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Effluent control and improving of the performance of biological wastewater treatment plant using neural networks

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ABSTRACT

In this paper we have developed two models to control the dissolved oxygen concentration which is an important key in the operation of wastewater treatment processes (WWTP) and the nitrate concentration of the sewage treatment plant in the activated sludge process: the first model is the Adaptive Control Neural Networks (ACNN) and the second model is the Adaptive Control Neural Networks PI (ACNN-PI). In order to use the BMS1 (Benchmark Simulation Model Nº 1) for the evaluation of the technical performance of these controls applied to wastewater treatment plants (WWTP). The control of wastewater treatment plants is not trivial because of the large disturbances of the influent, non-linearities, delays and interactions between variables and operating conditions. The predictive controllers of nonlinear models based on neural networks (NN) are designed to model unknown nonlinearities of wastewater treatment plants with high predictive performance. The control results obtained under disturbances in dry weather are satisfactory when our models are well applied and provide a very useful tool which can be used by WWTP operators in their daily management. Especially when you mix the ACNN nonlinear predictive control and the classic PI control. As well as the optimal control of oxygen and nitrates, it is possible to benefit from important properties in terms of process performance and energy costs such as energy consumption (EC) and effluent quality (EQ). The system adopted in this work offers significant reliable and economic and environmental benefits, depending on the performance criteria sought.

Key words : *Adaptative Control Neural Networks, PI, Neurone network, Benchmark Simulation Model Nº 1.*

Introduction

Activated sludge wastewater treatment processes are classified as non-linear systems difficult to control because of their large perturbations in pollutant load and influent flow rate, together difficult to be controlled because of their complex behaviour and uncertainties concerning the composition of the incoming wastewater.

The present paper deals with dynamic simulation and optimization of the benchmark wastewater treatment plant (BSM1), applied Adaptative Control Neural Network (ACNN) (Dong Wang *et al.*, 2021) to this Benchmark process. the simulation and opti-

mization steps were carried out using three experimental data sets corresponding to dry, rain and storm weather to maintain the effluent quality within regulations-specified limits.

The optimization step dealt with the determination of aeration and recycle profiles which minimize the energy consumption (Hong-Gui *et al*., 2019).

The progress of the biological reaction and the qualities of the effluents are treated by two key parameters: the concentration of dissolved oxygen and the concentration of nitrates in wastewater treatment plants Wwtps (Ivan Pisa *et al.*, 2019).

If the concentration of dissolved oxygen is higher than it will lead to a waste of energy and will also make the denitrification less efficient, and on the contrary, if the concentration of dissolved oxygen is too low, then there is not enough oxygen for biological growth and this also weakens the nitrogen removal capacity (Qiao *et al.*, 2014). The level of denitrification is related to the nitrate concentration, finding the correct concentration is of great importance to ensure the success of the denitrification process. Hence, for reasons of both economics and the treatment process, it is important to control the dissolved oxygen concentration and the nitrate concentration.

A multivariate adaptive control strategy is designed for a continuous aerobic wastewater treatment bioprocess (Xianjun Du *et al.*, 2018). Recently, artificial intelligence techniques have beenused in wastewater treatment plants, so we opted to choose the ACNN (Adaptive Control Neural Networks Model) (Dong Wang *et al.*, 2021) model to control the dissolved oxygen concentration of an aerobic reactor in a wastewater treatment plant wwtp.

The paper is structured as follows:

The first section presents the description of Benchmark for wastewater treatment with activated sludge with a simplified diagram of the treatment plant.

The second section reference modelling process which presents the model used to describe the biological phenomena involved in the biological reactor.

The third part summarizes the control of the wastewater treatment plant which is based on the model of the artificial neural network.

The fourth section contains the control methods of the wastewater treatment process and the simulation results contains the detailed model for the control of the wastewater treatment plant which is based from:

- Adaptive control neural networks ACNN of BSM.
- Adaptive control neural networks ACNN-PI of BSM1.

The last chapter is dedicated to the performance of the process control who gives an idea on the optimization of the total energy consumption.

Model benchmark description

The activated sludge wastewater treatment process is a dynamic system. In order to simulate the processes that occur in a biological treatment process, the benchmark represents a continuous-flow predenitrifying activated sludge process, which contains a reactor tank and a settling tank.

The biological reactor is composed of five perfectly agitated compartments where the first two are anoxic reactors (volume of each 1000 m^3) and the last three are aerobic reactor (volume of each 1333 m^3), which gives as total volume of the reactor 6000 m^3. The secondary settling tank is represented as a non-reactive, one-dimensional system divided into horizontal layers, according to the model of exponential double settling speed proposed by (TAKACS, 1991). Its total volume is equal to 6000 m^3.

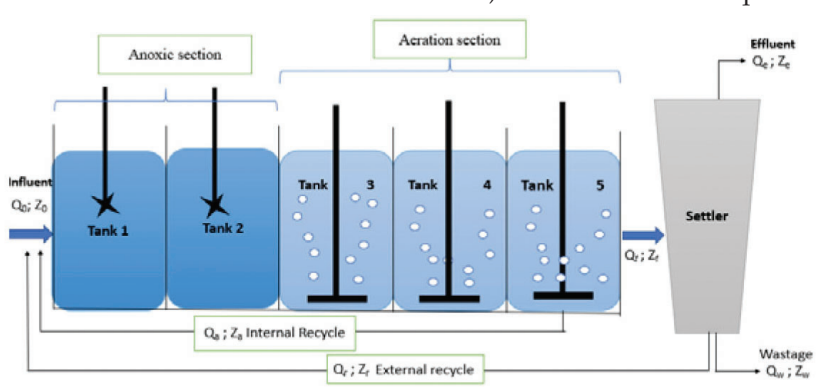

Fig 1. Schema of BMS1 plant (wwtp)

The wastewater follows first an anoxic treatment (units 1 and 2) biologically in free cultures according to which, in a first step, the organic carbon (COD) is essentially eliminated by heterotrophic bacteria. The effluent leaving the first stage is subjected to aerobic biological treatment in free cultures for the transformation of ammonium into nitrates.

Table 1. Average reactor/average design values

Réacteur	Value	Settler	Value
Volume-tank1	1000 m^3	Depth-Settler	4 m
Volume-tank2	1000 m^3	Area-Settler	1500 m^2
Volume-tank3	1333 m^3	Volume-Settler	6000 m^3
Volume-tank4	1333 m^3		
Volume-tank5	1333 m^3		

The affluent dynamics are defined by three data files: dry weather, rain and thunderstorm. The flow rates of the three data sets are shown in Figure 2.

Benchmark modelling process

In (Haralick *et al.*, 1973) is noticed that a synthesis of the control structure for wastewater treatment process is very complicated, because of its specific features. Those features include:

(i) multiple time scales variations of parameters in the biological process,
(ii) influent flow rates variations and pollutant concentrations,
(iii) non-linearity of the process,
(iv) biological sustainability assurance in spite of unknown disturbances,
(v) high disturbances amplitude with hard influence to the biological process,
(vi) the small number of measurable variables due to lack of sensors (Brdys *et al.*, 2008).

The lack of wastewater treatment process models implementation from literature are partially solved with development of the Benchmark Simulation Model No.1 (BSM1). It consists of five biological reactors connected in series, from which the first two are anoxic and the last three are aerated reactors and two recirculating loops: internal recycle from the last to the first reactors and external recycle, from the secondary settler to the first reactor (J.B. Copp (ed.), 2002). The reactors are modelled according to the Activated Sludge Model No. 1 (ASM1) presented in 1987 by (Henze *et al.*, 1987). The ASM1 has thirteen state variables and eight dynamic processes and it consists of a set of ordinary differential equations which describe the dynamic changes of the state variables. A schematic representation of the plant is presented in Figure 1.

The model used to describe the biological phenomena involved in the biological reactor is based on the Activated Sludge Model no.1 (ASM1) presented in Figure 1. The state variables with their definition are listed in Table 2.

Eight different processes are modelled, involving thirteen state variables. An internal recycle from the last tank to the first one is used to supply the denitrification step with nitrate.

The last tank has to reduce the Dissolved Oxygen (DO) concentration before the recycled water is fed back to the first anoxic tank. For the secondary settler the one-dimensional ten-layer system implementing the double exponential settling velocity model has been used (Cadet *et al.*, 2004). In order to investigate the control performance for disturbance rejection a set of three different weather conditions, i.e. dry weather, stormy weather and rainy weather, have been considered in special designed disturbance influent input files. See Nomenclatures below.

To model the biological phenomena and the decantation phenomena within this treatment process,

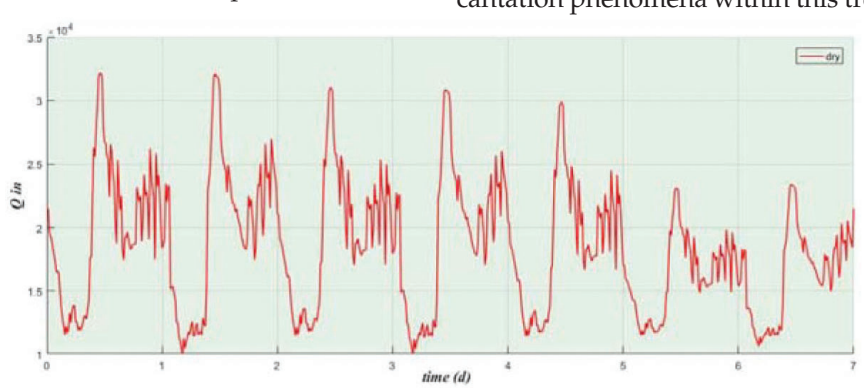

Fig 2. Influent flow disturbance in dry weather

two models were used: the ASM1 model, described above, for the biological part and the formulation applied to a 10-layer clarifier for decantation. For the biological part, the overall number of state variables is 65 and the number of parameters (yields and kinetics of biological reactions) is 19.

Number of compartments: 5.

Non-ventilated compartments: 1-2.

Ventilated compartments:

- 3-4 compartments with a constant oxygen transfer coefficient (K_{La}= 10h^{-1} = 240d^{-1}).

- Compartment 5 with the concentration of dissolved oxygen is controlled at level 2 g (-DCO).m^{-3} by manipulation of K_{La}.

The global modeling of the process is given by a material balance on each of the compartments

Compartment n ° 1: (k=1(tank1)

$$\frac{dZ_1}{dt} = \frac{1}{V_1}\left(Q_a Z_a + Q_r Z_r + Q_0 Z_0 + r_1 V_1 - Q_1 Z_1\right) \quad .. (1)$$

Compartment n°2 : k=2 to 5 (tank 2 to tank 5)

$$\frac{d\ z_k}{dt} = \frac{1}{V_k}\left(Q_{k-1} Z_{k-1} + r_k V_k - Q_k Z_k\right) \quad .. (2)$$

The nitrate concentration (S_{NO}) variation can be described by equations (1) and (2).

Special case for oxygen $S_{O',k}$:

The oxygen concentration S_O has a significant signature on those of S_{Not}, S_{NO} and $S_{NH}$where its dynamic equation reads,

$$\frac{d\ S_{O,k}}{dt} = \frac{1}{V_k}\left(Q_{k-1} Z_{O,k-1} + r_k V_k + (K_L a)_k V_k (S_O^{sat} - S_{O,k}) - Q_k S_{O,k}\right) \quad (3)$$

Where,

V_k : is the volume of the reactor k,

Q_k: represents the flow rate,

Z_k: denots the constitutes concentration,

r_k: is the observed conversion rate for the components.

And $S_0^* = 8mg/l$ is the saturation concentration for oxygen.

The design of a control system and the use of the mechanism model remains an arduous task.

The control of the wastewater treatment plant

The neural Networks (NN)

The basic unit in the artificial neural network is the neuron. Neurons are connected to each other by links known as synapses; associated with each synapse there is a weight factor. Usually neural networks NN are trained so that a particular set of inputs produces, as nearly as possible, a specific set of target outputs. (Nissrine Drioui *et al.,* 2019).

The model contains two feedforward neural networks (FNN) with similar structure, one to estimate each process output: SO,5 and $S_{NO,2}$. (see fig 3) (Nissrine Drioui *et al.,* 2019).

The manipulated variables and perturbations are introduced as inputs to the feedforward neural networks (FNN) along with the one and two-step delayed outputs.

''The FNN is widely used in the modeling, identification and control'' (Ersu, 2012, Mirghasemi *et al.,* 2014) because of its simplicity and efficiency.

The multi-layer perception (MLP) is an efficient feedforward neural networks FNN and is chosen in this study

The Adaptative Control Neural Networks (ACNN) is used as loop controllers of the dissolved oxygen concentration and nitrate concentration.

Problematic

Consider a general nth-order single-input-single-output (SISO) nonlinear systems (Carlos Alberto *et al.,* 2012).

$$\begin{aligned} x^{(n)} &= f(x,t) + g(x,t)u + d \\ y &= x \end{aligned} \quad .. (4)$$

Where *f(x)* and *g(x)* are unknown continuous function, in order to simplify the discussion, we suppose *g(x)* as a positive constant, u∈ and y∈ are the input and output of the system, respectively, x = [$x_1 x_2$, .., x_n] e is the system state vector.

Our aim is to find an adaptive control neural networks law, such that the concentration of and can track the set point nicely. The tracking error is defined as $e = y_d - y$

Define the filtering error as

$$s = e^{(n-1)} + k_1^{(n-2)} + \cdots + k_n \int_0^t e(\tau) d\tau \quad .. (5)$$

If the function *f*(x) and *g*(x) are known, we can get the ideal control law (Jean-Jacques, 1991):

$$u^* = \frac{1}{g_n}\left[-f_n + y_d^{(n)} + k^T e - d\right] \quad .. (6)$$

Where, $f_n(x)$ and $g_n(x)$ are the normal function of the *f(x)* and *g (x)*; d(x) is the lumped uncertainty.

If $k = [k_1, k_2, \ldots, k_n]^T$ are chosen to correspond to the coefficient of a Hurwitz polynomial, which can

guarantee all roots lie on the left plane, then, it implies $\lim_{t\to\infty} e(t) = 0$. However, the function $f(x)$ and are unknown, so that the ideal control law cannot be executed. ''Using the excellent approximating ability of neural network, the ideal control law is approached by forward neural network (FNN) in this paper' 'See more (Jean-Jacques, 1991).

Multi-layer perception (MLP)

The FNN is widely used in the modeling, identification and control''(C. Ersu, 2012; Mirghasemi *et al.*, 2014; Ivan Pisa *et al.*, 2019) because of its simplicity and efficiency. The multi-layer perception (MLP) is an efficient forward neural network (FNN) and is chosen in this study. The typical three-layer structure of the MLP can be illustrate as Fig. 3.

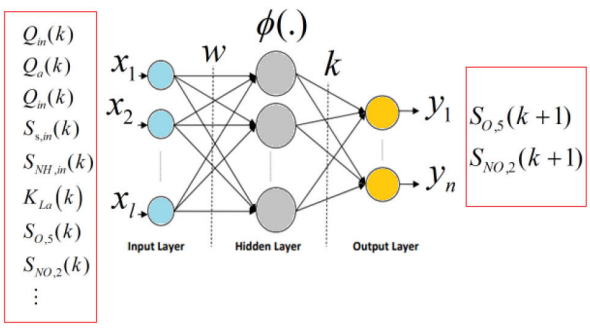

Fig. 3. The FNN as predictive model

The relation between input and output can be described as

$$y = w^T \phi(kx) \qquad .. (7)$$

where $x = [x_1, x_2, \ldots, x_l]$ and $y = [y_1, y_2, \ldots, y_l]$ are the input vector and output vector of the MLP, ''respectively; let the number of the hidden nodes be m; $k \in \square^{m\times l}$ represents the weight matrix connecting the input nodes and the hidden nodes, and the weights matrix connecting the hidden nodes and the output nodes is $w \in \square^{m\times n}$''.

The sigmoid function is defined as hidden activation function

$$\phi(z) = \frac{1}{1+e^{-z}} \qquad .. (8)$$

The values of the sigmoid function and its derivation are all within the scope of 0 to 1.

Approximation of neural networks controller

''The ideal control law is approximated by MLP in this paper, and can be expressed as'' (Hsu ,2008)

$$u^* = u^*_{nn} + \Delta = w^{*T} \phi(k * s) + \Delta \qquad .. (9)$$

Assume that u*m is the optimal control law under the optimal weights matrix w* and k^* ; Denotation of Ä represents the approximation error. Since the optimal neural network weights are unobtainable, an estimation of u_{nn} is given by (11)

$$u_{nn} = \hat{w}^T \phi(\hat{k}s) \qquad .. (10)$$

Where $\hat{w} \in \square^{m\times 1}$ and $\hat{k} \in \square^{m\times 1}$ are the estimated values of the optimal weights and Define the estimated error

$$u = u^* - u_m \qquad .. (11)$$

In (Hsu, 2008), ''the proof that the approximation error is bounded when using the MLP to approach the ideal computation control law has been given''

Control neural networks

In this paper, the controlled variables considered for the BSM1 protocol are selected to apply a multivariable control scheme model.

The concentration of dissolved oxygen in the last aerated reactor and the concentration of nitrates at the end of the anoxic zone ($S_{o,5}$ and $S_{NO,2}$) are controlled in two methods using as variables manipulated the oxygen transfer coefficient in the last reactor ($K_{La,5}$) and internal recycling flow (Q_a).

The instructions are chosen in order to maintain $S_{O,5}$ et $S_{NO,}$ around 2 mg. L^{-1} et 1 mg. L^{-1} respectively.

The limits imposed by the regulations on the concentration of nutrients and carbonaceous compounds in the effluent are presented in (Alex J.; Benedetti L.; Copp J.; Gernaey K.; Jeppsson U.; Nopens I.; Pons M.; Rieger L.; Rosen C.; Steyer J.; Vanrolleghem P.; Winkler S. 2008).

In order to assess the control performance, part of the dry BSM1 profile is used in this study to characterize the behavior of the influent.

Adaptative Control Neural Networks ACNN of BSM1

The disturbances considered are: the influent flow Q_{in} Dry Weather Influent, (Alex *et al.*, 2008) (Dong Wang *et al.*, 2021), the concentration of easily biodegradable substrate $S_{S,in}$ and the ammonium concentration $S_{NH,in}$ in the influent of the controlled process of activated sludge is illustrated in Fig. 4

Our task is to control the dissolved oxygen level in the final compartment of the reactor by manipu-

lation of the oxygen transfer coefficient $K_{La,5}$ and the nitrate level in the last anoxic tank by manipulation of the internal recycle flow rate Q_a.

The control structure proposed of the system, based on the ACNN, is shown too in Fig. 4.

The general formulation of the control neural network consists of an online calculation of future control actions u by solving the following optimization problem subject to constraints on the inputs, predicted outputs and changes in the variables handled, the following formulation:

$$\min_{\Delta u} J(k) = \sum_{i=H_w}^{H_p} w_y \left(\hat{y}(k+i) - r(k+i)\right)^2 + \sum_{j=0}^{H_{c-1}} w_u \left(\Delta u(k+i)\right)^2 \quad (12)$$

Where, $\hat{y} = \begin{pmatrix} S_{NO,2} \\ S_{O,5} \end{pmatrix}$, $u = \begin{pmatrix} Q_a \\ K_{La,5} \end{pmatrix}$, $r = \begin{pmatrix} S_{ref\_NO,2} \\ S_{ref\_O,5} \end{pmatrix}$

Indicates the current sampling instant,

$y(k+i/k)$ is a vector of the predicted output values,

$r(k+i)$ is a vector of the future set-point values,

Δu are the changes in the manipulated variables,

H_p is the upper prediction horizon,

is the lower control horizon,

H_c is the control horizon. ($H_w = 1$ and $H_c = 1$, for simplify)

The matrices $H_w = \begin{pmatrix} \lambda Q_a & 0 \\ 0 & \lambda K_{La,5} \end{pmatrix}$ and $H_y = \begin{pmatrix} \lambda S_{NO,2} & 0 \\ 0 & \lambda S_{O,5} \end{pmatrix}$ contain the weights associated with manipulated variables and with the reference tracking errors respectively.

The bounds and model constraints are based on the effluent quality conditions listed in (Alex *et al.*, 2008).

In the typical MPC formulation, a linear process model is used to predict the future outputs of the plant.

As the ACNN proposed here uses the neural network model, its implementation requires the solution of a nonlinear optimization problem online. It involves a significant computational effort; however, it is compensated by the improvement in the operational performance that can be achieved by using a more realistic representation of the behavior of such complicated nonlinear process (Nissrine Drioui *et al.*, 2019).

The simulation of the controlled process with the optimization function at time k, is

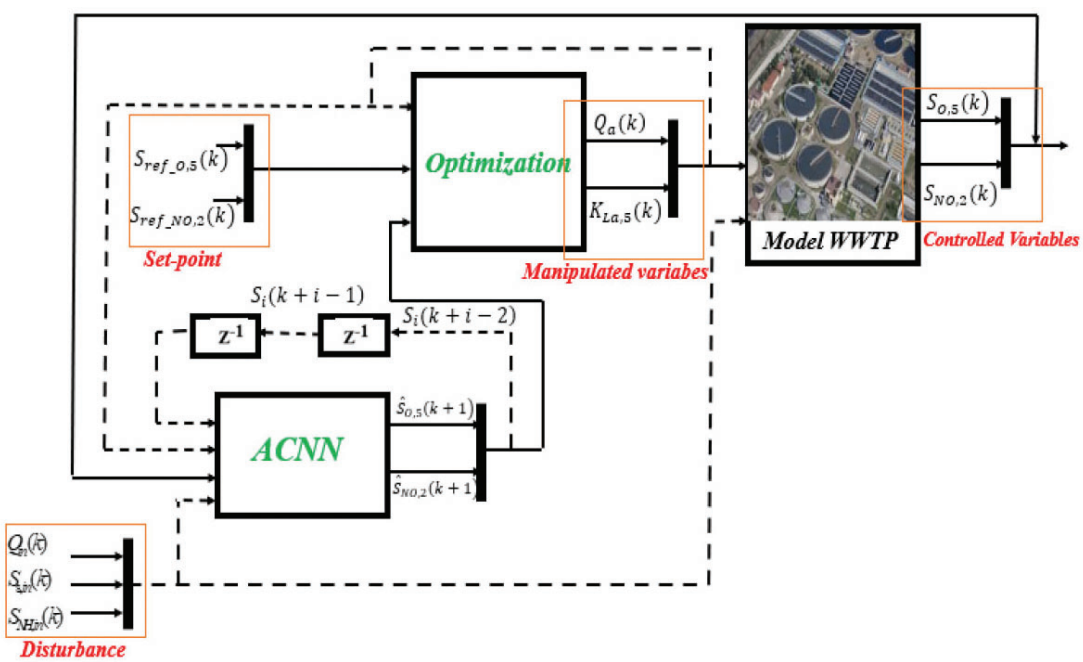

Fig. 4. ACNN model of control scheme

$$\min_{u} \; J(k) = \left[\sum_{i=1}^{7} \begin{pmatrix} \hat{S}_{NO,2}(k+i)-1 \\ \hat{S}_{O,5}(k+i)-2 \end{pmatrix}^{T} \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} \hat{S}_{NO,2}(k+i)-1 \\ \hat{S}_{O,5}(k+i)-2 \end{pmatrix} \right] + \left[\begin{pmatrix} \Delta Q_a(k+i) \\ \Delta K_{La,5}(k+i) \end{pmatrix}^{T} \begin{pmatrix} 1e-9 & 0 \\ 0 & 1e-5 \end{pmatrix} \begin{pmatrix} \Delta Q_a(k+i) \\ \Delta K_{La,5}(k+i) \end{pmatrix} \right] \quad .. (13)$$

For sampling time: 10 min

Fig. 5 to Fig. 9 show the behaviour simulations, the output variables and the variables manipulated for the predictive neuron control diagrams presented in the previous figure (Fig. 4).

What is quite remarkable from Fig. 5, that there is a remarkable change in the values of the internal recycling rate as a function of time which is generally due to system disturbances and the effect of the various adjustment parameters on the performance of the control. while the weather condition chosen is dry weather.

From Figure 6 we notice that the values of KLa5 were approximately close to one another under the meteorological conditions indicated (dry weather), that is to say that there is very little variation on the manipulate parameter KLA,5 which do not significantly modify its values; but the measured values are always below the set point

To compare the tracking of the oxygen path below; Fig 7 shows the control performance as can be seen. The ACNN controller implemented is more efficient and considerably improved, all respecting the surrounding of the set point given by 2 mg/l.

As we can see, the simulation of the nitrate behavior shows that there was no significant difference between the performances of the ACNN controllers and the performances of the ACNN-PI controllers, this shows that the nitrates control shows a good performance with a remarkable error,

This means that the nitrate control shows good performance and better control with the combination of the ACNN controller with the PI controller.

Adaptative Control Neural Networks ACNN-PI of BSM1

This is to be expected due to the assumption of small angle of attack. The figure also shows that the current results are closer

To find a good results better performance of our system with a negligible error, we propose to combine ACNN with PI control for this process which becomes ACNN-PI. The proposed ACNN-PI

Fig. 5. Variation of Q_a in ACNN and ACNN-PI model

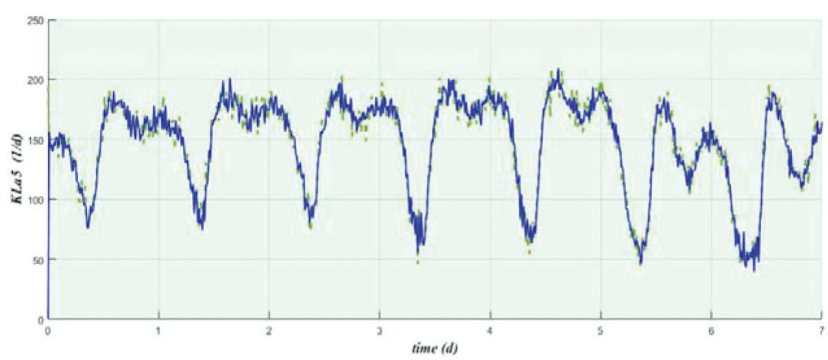

Fig. 6. Variation of K_{La5} in ACNN model

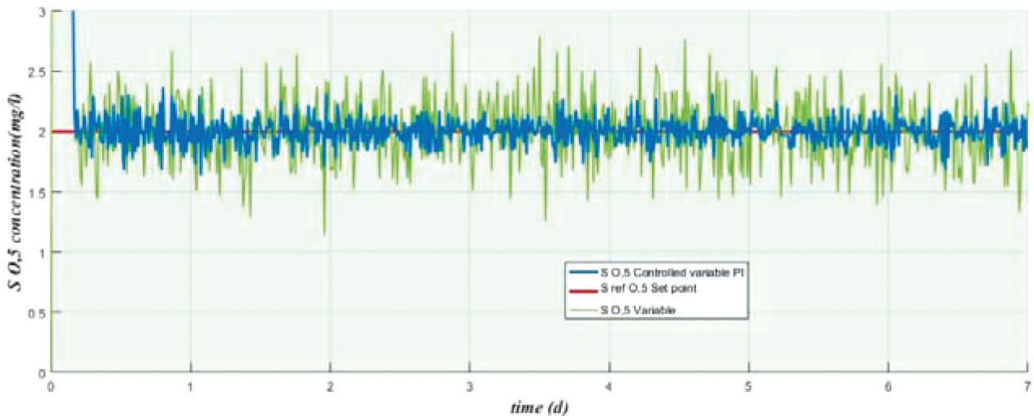

Fig. 7. Performance of ACNN controller in dry weather for $S_{0.5}$ concentration

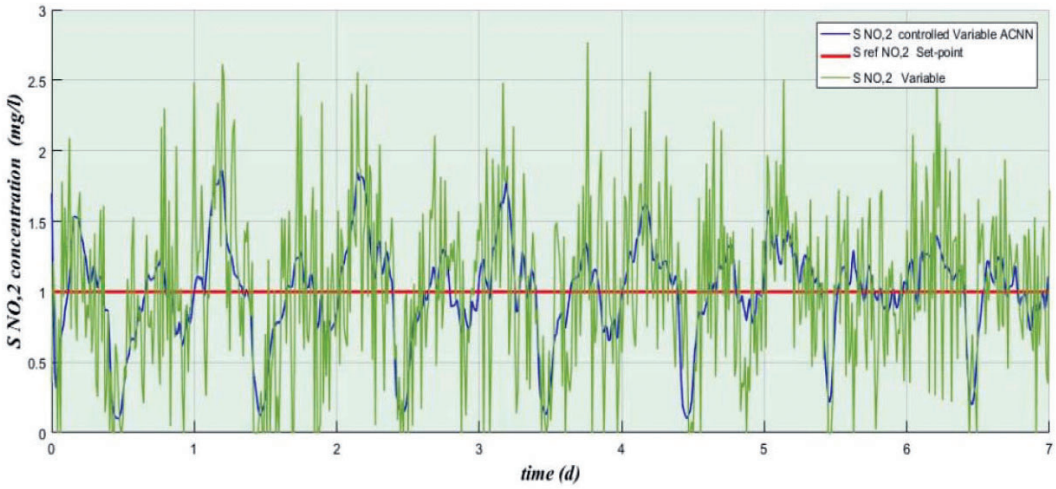

Fig. 8. Performance of ACNN controller in dry weather for $S_{NO,2}$ concentration

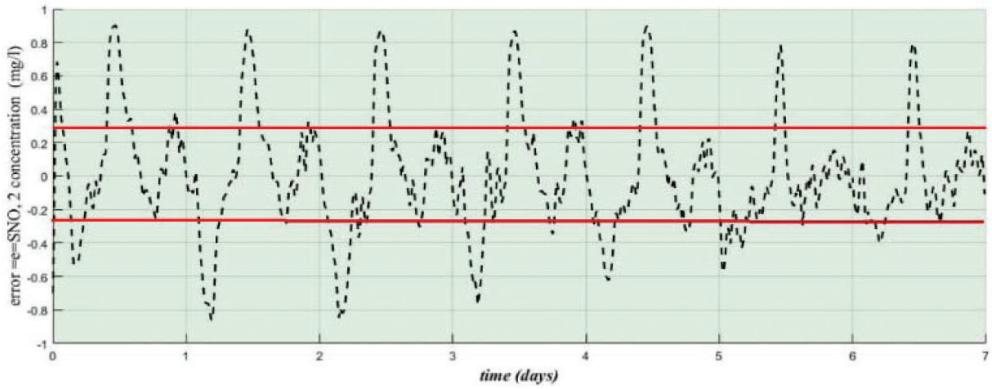

Fig. 9. Error of $S_{NO,2}$ concentration in ACNN model

scheme is shown below in Fig. 10.

The results of the simulations examined in Fig. 11 to Fig. 14 indicate a better control quality of the combined ACNN-PI scheme.

The dissolved oxygen variable with the ACNN-PI coupled control ensures better efficiency and performance while respecting the set point.

The nitrate variable simulation shows that the PI-ACNN coupling ensures good performance and better results with a decrease in error which is very re-

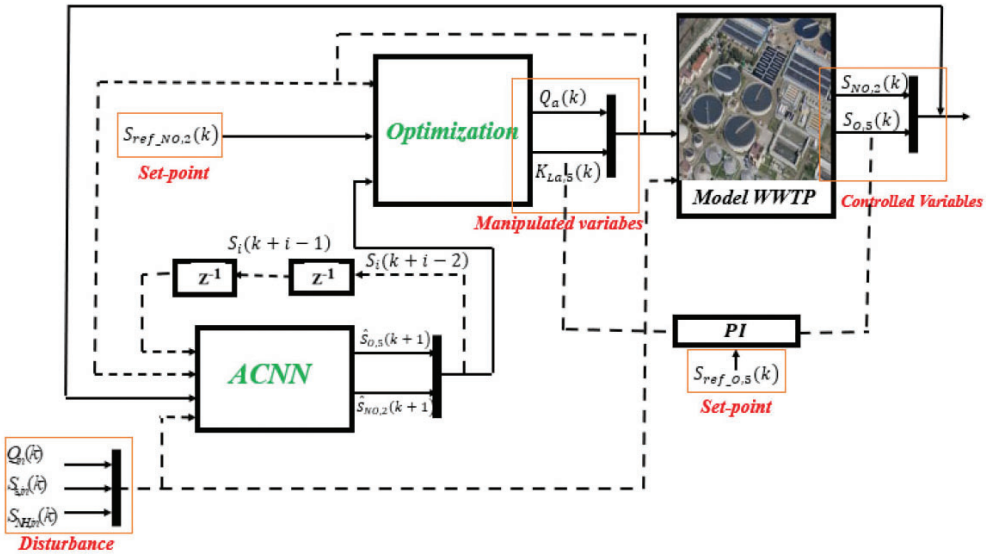

Fig 10. ACNN-PI model of control scheme

markable around the setpoint.

Control The performance of the process control

Numerous simulations of the BSM1 controlled with the ACNN/ACNN-PI are performed studying the effect of the different tuning parameters on the control performance. The indices defined in the benchmark are used to evaluate the plant behavior, namely, the EQ, AE and PE indices.

Since the aeration energy consumption (AE) and the pump energy consumption (PE) account for more than 70% of the total energy consumption, the optimization objective EC is defined as the sum of AE and PE (Luca *et al.*, 2019), as follows:

EC= AE + PE

As defined in BMS1, AE and PE can be calculated as (Hasanlou *et al.*, 2019)

$$AE = \frac{S_{O,sat}}{T*1.8*1000}\int_{kT}^{(k+1)T}\sum_{i=1}^{5} V_i.K_{Lai}(t)dt \quad .. (14)$$

$$PE = \frac{1}{T*1000}\int_{kT}^{(k+1)T}\left(4Q_a(t)+8Q_r(t)+50Q_w(t)\right)dt \quad .. (15)$$

where V_i and K_{Lai} are the volume and oxygen transfer coefficient of the ith unit, respectively. $S_{O,sat}$ is the saturation concentration for oxygen. T is the optimal cycle.

Q_a, Q_r, and Q_w are, respectively, the internal recircu-

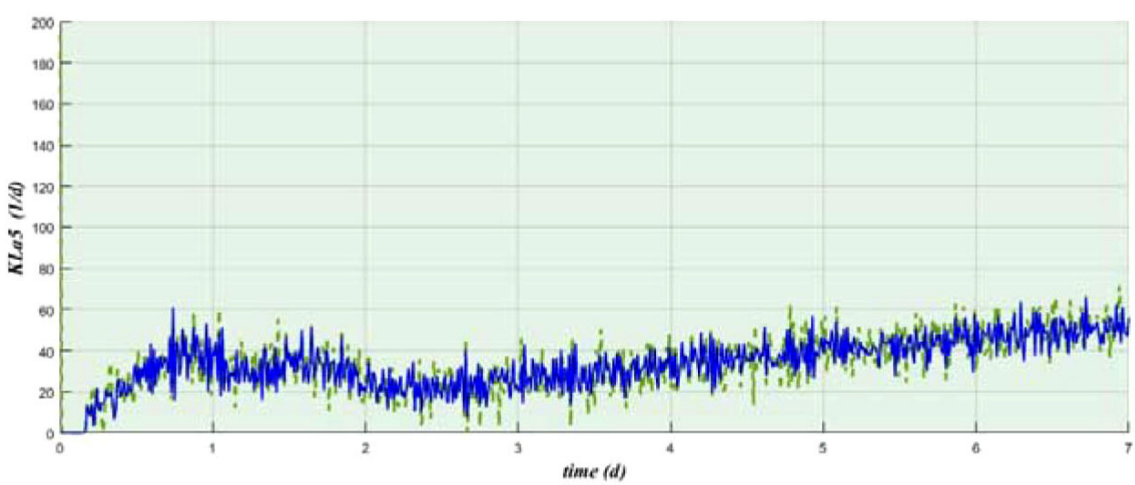

Fig 11. Closed loop system with ACNN model

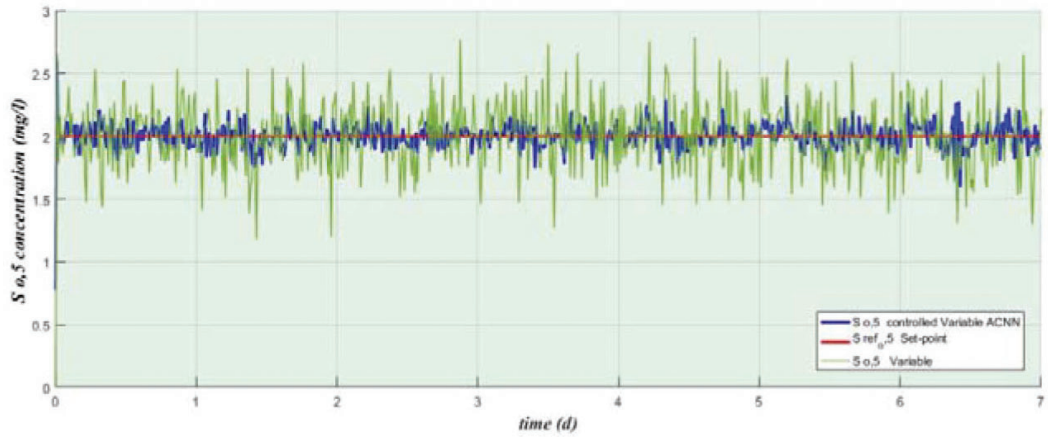

Fig 12. Performance of ACNN-PI controller in dry weather for $S_{0.5}$ concentration

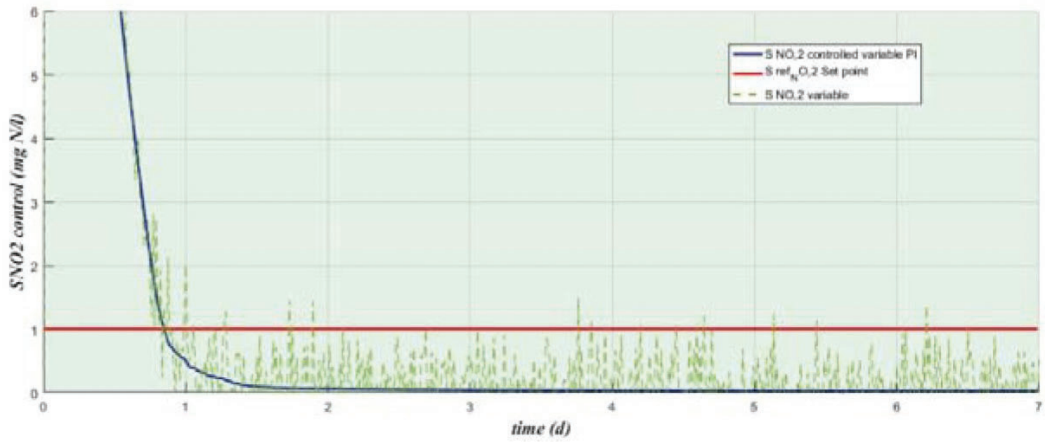

Fig 13. Performance of ACNN-PI controller in dry weather for $S_{NO,2}$ concentration

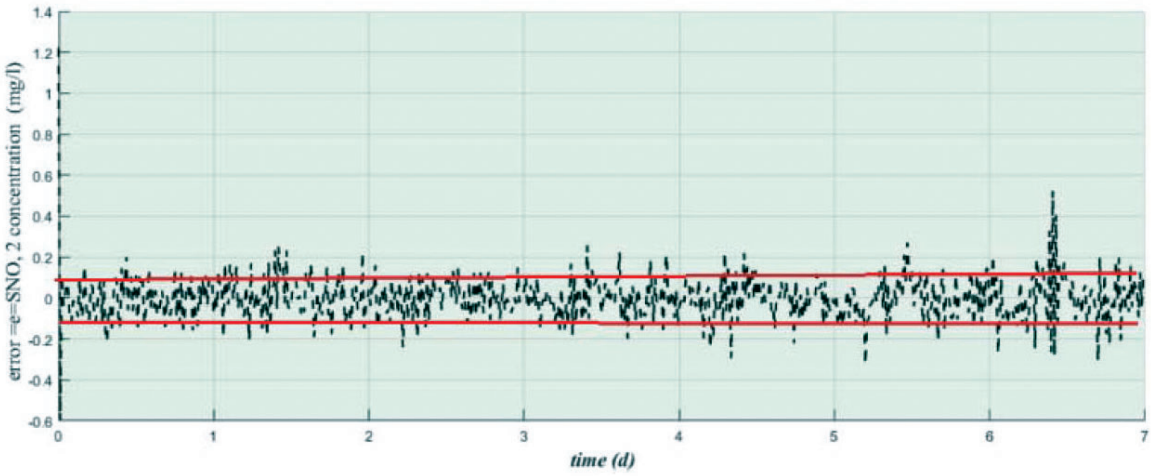

Fig. 14. Error of $S_{NO,2}$ concentration in ACNN-PI model

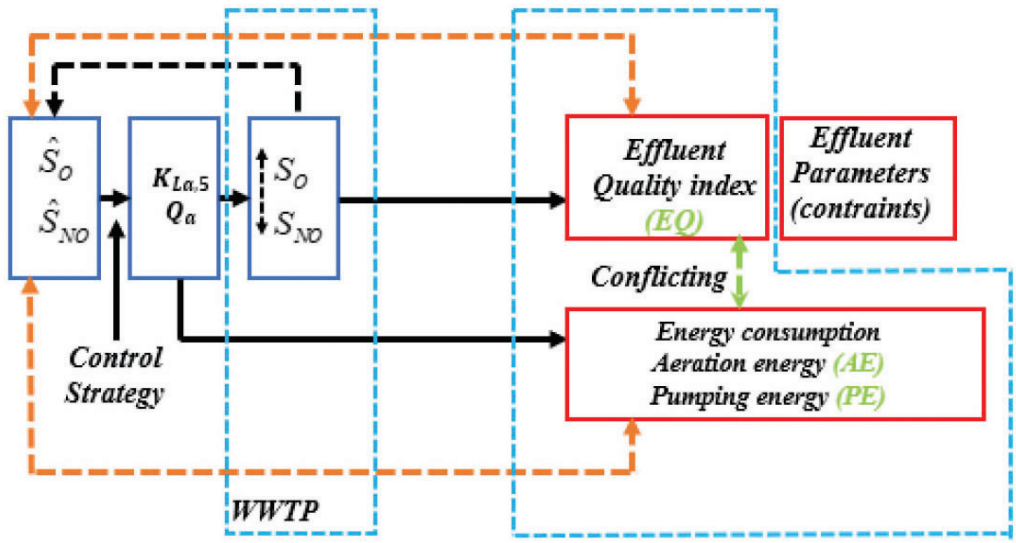

Fig. 15. Relationships among the optimized variables, manipulated variables and performance indexes in the WWTP

lation flow rate, the external recirculation flow rate, and the sludge flow rate.

Moreover, EQ is defined as

$$EQ = \frac{1}{T.1000}\int_{t_0}^{t_f}\begin{pmatrix} 2.SS_e(t) + COD_e(t) \\ +3.S_{NNj,e}(t) + 10.S_{NO,e}(t) \\ +2.BOD_{5,e}(t) \end{pmatrix} Q_e(t)dt \quad .. (16)$$

where *SSe*, *CODe*, *SNKj,e*, *SNO,e*, and *BOD5,e* are, respectively, the effluent concentrations of suspended solid, chemical oxygen demand, nitrogen, nitrate nitrogen, and biochemical oxygen demand of 7 days; *Qe*is the effluent flow rate.

The constraint condition on the process values of five kinds of effluent parameters given in BSM1, as follows (Alex *et al.*, 2008):

$$S_{NH,e} \le 4mg/l, \quad N_{tot,e} \le 18mg/l, \quad BOD_{5,e} \le 10mg/l$$
$$COD_e \le 100mg/l, \quad SS_e \le 30mg/l$$

where *Ntot,e* is the effluent total nitrogen which is the sum of *SNO,e* and *SNKj,e*.

Since wastewater treatment plants have no economic income, minimizing operating costs becomes much more important. The pumping energy (PE), the ventilation energy (AE) and the overall quality of the effluents (EQ) for our control diagrams are summarized in the table below Table 3.

The aim of optimal control is to achieve the best balance between EC and EQ by dynamically adjusting the set-points of $S_{O,5}$ and $S_{NO,2}$.

In the WWTP, the setpoints of $S_{O,5}$ and $S_{NO,2}$. not only affect EC but also show a close relationship with EQ. In the figure below the relationships among the optimized variables, manipulated variables and performance indexes in the WWTP.

The simulations show a better general performance of the ACNN / ACNN-PI scheme which is confirmed by the performance control indices, see the figures below for 7 days:

The results of the progression of AE, EQ and PE are summarized in the following table:

The best results are observed for the combined ACNN-PI scheme, which shows better effluent quality and minimal aeration energy, with lower pumping energy consumption. Both methods are very in-

Table 3. Economic index for the WWTP

EQ(kg poll.units)	AE (kWh/d)	PE (kWh/d)	
Original BMS1 version (Alex *et al.* 2008)	8098.5502	7238.6559	1851.5579
ACNN	7150.13	3514.34	212.97
ACNN-PI	7017.91	3121.67	198,65

teresting and satisfactory for controlling the process of activated sludge.

The assessment took place in two levels:

% The first one concerned the control performance, serving as evidence for proper application of the proposed to control, traditional Integral Square Error (ISE) is calculated respect to the two controlled variables ($S_{NO,2}$ and $S_{O,5}$).

% The second one, however, provided the measures for the impact of the control ACNN/ACNN-PI on plant performance, and included the Effluent Quality Index (EQI) and Overall Cost Index (OCI) indicators of WWTP.

Table 4 gives the performance assessment criteria definition with the used indices being as follows: (H. Hasanlou *et al.*, 2019)

$$OCI = AE + PE5 + SP3 + EC + ME \quad .. (17)$$

$$EQI = \frac{1}{T*1000}\int_0^7 (B_{SS}TSS_e(t) + B_{COD}(t).COD_e(t) + B_{BOD5}.BOD5_e + B_{NK_j}TKN_e(t) + B_{NO}.S_{NO_e}(t))Q_e(t)dt$$

$$SP = \frac{1}{T}\left(TSS_a(7) - TSS_a(0) + TSS_s(7) - TSS_s(0)\right) + \int_0^7 TSS_W.Q_w dt)$$

$$EC = \frac{COD_{EC}}{T.1000}\int_0^7 \left(\sum_{i=1}^{n} q_{EC}\right)dt$$

$$ME = \frac{24}{T}\int_0^7 \sum_{i=1}^{5}\left[0.005.V_i \;\; if \;\; K_L a_i(t) \prec 20d^{-1} \; otherwise 0\right] \quad .. (18)$$

The table shows the satisfactory results of our models (ACNN and ACNN-PI) and especially for ACNN-PI

For a more comprehensive comparison, some related referenced papers have been compared with

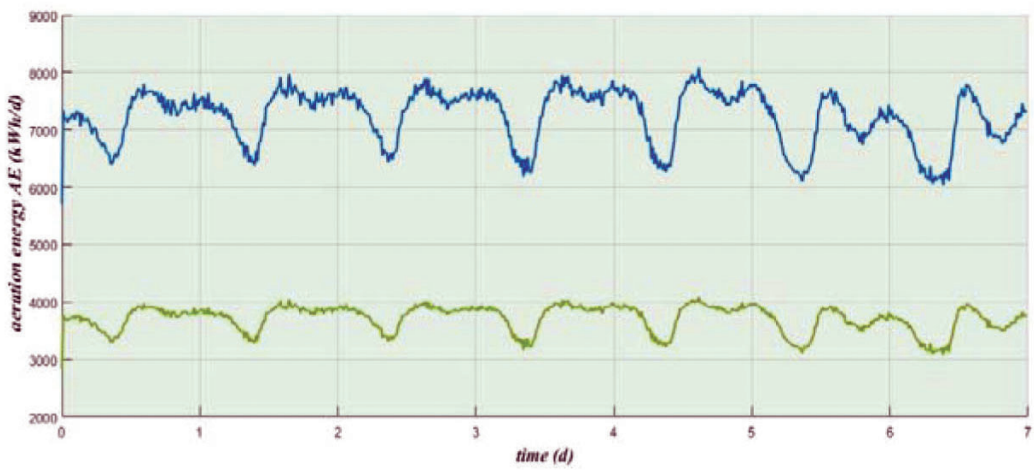

Fig. 16. Progression Aeration Energy (AE)

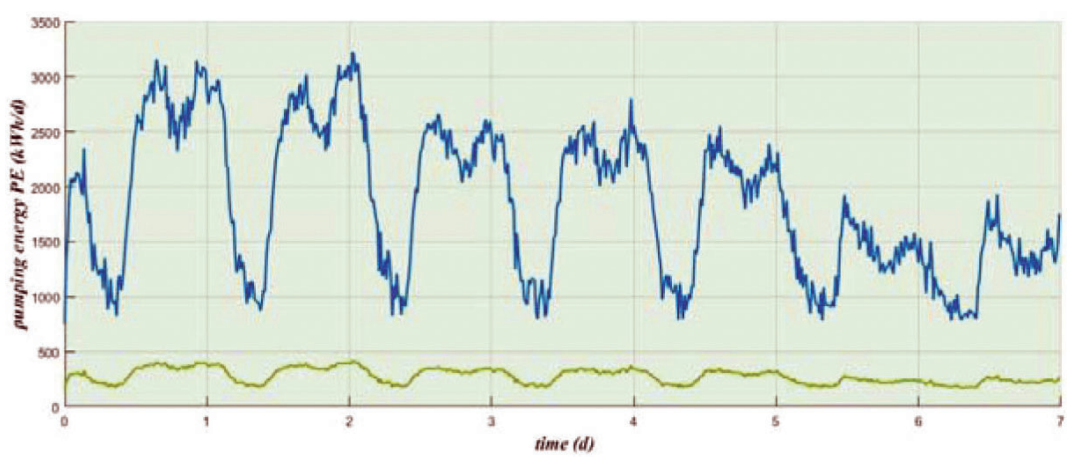

Fig. 17. Progression Pumping Energy (PE)

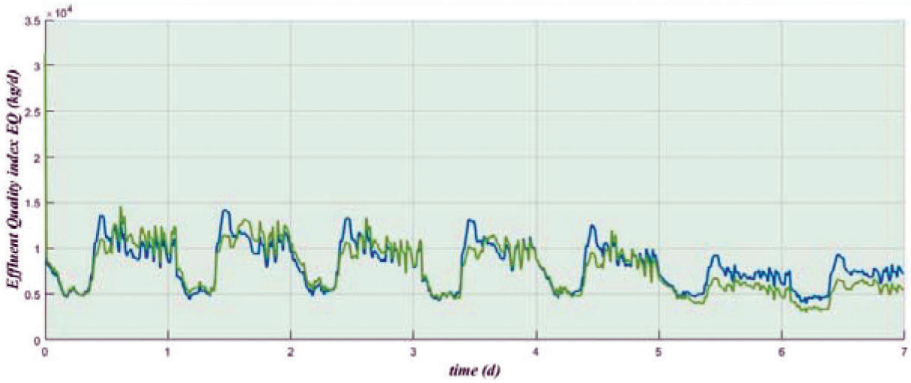

Fig. 18. Progression Effluent Quality (EQ)

the proposed ACNN/ACCN-PI control scheme for different weather disturbances in Table 5.

Statistical criteria were also taken into account to allow comparison with the original version of BSM1.

Integral of Square Error (ISE), Integral of absolute error (IAE), average of the absolute error (mean (|e|)), Maximum absolute deviation, Standard deviation of error (std (e)) and Variance of error (var(e)) (Alex *et al.*, 2008).

Conclusion

In this work, we have developed two models of neu-

Table 4. Quality indicators for the WWTP

	EQI(Effluent Quality index) (kg poll.units/d)	IQI(Influent Quality index) (kg poll.units/d)	OCI (using new aeration and pumping costs)
Original BMS1 version (Alex *et al.*, 2008)	8098.5502	42042.8148	21695.8028
ACNN	7150.13	51017.21	16221.12
ACNN-PI	7017.91	51001.01	16120.73

Table 5. Performance of active controller during 7 days for nitrate for second anoxic reactor $S_{NO,2}$ and oxygen for last aerobic reactor $S_{O,5}$

Controlled variable	SNO,2 Original BMS1 version (Alex *et al.*, 2008)	SNO,2 ACNN	SNO,2 ACNN-PI	SO,5 Original BMS1 version (Alex J. et al. 2008)	SO,5 ACNN	SO,5 ACNN-PI
Average value of absolute error (mean(|e|))(mg N/l)	0.2568	0.2010	0.2001	0.0809	0.0519	0.0500
Integral of absolute error (IAE) (mg N/l)*d	1.7979	1.6020	1.5989	0.5668	0.4234	0.3210
Integral of square error (ISE) (mg N/l)^2*d)	0.83602	0.6345	0.6120	0.0902	0.0620	0.0513
Maximum absolute deviation from nitrate setpoint (max(e)) (mg N/l)^2*d)	0.9035	0.7017	0.7017	-	-	-
Maximum absolute deviation from oxygen setpoint (max(e)) (mg N/l)^2*d)	-	-	-	1.2217	1.5121	1.5121
Standard deviation of error (std(e))(mg N/l)	0.3455	0.2100	0.1998	0.1135	0.0987	0.0900
Variance of error (var (e))((mg N/l)^2)	0.1194	0.1000	0.0987	0.0128	0.0101	0.0101

ral networks to control dissolved oxygen and nitrate from the WWTP treatment plant, in this case adaptive control neural networks ACNN and ACNN-PI. This is to face the problem of multivariable monitoring control in the STEP. The BSM1 simulation protocol was used to gather the operating data of the process and as a reference to test the controllers.

In addition, the implementation of ACNN has produced a reduction in pumping energy (PE) and improved the quality of effluents (EQ). The combination of ACNN and PI controllers in each loop also improves aeration energy (AE), which is why a good control technique for the activated sludge process is a mixture of non-linear predictive control and classic control. (ACNN-PI).

Nomenclatures

X_p : Particulate products arising from biomass decay
X_{BA} : Active autotrophic biomass
S_{ND} : Nitrate and nitrite nitrogen
X_{BH} : Active heterotrophic biomass
S_O : Oxygen
S_{ALK} : Alkalinity
X_I : Particulate inert organic matter
X_{ND} : particulate biodegradable organic nitrogen
S_{NH} : NH+ nitrogen
S_S : Readily biodegradable substrate
S_I : Soluble inert organic matter
X_S : Slowly biodegradable substrate

Greek Symbols

Δ : represents theapproximation error
e : the tracking error
ϕ : The sigmoid function

Abbreviations

BSM1	Benchmark Simulation Model N°1
WWTP	Wastewater treatment plant
ACNN	Adaptative Control Neural Networks
ECEQPEAE	Energy consumptionEffluent quality Pumping Energy (PE)Aeration Energy (AE)

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