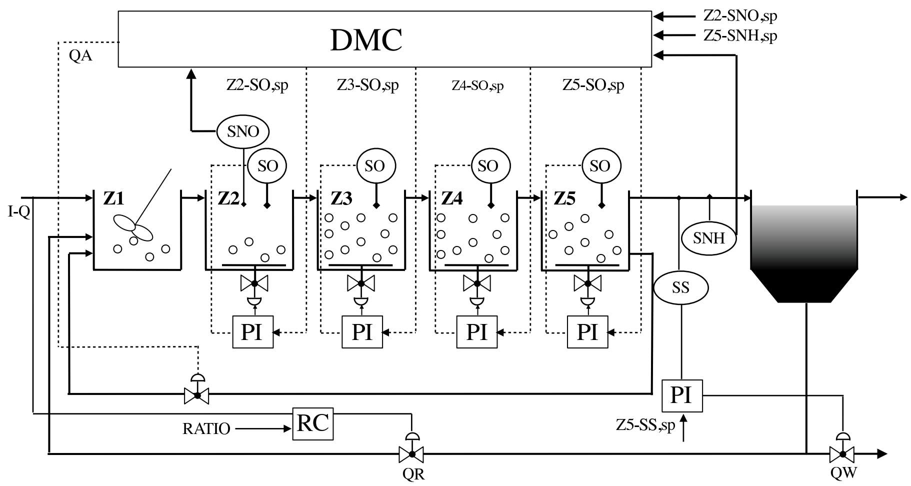
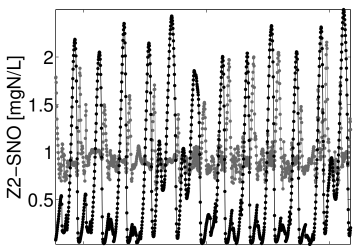
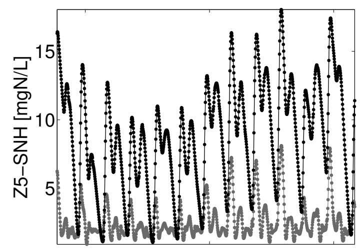


Figure 10: Benchmark Simulation Model No.1: Configuration C6

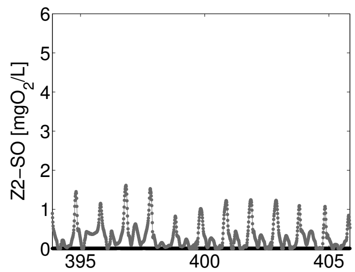
12 for a period of approximately 10 days corresponding to a low temperature time in the LT data. In particular, Figure 11 reports the DMC performances. It evidences how compared to the default BSM1, the selected configuration is able to keep the nitrate concentration in Z2 close to its set-point (Figure 11(a)) and the ammonia level at the end of the bioreactor rather low (Figure 11(b)), confirming the ability of the system to compensate the effects of temperature on the nitrification process. This is achieved by increasing the dissolved oxygen in Z2 (Figure 11(c)) and decreasing it in zone Z3 (Figure 11(d)) and zone Z4 (11(e)). Being the maximum achievable value of dissolved oxygen set equal 2.5 mg L^{-1}, $Z5$-SO-SP is slightly higher that the



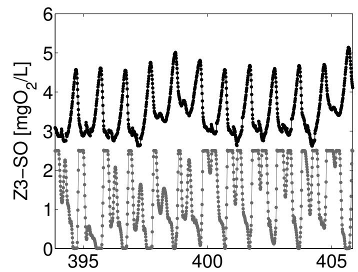
(a) Nitrate in Z2



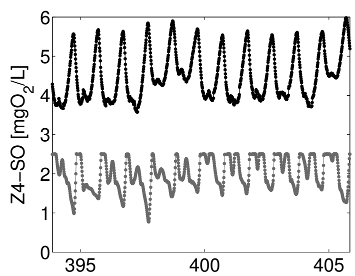
(b) Ammonia in Z5



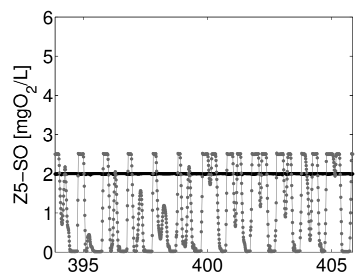
(c) Dissolved oxygen in Z2



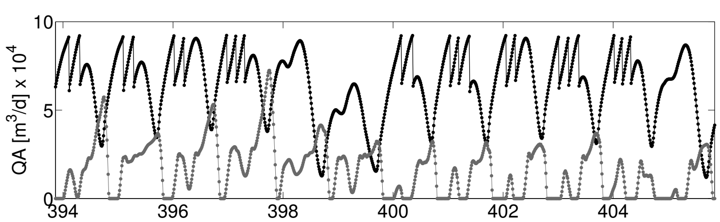
(d) Dissolved oxygen in Z2



(e) Dissolved oxygen in Z4



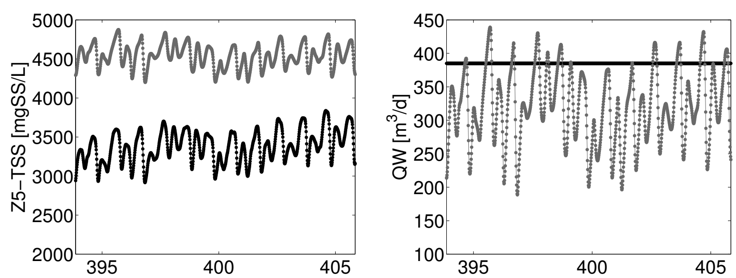
(f) Dissolved oxygen in Z5



(g) Internal recirculation

Figure 11: Comparison – LT simulation for approximately 10 days. Controlled variables: Nitrate in Z2 (a) and ammonia in Z5 (b); manipulated variables as dissolved oxygen in Z2 (c), Z3 (d), Z4 (e), Z5 (f) and internal recirculation (g) in the C6 (grey) and BSM1 default (black) configurations.

BSM1 default set-point (Figure 11(f)). From Figure 11(g) is also noticeable the smoother adjustment given by the DMC controller to the internal recirculation flow rate compared to the BSM1 controller. Unlike the DMC, the BSM1 nitrate controller needs the anti-windup to avoid saturation of the manipulated variable at low temperature; otherwise, in such conditions, the controller would not be able to efficiently transform ammonia into nitrate. Clearly, the results of the DMC must be considered together with the performances of the suspended solids control during the same time period (Figure 12). It can be noticed that $Z5\text{-}SS$ (Figure 12(a), 12(b)) is kept close to it set-point with slow and smooth adjustments of the excess sludge flow rate.



(a) Suspended solids in Z5 (b) Excess sludge flow rate

Figure 12: Comparison – LT simulation for approximately 10 days. Controlled (a) and manipulated variable (b) in the sludge feedback controller for the C6 (grey) and BSM1 default (black) configurations.

5. Conclusion

This paper presented the development of model based control strategies for an activated sludge process in a biological wastewater treatment plant.

In particular, the proposed control strategies were applied to the Benchmark Simulation Model No.1 used as a virtual plant, with the main purpose of minimising energy consumption by guaranteeing good nitrogen removal efficiency. The DMC algorithm in its linear formulation was used to obtain the optimal control of ammonia and nitrate concentration by using as manipulated variables dissolved oxygen concentrations in the bioreactor, and internal recycle flow rate. First, the identification problem related to the obtainment of the input-output predictive models to be used for control development was addressed by means of a Recurrent Neural Network. The modelling approach based on neural networks showed to be able to capture the main characteristics of the output step responses, when input disturbances were varied according to the long term simulation input data and the inlet ammonia flow rate was assumed as only measured disturbance. Dynamic matrices for the different configurations of the model predictive control were then obtained by averaging the responses predicted by the neural model at different manipulated input conditions. Four different DMC configurations were compared, and the selected one, which led to lowest energy consumption involved five manipulated variables (i.e. dissolve oxygen in the bioreactor, except that in the first anoxic zone, and the internal recycle flow rate) for the two controlled variables (ammonia in the 5^{th} zone and nitrate in the 2^{nd} zone of the bioreactor). It is important to underline that the coefficients of the dynamic matrix used in the model predictive control were kept constant, even if the activated sludge process is highly nonlinear. Even with this assumption, DMC performance was satisfactory for different weather scenarios and persistent disturbances, as it was simulated by the long-term input data, indicating that the proposed controllers showed robust performance. Anyway, ammonia removal efficiency decreases during the coldest period of long term simulation, because temperature lowering has a negative effect on reaction rates. The control configuration had been improved by adding two further controllers: a ratio control to maintain constant the ratio between recycle flow rate and inlet flow rate, and a feedback control to maintain at a target value the suspended solid in the bioreactor exit stream. This last configuration was able to significantly improve the system performance both in terms of energy consumption and ammonia and nitrogen removal even at low temperature.

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