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Abstract

Lately machine learning-based control and optimization systems are playing an important role in the operation of wastewater treatment plants in terms of reduced operational costs and improved effluent quality. In this paper, a machine learning-based control strategy is proposed for optimizing both the consumption and the number of regulation violations of a biological wastewater reactor. The methodology proposed in this study uses neural networks as a soft-sensor for the on-line prediction of the effluent quality and as an identification model of the plant dynamics, all under a neuro-genetic optimum model-based control approach. The complete scheme is tested on a simulation model of the activated sludge process of a large-scale municipal wastewater treatment plant running under the GPS-X simulation frame and validated with operational gathered data, showing satisfactory optimal control performance by minimizing operational costs while satisfying the effluent requirements, thus reducing the investment in expensive sensor devices.

Keywords	Neural Networks; Genetic Algorithms; Soft Sensing; Optimized Control; Activated Sludge Process;
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Cover Letter

Manuscript: Control and Soft-Sensing Strategies for a Wastewater Treatment Plant by Using a Neuro-Genetic Approach

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4. Special Considerations

In this paper, a neurogenetic-based control strategy is proposed for optimizing both the consumption and the number of regulation violations of a biological wastewater reactor. The methodology proposed in this study uses neural networks as a soft-sensor for the on-line prediction of the effluent quality and as an identification model of the plant dynamics, all under a neuro-genetic optimum model-based control approach. The complete scheme is tested on a simulation model of the activated sludge process of a large-scale municipal wastewater treatment plant running under the GPS-X simulation frame and validated with operational gathered data, showing satisfactory optimal

control performance by minimizing operational costs while satisfying the effluent requirements, thus reducing the investment in expensive sensor devices.

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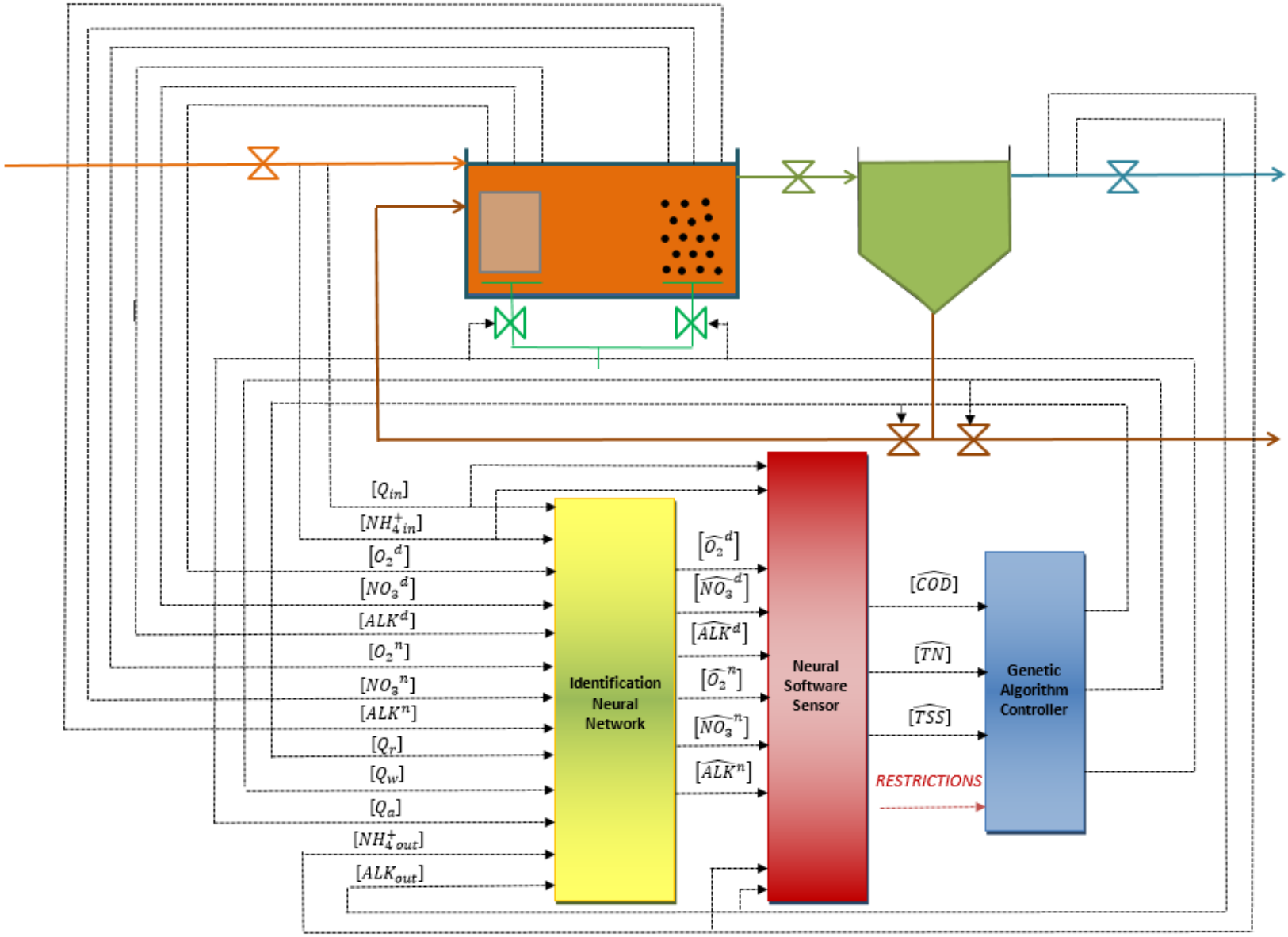
Highlights

> We develop an adaptive neural-network-based soft sensor to predict effluent characteristics > We estimate primary variables from secondary variables in activated sludge process> It is implemented a genetic algorithm to determine the control actions> This strategy presents better results complying with legal constraints and reduced expenses.

Abstract

Lately machine learning-based control and optimization systems are playing an important role in the operation of wastewater treatment plants in terms of reduced operational costs and improved effluent quality. In this paper, a machine learning-based control strategy is proposed for optimizing both the consumption and the number of regulation violations of a biological wastewater reactor. The methodology proposed in this study uses neural networks as a soft-sensor for the on-line prediction of the effluent quality and as an identification model of the plant dynamics, all under a neuro-genetic optimum model-based control approach. The complete scheme is tested on a simulation model of the activated sludge process of a large-scale municipal wastewater treatment plant running under the GPS-X simulation frame and validated with operational gathered data, showing satisfactory optimal control performance by minimizing operational costs while satisfying the effluent requirements, thus reducing the investment in expensive sensor devices.

Wastewater Biologic Reactor



Neuro-Genetic Control

CONTROL AND SOFT SENSING STRATEGIES FOR A WASTEWATER TREATMENT PLANT BY USING A NEURO-GENETIC APPROACH

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Abstract

Lately machine learning-based control and optimization systems are playing an important role in the operation of wastewater treatment plants in terms of reduced operational costs and improved effluent quality. In this paper, a machine learning-based control strategy is proposed for optimizing both the consumption and the number of regulation violations of a biological wastewater reactor. The methodology proposed in this study uses neural networks as a soft-sensor for the on-line prediction of the effluent quality and as an identification model of the plant dynamics, all under a neuro-genetic optimum model-based control approach. The complete scheme is tested on a simulation model of the activated sludge process of a large-scale municipal wastewater treatment plant running under the GPS-X simulation frame and

validated with operational gathered data, showing satisfactory optimal control performance by minimizing operational costs while satisfying the effluent requirements, thus reducing the investment in expensive sensor devices.

Keywords: Neural Networks, Genetic Algorithms, Soft-Sensing, Optimized Control, Activated Sludge Process

1. Introduction

Water management is currently facing a major challenge, and Europe has the responsibility to meet the objectives set by the 2000/60/EC Water Framework Directive of the European Parliament and to ensure the protection of water while promoting its sustainable use to safeguard the availability of this precious long-term natural resource [European Commission 2010].

Wastewater generated by human activity is currently a serious problem, and one of the most important sources of pollution for watercourses and aquifers, and the increasing volumes of wastewater with high pollutant loads that our society produces requires the extensive and intensive wastewater treatments.

Technologically advanced alternatives to solve the purification problems are available on the market, and with its implementation it would be possible curbing the appearance of pollutant discharges and their consequences and at the same time advancing in their prevention, relying on the application of effective treatments both in costs of operation and maintenance as in improved water quality [Santin et al. 2017]. Besides, the efficiency of a water treatment plant is strongly linked to the energy consumption of plant actuators, mainly pumping costs and cost of the sensory system and laboratory analysis necessary for plant state monitoring. Therefore, an optimized treatment at a global level would entail a huge reduction in operating costs, as well as a notable reduction in levels of effluent pollution.

Nowadays, advanced control and optimization systems are playing a fundamental role in the operation of wastewater treatment plants, as they allow efficient plant management (Hreiz et al. 2015), being the active

sludge process one of the most used technologies for this purpose by removal of organic pollutants, nitrogen and phosphorus in wastewater (Van Haandel 2012). The active sludge process can be considered as a complex dynamic system characterized by a non-linear behaviour, uncertainty in process parameters, external disturbances due to atmospheric phenomena, and multivariate I/O structure (Makinia 2010).

Also, on-line monitoring and control of the active sludge process effluent variables such as chemical oxygen demand and total nitrogen are difficult to perform, since either they are usually determined off-line under uncertainty or they require expensive sensors, which implies a strong operational restriction (Akına and Ugurlub 2005). The use of software sensors allows the estimation of these off-line primary variables through the use of on-line secondary variables (Haimi et al. 2013). In addition, on-line control strategies that take into account the dynamic behavior of the activated sludge process should also consider the optimization of control operation so as to reduce energy consumption associated with aeration and pumping processes (Gearney et al. 2014), and several studies have investigated this problem when applied to a process of active sludge through the use of dynamic optimization methods (Fikar et al 2005) (Mulas 2006), or model-based predictive control schemes (Bryds et al. 2008) , (Piotrowski 2008), (Han and Qiao 2014).

Machine learning-based methodology, defined as a set of algorithms that allow performing tasks of identification, control, and optimization of plants based on a set of registered operational data represented with multiple levels of abstraction are increasingly in use. For this purpose, they make use of connectionist structures of artificial neural networks (ANN) with multiple layers (Haykin 2008). On the other hand, genetic algorithms are used both for the optimization of the structure of neural networks of great dimension and for the extraction of characteristics that can be used for the tasks of identification and optimal control (Lamos-Sweeney 2012).

Neural networks have been successfully applied for prediction and control of wastewater treatment plants (Baruch and Mariaca-Gaspar 2009) and different adaptive schemes have been used as software sensors, either based on neural networks (Dogan et al 2008) (Fernandez de Canete et al. 2016) or hybrid schemes (Noori et al 2013) to estimate effluent characteristics. On the other hand, genetic algorithms are heuristic search algorithms, which derive their behavior from the evolutionary processes in nature and perform complex nonlinear optimization tasks such as non-convex problems, non-continuous objective functions,

etc. Genetic algorithms have been successfully applied in the field of biological wastewater treatment for optimization and control (Holenda et al. 2007), (Duzinkiewicz et al., 2009) (Piotrowski 2016).

The combination of hybrid GA systems with neural networks facilitates the search for the optimum in comparison to the local and global search optimization methods such as sequential quadratic programming, reduced generalized gradient among others (Hreiz et al., 2015). In (Bagheri et al. 2015) it is developed a hybrid artificial neural network-genetic algorithm models to predict the sludge volume index (SVI) accurately, so as genetic algorithm was utilized to optimize weights and thresholds of the neural network models. A method to increase the efficiency of water treatment plants, that adjusts operating requirements based on the nature of the water inflows has been presented in De (2019), preventing the unneccesary waste of plant resources. Nevertheless, to our best knowledge, there are hardly any works where neural networks and genetic algorithms are applied together to optimum control of wastewater treatment plants.

Despite the good results obtained by the use of these adaptive estimation and control structures applied to the control of biological reactors, it is necessary to highlight their lack of application to wastewater plants in real-time since most of these applications are based on simulation models using an unusually low, and unrealistic, sampling time (Fang et al. 2011) (Qiao et al. 2013).

In this paper, a machine learning approach is applied both to the prediction of effluent variables and to the modelling of a nonlinear wastewater process by using neural networks. These neural models, combined with a genetic algorithm-based scheme, have been effectively used for optimum control of an activated sludge process-simulation model running under GPS-X framework by using a function involving aeration, pumping and disposal costs. The proposed neurogenetic control strategy optimizes both the consumption and the number of regulations violations during plant operation while the sampling-time selection enables its application to real-time wastewater plants monitoring and advanced control.

This paper is organized as follows: In section 2, the activated sludge process is described together with the activated sludge process simulation model under GPS-X. Both the neural network soft estimation and the neural identification structure are detailed in section 3, together with the derivation of the objective cost function used for the neurogenetic control and its corresponding design. The performance of both the neural

plant model, and the neural soft estimator for chemical oxygen demand (*COD*), total nitrogen (*TN*) and total suspended solids (*TSS*) applied to the referred activated sludge plant model are shown in section 4, where the performance of the neurogenetic controller under dry, rainy and stormy conditions is also shown with promising results. A discussion section is included detailing the advantages and limitations of the proposed approach and comparisons with other alternate solutions, and a final summary is also comprised in section 5, to explain the motivation here followed. Finally, future works will be presented in Section 6.

2. Wastewater Process Description

In this paper, we have considered an activated sludge process operated at the TecnoCasic wastewater treatment plant located near Cagliari (Italy) and reported previously by (Mulas 2006). The wastewater treatment process includes a mechanical treatment to remove floating and settleable solids, a biological treatment with activated sludge for the removal of nitrogen and organic pollutants as well as other operations such as sludge treatment and disinfection treatment.

The general layout of the aforementioned ASP is described in (Fernandez de Canete et al 2016). The bioreactor is a 2000 m^3 volume basin constituted by a predenitrification anoxic zone followed by an aerobic nitrification zone with oxygen, nitrogen and alkalinity sensors located both in the anoxic and in the aerobic zones to provide information about the aeration process. The microbiological population is maintained through both internal recirculation of sludge removed from the aerobic basin and external recirculation of settleable sludge withdrawn from a secondary settler with a surface area of 707 m^2, and 4 m depth. The average nominal influent conditions considered for the plant under dry, rainy, and stormy weather are reported in Table 1.

/Table 1 here /

The wastewater plant considered is equipped with on-line sensors to measure flow rate Q_{in} and ammonia NH_{4in}^{+} in the influent, while dissolved oxygen O_2, dissolved nitrate NO_3 and alkalinity ALK sensors are arranged in each tank, with additional on-line sensors to measure ammonia NH_{4out}^{+} and alkalinity ALK_{out} in the effluent. The bioreactor operation include the pumping of external recycle flowrate Q_r, waste sludge

flowrate Q_w and constant internal recycle flowrate Q_A, while fine-pore air diffusers generate an airflow rate Q_a to be distributed by the basins. Additionally, off-line laboratory measurements of COD, TN, and TSS concentrations were also taken both for the influent and effluent streams.

An ASM1-type model was derived in (Fernandez de Cañete et al 2016) to represent the behavior of the TecnoCasic wastewater bioreactor while the secondary settler representation was based on the work of (Takacs et al. 1991). According to the sensors layout of the bioreactor (Fig. 1), two anoxic denitrification (*d*) areas and three aerated nitrification (*n*) areas are going to be considered, each one equipped with a double set of sensors, thus resulting in six virtual tanks. In Fig. 2 it is shown a GPS-X 6.0 computer simulation model of the ASM1 process (Hydromantis 2016)

/ Figure 1 here /

/Figure 2 here /

The ASM1 GPS-X model details are referred to in (Fernandez de Canete et al), where dynamic simulations have been made to reproduce the behaviour of the TecnoCasic plant by using experimental data available both from the on-line sensors of the plant and from the effluent concentrations, so as to calibrate the model kinetic and stoichiometric parameters.

3. Neural Soft-Sensor, Identification Model and Controller

The complete controlled system is composed of a neural network identification model of the process and a control scheme based on a genetic algorithm that utilizes the effluent values of *COD*, *TN* and *TSS* as input variables to get the quasi-optimal control law subjected to ASP operational constraints. It uses a neural soft-sensor estimator for both determining and monitoring these *COD*, *TN* and *TSS* effluent primary variables from secondary variable measurements (Fig. 3).

/ Figure 3 here /

The control strategy presented in this paper is based on a decision-making process using neural networks combined with GA. For each situation (the current and past states), the control scheme tries to reach the optimal decision (control action) according to the different possible scenarios (dynamic system modeled by a neural network) and to the objective (goal) while assuring no violation of effluent constraints.

To make the design of both, the estimators and the neural model, as part of the neurogenetic control, specific tools have been used in MATLAB code for dealing with the modeling and multivariable control of plants (Fernandez de Canete et al. 2016). The connection between the monitoring system and the MATLAB neurogenetic controller is realized through the interface MATLAB-GPS-X 6.0.

This section is divided as follows: firstly, the neural soft-sensor estimator is presented, the main details of the neural identification model will be included below, and the complete control strategy will be described finally.

3.1. Neural Soft-Sensor

The use of software sensors to infer hard-to-measure primary variables from easy-to-measure secondary variables (Brosilow and Joseph 2002) is a common solution to overcome the drawbacks due to the acquisition and maintenance cost of expensive *TN* and *TSS* on-line sensors (Van der Broeke et al 2014) or due to the use of off-line measured variables as *COD*. Furthermore, legal restrictions are set precisely in the maximum values of these primary variables regarding effluent concentrations. For the TecnoCasic plant, these constraints are listed in Table 2.

/ Table 2 here /

A neural network-based soft-sensor has been developed relating the wastewater plant concentrations (*COD*, *TN,* and *TSS* at the effluent stream) with sampled values of secondary variables that can be measured on-line in a reliable, accurate and non-expensive way. The set of secondary variables are chosen among those that are provided by the sensory system that is physically installed on the TecnoCasic wastewater plant which it is also present in the GPS-X model.

To select the most suitable secondary variables for our control purposes, a multivariate statistical technique based on the PCA methodology has been applied as is reported in (Zamprogna et al 2005). After applying the selection method, the inputs to the neural soft estimation network turned out to be a subset of delayed values of secondary variables Q_{in}, NH_{4in}^{+}, O_2, NO_3, ALK, NH_{4out}^{+}, ALK_{out} sampled at $T_{\text{s}} = 15$ min, whereas the outputs are given by $\widehat{COD}(t)$, $\widehat{TN}(t)$ and $\widehat{TSS}(t)$ primary variable estimations, all computed using a larger sampling interval of $T_{\text{p}} = 3$ h.

Specific tools have been used in MATLAB code to deal with the design, training, and validation of the neural estimator whose details are reported in (Fernandez de Canete et al 2016), while the structure of the neural soft estimator is illustrated in Fig. 3 as part of the neurogenetic control structure.

3.2. Neural Identification Model

The goal of the identification model of the plant is to capture the dynamic behavior by relating the evolution of the secondary variables (influent flowrate Q_{in}, ammonia NH_{4in}^{+}, dissolved oxygen O_2, dissolved nitrate NO_3 and alkalinity ALK in each tank together with ammonia NH_{4out}^{+} and alkalinity ALK_{out}) with the three control input variables, (external recirculation flowrate Q_r, waste sludge flowrate Q_w and air flowrate Q_{a_i} in each aerated tank) in addition to current and past values of the aforementioned secondary variables. Therefore, the outputs of the neural identification model (O_2 and NO_3 concentrations NH_4^{+}, alkalinity) are going to be used in the inference of the primary variables *COD, TN* and *TSS* through the use of the neural software sensor as described previously, while the input variables of the neural identification model will be chosen among the secondary variables of the plant (that are also part of the referred sensory system that is present in the plant) at previous time steps together with the output signals of the actuators (the airflow rates both in the anoxic and aerobic areas and the recirculation and sludge excess flowrates). In Fig. 3 it is shown the neural identification structure as part of the neurogenetic control scheme.

The input layer dimension is selected by using the multivariate statistical approach based on PCA, as was described formerly for the neural network soft-sensor estimator. In this way, the procedure is defined as follows. Due to the characteristics of the wastewater treatment process, up to 45 previous time steps of each of the sensors measurements are considered as possible inputs for the identification network. In this way if

a similar notation as the used in the previous section is used, the secondary variables set would be (Q_{in}, NH_{4in}^{+}, $O_{2,}$ $NO_{3,}$ ALK, $NH^{+}{}_{4out,}$ ALK_{out}, $Q_{r,}$$Q_{w}$,$Q_{a_i}$) and the primary variables set would be the estimation of the referred secondary variables that are, in turn, inputs to the inference soft-sensor. The variable selection process is similar to the one exposed in the previous section.

3.3. Neurogenetic Controller

Once the inference soft-sensor and the dynamical identification model of the plant are developed and validated, the next stage in the controller design will consist in developing the control subsystem. This subsystem is responsible for calculating the action that must be applied to the different actuators, so the system evolves following the desired path taking into account a specific cost function.

For a given plant state history and control action, the evolution of the system will be forecasted using the dynamical model of the plant. Therefore, this subsystem should estimate a control action that minimizes the cost function while minimizes the number of constraints violations. Thus, the future output of the system can be predicted depending on the control inputs and the plant state evolution through a nonlinear function.

In this way, the optimization problem for controlling the wastewater treatment process can be stated as a problem of finding the input that minimizes the norm of the cost function, multiplied by a weighting matrix between the reference command to follow and the neural network model output, considering the input and the past and current states of the wastewater plant.

As for the control strategy proposed in this paper, the control action will be estimated following an optimization schema based on genetic algorithms (GA). These methods are based on the genetic processes of biological organisms. Natural populations evolve according to the survival of the fittest principles. So the individuals that are better adapted to the environment tend to have relatively a higher number of offspring in a way the genes from these highly adapted individuals spread to an increasing number of individuals in each successive generation. It should also be taken into consideration that the string characteristics from different ancestors can sometimes produce offspring that are even better adapted to the environment. In this way, species evolve to become better suited to their environment in an iterative way.

One big advantage this kind of algorithms has is the fact that for obtaining the optimum, it does not depend on the derivatives of the function to optimize, so all kind of functions can be optimized using this approach

The proposed goals of the control strategy consist of minimizing both the operational costs and the effluent limits violations. In the case of the present study, the operational cost function $TC(t)$ will follow the expressions developed in (Foscoliano et al. 2016) so that

$$TC(t) = k_E \cdot (AE(t) + PE(t) + ME(t)) + k_D \cdot SP(t) \tag{1}$$

where $AE(t), PE(t)$ and $ME(t)$ are the aeration, pumping and mixing costs respectively, while $SP(t)$ represents the sludge production disposal term, being k_E the electricity price with an assumed fixed value (Grave et al 2016) and k_D the unitary disposal cost.

The aeration energy cost over a certain range of time T_r can be expressed as follows in the expression

$$AE(t) = \frac{S_O^{sat}}{T_r \cdot 1800} \int_t^{t+T_r} \sum_{i=1}^{8} V_i \, K_{La_i}(t) dt \tag{2}$$

where K_{La_i} is the oxygen mass transfer coefficient tightly related with the aeration flow Q_{a_i}, which are evaluated using the expressions from (Hreiz et al. 2015b), V_i is the volume of the bioreactor and S_O^{sat} is the oxygen saturation concentration.

The pumping cost is directly related to external recycle flowrate Q_r,waste sludge flowrate Q_w and internal recycle flowrate Q_A (held as constant) according to the expression

$$PE(t) = \frac{1}{T_r} \int_t^{t+T_r} (0.008Q_r(t) + 0.05Q_w(t) + 0.004Q_A)\, dt \tag{3}$$

with pumping unitary coefficients described in (Alex et al. 2008). In the same way, mixing energy should be supplied according to the expression

$$ME(t) = \frac{24}{T_r \cdot 1800} \int_{t}^{t+T_r} \sum_{i=1}^{8} \begin{cases} (0.0035\ V_i) & K_{La_i} < 20 \\ 0 & otherwise \end{cases} dt \tag{4}$$

since the anoxic zones should be mixed to avoid settling conditions. Finally, the sludge disposal cost should be added as

$$SP(t) = \frac{1}{T_r \cdot 1000} \left(TSS_x(t+T_r) - TSS_x(t) + \int_{t}^{t+T_r} (TSS_w(t)\ Q_w(t)) dt \right) \tag{5}$$

where TSS_x is the total solid concentration in the activated sludge reactors and in the secondary settler while TSS_w represents the total solid concentration in the waste sludge flowrate whose respective evolutions are estimated by using the dynamic clarification-thickening process described in (Takacs et al. 1991).

As it was stated, the second goal of the control strategy consists of minimizing the effluent limits violations. In this case, the Effluent Quality Index (EQI) will be used. The referred index is related to the fines paid due to the discharge of pollutants into receiving waters and is expressed as follows

$$EQI(t) = \frac{1}{T_r \cdot 1000} \left(\int_{t}^{t+T_r} \left(\left(B_{SS} TSS(t) + B_{COD} COD(t) + B_{TN} TN(t) + B_{NH_4^+} NH_{4_{out}}^{+}(t) \right) Q_{out}(t) \right) dt \right) \tag{6}$$

with values given of $B_{SS} = 2, B_{COD} = 1.2, B_{TN} = 30, B_{NH_4^+} = 30$, being Q_{out} the measured effluent flowrate.

Because more than a single criterion is required to be optimized, a multi-objective control function will be used. The 'Pareto dominance' concept will be used for the optimum search in which a given solution dominates another one only if it leads to an equal or better performance in every evaluation criterion. Therefore, a solution is said to be Pareto-optimal if any other feasible solution does not dominate it.

So, the optimization problem can be expressed as

$$min_u J(x,u,T_r) = [TC(t),EQI(t)] \quad (7)$$

subjected to several conditions, that is, (1) the process that is approximated according to the neural identification model and neural-soft predictive sensor presented in previous subsections, (2) the initial conditions of the system and (3) the operational constraints imposed.

4. Results

As it was stated in previous sections, the complete neuro-genetic controller is developed following three different phases.

The first stage will be responsible for determining the neural software sensor of the dynamic process. Secondly, a neural network-based model of the process dynamics is determined by using samples of the complete I/O values set. And, finally, this latest neural model is used to derive the genetic based controller whose objectives include, as it was stated in a previous section, the minimization of both the cost function and the number of effluent constraints violations.

The wastewater treatment plant model has been developed using Hydromantis GPS-X 6.0 while the MATLAB environment is the 2017 version. The proposed neural networks were developed using the MATLAB specific neural network library. The Genetic Algorithms were coded in MATLAB without using any specific library. The connection between the Hydromantis wastewater plant model was made by means of the MATLAB link provided in the Hydromantis GPS-X environment.

4.1. Results with Software Sensor and Identification Model

The structure of the software sensor is a two hidden layer perceptron with a 100-55-25-3 neuron architecture, where the hidden layer configuration was selected after a trial-and-error procedure using a pruning algorithm based on the Optimal Brain Surgeon methodology (Fernandez de Cañete et al., 2016).

The neural identification network is responsible for learning the dynamic behaviour of the secondary variables, in a way it can relate the level of the secondary variables with the control inputs and past states. Therefore, the outputs of the neural identification model are the values of the secondary variables in the following time step while the input of the neural model will consist in a combination of selected measurable secondary variables at previous time steps together with the control actions.

Due to the specific dynamical characteristics of the plant process, up to 20 previous time step of each of the sensors measurements are considered as input candidates for the identification neural network, following the same strategy that was presented in a previous section for determining the input set for the software sensor network.

The behaviour is modeled using a single neural network per secondary variable with 50-35-15-1 feedforward architecture. The network was trained using a Levenberg-Marquardt algorithm and validated by comparing the obtained output against the values obtained for the referred variables under dry, rainy, and stormy conditions.

The neural net was trained with a different subset of 1500 points selected randomly from a simulation data set with a sampling $T_s = 15$ min. The simulation set was obtained by using PID algorithms controlling the O_2 level in the aerobic tanks considering a wide operating range.

The neural net was also validated with a subset consisting of a simulation lasting time of five days of operation and comparing its outputs to the outputs of the system in independent experiments. A comparison between real and predicted data by the neural identification model is depicted in Fig. 4, showing the ability of the neural model to accurately describe the process behaviour under variant conditions inside the operating range.

It also has to be remarked that the neural identification model was implemented in a way that it was re-trained if the absolute value of the absolute error between the predicted output and the process output is above a given threshold.

/ Figure 4 here /

4.2. Results with Genetic Controller

The GA controller is characterized by a population of 250 inhabitants, 250 generations, a mutation rate of a 2.5% and a codification depth of 8 bits. The optimum is accepted if it is invariant in 15 iterations. All these parameters were estimated for achieving a time response lower than 5 s for the computational system used for controlling the neural model of the dynamic wastewater treatment model process.

The output will be compared against a multi decoupled PID control scheme, to validate the proposed control scheme, in a such a way that the effluent quality is indirectly controlled. In the case of the present paper, the relative Gain matrix methodology (Skogestad, 1997) is used to provide the pairing between the controlled and manipulated variables.

The resulting control pairing is shown in Table 3 where Q_{a_i} is the i^{th} airflow inlet, O_{2i} represents the O_2 concentration at the *i-th* section, Q_r is the recycled sludge valve actuation and Q_w is the valve actuation of the waste sludge.

/ Table 3 here /

The different parameters of the PID controllers have been defined following the Ziegler-Nichols tuning methodology, and an additional fine-tuning has been implemented to reduce the ISE performance criterion.

The influent data are provided over short period T_r of 14 days with $T_s = 15$ min sampling time. The 14-days data files consider three different weather conditions, dry (normal influent variation for the TecnoCasic WWTP), storm (same as dry weather with one storm event) and rain (dry weather with one rain period) following the approach described in (Alex et al., 2008).

The chemical oxygen demand *COD* concentration in the effluent for dry, rainy, and stormy weather conditions is shown in Fig. 5, when using the control strategies mentioned above.

/ Figure 5 here /

The total suspended solids *TSS* concentration in the effluent is depicted in Fig. 6 also for the three aforementioned different weather conditions. In the same way, the Total Nitrogen concentration *TN* in the effluent under the same operational conditions is shown in Fig. 7.

/ Figure 6 here /

/ Figure 7 here /

The forecasted values of the effluent values are tested against the outcome of the model in order to check whether the software sensors [Fernandez de Cañete et al. 2016] present a similar forecasting accuracy than what it was evaluated in the open loop experiments reported in the former section.

In order to assess the prediction results, mean absolute percent error (MAPE), maximum absolute percent errors (MaxAPE) and correlation coefficient of prediction error (R^2) as defined by

$$MAPE = \frac{1}{N}\sum_{i=1}^{n}\left|\frac{Y_{pred,i} - Y_{observed,i}}{Y_{observed,i}}\right|$$

$$MaxAPE = \max_{N}\left|\frac{Y_{pred,i} - Y_{observed,i}}{Y_{pred,i}}\right|$$

$$R^2 = \frac{\sum_{i=1}^{N}\left(Y_{pred,i} - \overline{Y}_{pred}\right)\cdot\left(Y_{observed,i} - \overline{Y}_{observed}\right)}{(N-1)S_{Y,pred}S_{Y,observed}}$$

have been calculated, with N number of samples, $Y_{pred,i}$ the *ith* output of the neural predictor, $Y_{observed,i}$ the *ith* observed GPS-X output , $\overline{Y}$ mean value and S_Y standard deviation, and whose results for the three effluent primary variables are listed in Table 4 both for PID and for neurogenetic controllers with similar prediction results.

/ Table 4 here /

The resulting airflows for each of the eight different zones (2 anoxic and 3 double aerobic) under the three weather conditions as reported previously can be seen in Fig. 8 for neurogenetic and PID control schemes.

/ Figure 8 here /

A summary of the economic consumption performance and the effluent quality can be seen in Table 5. In the three different weather conditions, the neurogenetic control schema improves the fine-tuned multi-PID control strategy.

/ Table 5 here /

Table 5 confirms that the neurogenetic control behaves better than the decoupled PID control. The global energy (sludge production, aeration energy and pumping energy) is significantly reduced under different weather conditions and so does the effluent quality index as well, preventing each effluent variable *COD*, *TSS*, *TN and* $NH_{4_{out}}^{+}$ from violating the constraints referred to in Table 3, with a broader operational range than those acquired with decoupled PID feedback controllers. It can also be observed that during a rainy period mean values of controlled effluent variables are reduced compared to dry period due to dilution caused by a significantly increased influent flowrate to the wastewater plant, while a similar control performance is exhibited during a stormy period though of lower intensity.

5. Discussion

The main advantages of the application of machine learning techniques for the identification of wastewater treatment processes reside in their capability of grasping the dynamics of the system by using solely operational data. Once trained, the resulting identification model can be used for control purposes as the output can be forecasted for different input sets depending on the current and past states optimizing a cost function as it has been shown in the present paper.

An additional advantage is related to the wastewater treatment as some of the variables that rule the process are not usually measured in real-time due to the high cost of the sensors and/or the related high maintenance costs. In this way control schemes can only be validated by off-line laboratory measurements. Therefore, the use of neural networks enables the development of software-based sensors by using available secondary measurements to infer primary outputs values and, for control purposes, predictions.

One of the main difficulties in designing neural network-based software sensors resides in selecting the most significant set of secondary variables, the final network structure and the proper value of the sample time, that should be selected according to the dynamics of the process. The set of secondary variables should be capable of grasping the behaviour of the primary variables, but introducing a very large space dimension may lead to overfitting and, in extreme cases, induce large computational time. In the present paper a PCA based method has been used due to its ability to construct "synthetic" variables that are maximally independent in a linear sense while it removes correlations among the variables.

The selection of the sampling time is intrinsically linked to the dynamical characteristics of the process to be modelled/controlled. In the case of biological wastewater treatment plants, it is a well-known fact that it involves a wide range of time constants. The changes of dissolved oxygen concentration may occur in the range of minutes while the time constant for substrate concentration could reach hours, depending on the hydraulic retention time and the reaction rate. The variation of the microbial population occurs in a range of days. On the other hand, the typical time delay of the hardware instrumentation might range from the few minutes of the dissolved oxygen to more than 10 minutes for the ammonia and nitrogen analysers to few hours for the solids concentration.

For these reasons, the sampling times were chosen so that the process dynamics in the activated sludge process and the realistic time response of the hardware instruments were taken into account. In our particular case, the value of $T_{\mathrm{p}} = 3$ h compatible with a successful prediction was selected, since this is the minimum value currently used during the off-line measurement procedure which is performed on the effluent stream in the TecnoCasic plant. Larger values for sample time would render an unstable prediction.

In the case of the optimization problem a genetic algorithm approach has been chosen due to its flexibility as it is based on the testing and the selection of fittest individuals. Unlike traditional high climbers approaches they do not evaluate and improve a single solution but a set of solutions having the flexibility, efficiency and robustness as their main properties. The strength of this parallel process is enhanced by the mechanics of population modification, making GAs adequate candidates even for *NP*-hard problems (Baese et al. 2014). In the case of the present paper, the input to the cost function is a set of possible valid control inputs and the genetic algorithm chooses the set that optimizes the cost function that involves both energy consumption and constraints violations.

The presented obtained results show that the proposed method and values results in an adequate performance and it is a relatively simple approach as both the software sensor as the dynamical model development are based in I/O operational monitoring data. In contrast to this, the performance of the neural predictor relies tightly on the I/O data content, so that they must be representative of the entire operational workspace. Otherwise, the generalization capabilities exhibited by the neural networks would be reduced, causing malfunction. And also, the optimization algorithm does not impose hard constraints in the cost function to be used as it relies on evaluating the cost function in the possible input set.

Besides, the practical implementation of the proposed approach requires a minimal configuration regarding the monitoring system to capture the easy to measure variables and periodically checking the performance of the software sensor and the dynamic neural identification model.

In summary, the proposed approach described in the present paper is based on the use of machine learning supervised networks for both soft-sensing and dynamics identification and the usage of genetic algorithms to choose the pseudo-optimal control action in reference to a defined cost function taking into account the present and past states of the system. The usage of neural network approaches represents one of the most commonly used as a modelling method for the reconstruction of the desired outputs in Chemical Processing. In fact, according to (Haimi et al. 2013) the neural soft-sensor has become the most popular technique used for data-driven sensors development due to its better performance.

6. Conclusions and Future Works

In the present paper, an adaptive neural network has been applied to the estimation of the effluent characteristics of a wastewater treatment process from secondary variables, while an additional neural network is developed to estimate the dynamic behaviour of the referred secondary controllable variables.

A pseudo-optimal genetic algorithm has been implemented to determine the control actions based on the legal effluent concentration constraints and the economic costs involved in the actions of the actuators. The whole neuro-genetic system composed of the software sensor module, the identification network, and the genetic control module has been coded using specific tools within MATLAB and GPS-X software.

The proposed control schema offers the possibility of real-time implementation as it offers a high-speed response to influent condition changes. This strategy presents for the referred model better results than the ones obtained using traditional PID decoupled control, both complying with the legal constraints and lower economic expenses.

It is also necessary to highlight the potential benefits of artificial neural networks combined with GA when applied to the multivariable control of nonlinear plants, with a first-principles model as was demonstrated with a wastewater treatment process. Although the proposed schema has been applied to a mathematical software model of the physical process, it can be easily extended to industrial processes.

The future work involves the application of this strategy to a physical wastewater process as the research group the authors collaborate with is currently designing a neuro-genetic control system that is going to be applied to control an experimental plant that is sited within the University of Malaga facilities.

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List of Figure Captions

Fig. 1. Schematic representation of the Activated Sludge Process of the TecnoCasic WWTP

Fig 2. Schematic diagram of the ASP simulation model of the TecnoCasic wastewater plant in GPS-X 6.0

Fig. 3. Schematic of the neurogenetic control system of the wastewater TecnoCasic GPS-X plant showing the neural network identification, neural software sensor and genetic controller

Fig 4. Verification for prediction of controlled variables $O_{22,}$ $O_{28,}$ $NH^{+}{}_{4out,}$ ALK_{out} for the neural network identification model of the wastewater treatment process

Fig 5. Comparison between the COD effluent output using the neurogenetic control scheme (green) against decoupled PID controllers (blue)

Fig. 6. Comparison between the TSS effluent output using the neurogenetic control scheme (green) against decoupled PID controllers (blue)

Fig 7. Comparison between the Total Nitrogen effluent output using the neurogenetic control scheme (green) against decoupled PID controllers (blue)

Fig 8. Comparison between airflow rates for each zone both for the neurogenetic control scheme and for decoupled PID controllers under different weather conditions

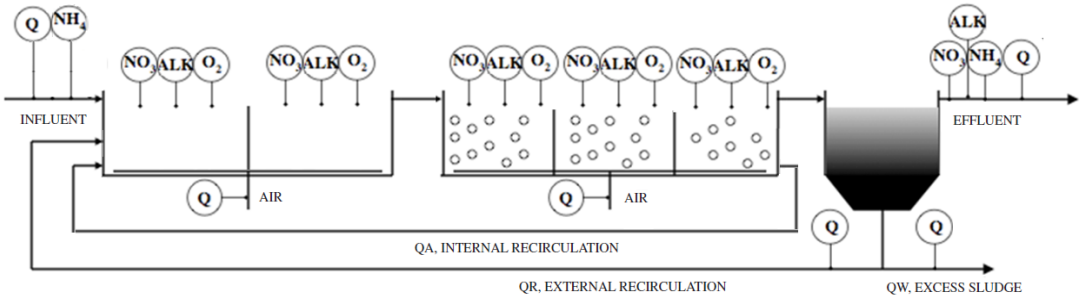
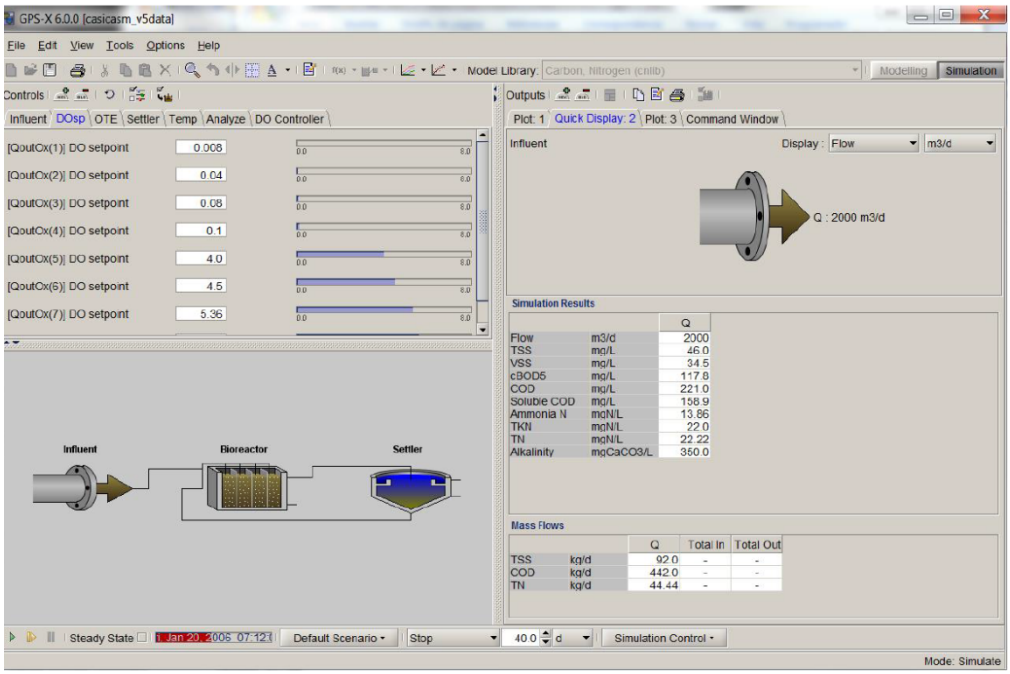
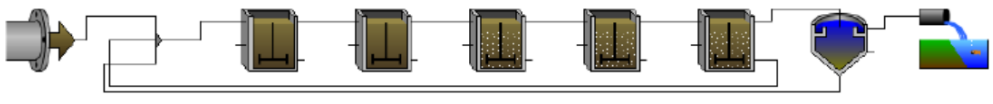

Q
NH4
NO3
ALK
O2
INFLUENT
AIR
EFFLUENT
QA, INTERNAL RECIRCULATION
QR, EXTERNAL RECIRCULATION
QW, EXCESS SLUDGE

Fig. 1


GPS-X 6.0.0 [casicasm_v5data]
File Edit View Tools Options Help
Model Library
Carbon, Nitrogen (cntlib)
Modelling
Simulation
Controls
Influent DOsp OTE Settler Temp Analyze DO Controller
[QoutOx(1)] DO setpoint 0.008
[QoutOx(2)] DO setpoint 0.04
[QoutOx(3)] DO setpoint 0.08
[QoutOx(4)] DO setpoint 0.1
[QoutOx(5)] DO setpoint 4.0
[QoutOx(6)] DO setpoint 4.5
[QoutOx(7)] DO setpoint 5.36
Outputs
Plot: 1 Quick Display: 2 Plot: 3 Command Window
Influent
Display : Flow m3/d
Q : 2000 m3/d
Simulation Results
Q
Flow m3/d 2000
TSS mg/L 46.0
VSS mg/L 34.5
cBOD5 mg/L 117.8
COD mg/L 221.0
Soluble COD mg/L 158.9
Ammonia N mgN/L 13.86
TKN mgN/L 22.0
TN mgN/L 22.22
Alkalinity mgCaCO3/L 350.0
Mass Flows
Q Total In Total Out
TSS kg/d 92.0 - -
COD kg/d 442.0 - -
TN kg/d 44.44 - -
Influent
Bioreactor
Settler
Steady State
Default Scenario
Stop
40.0 d
Simulation Control
Mode: Simulate

(a)



(b)

Fig. 2

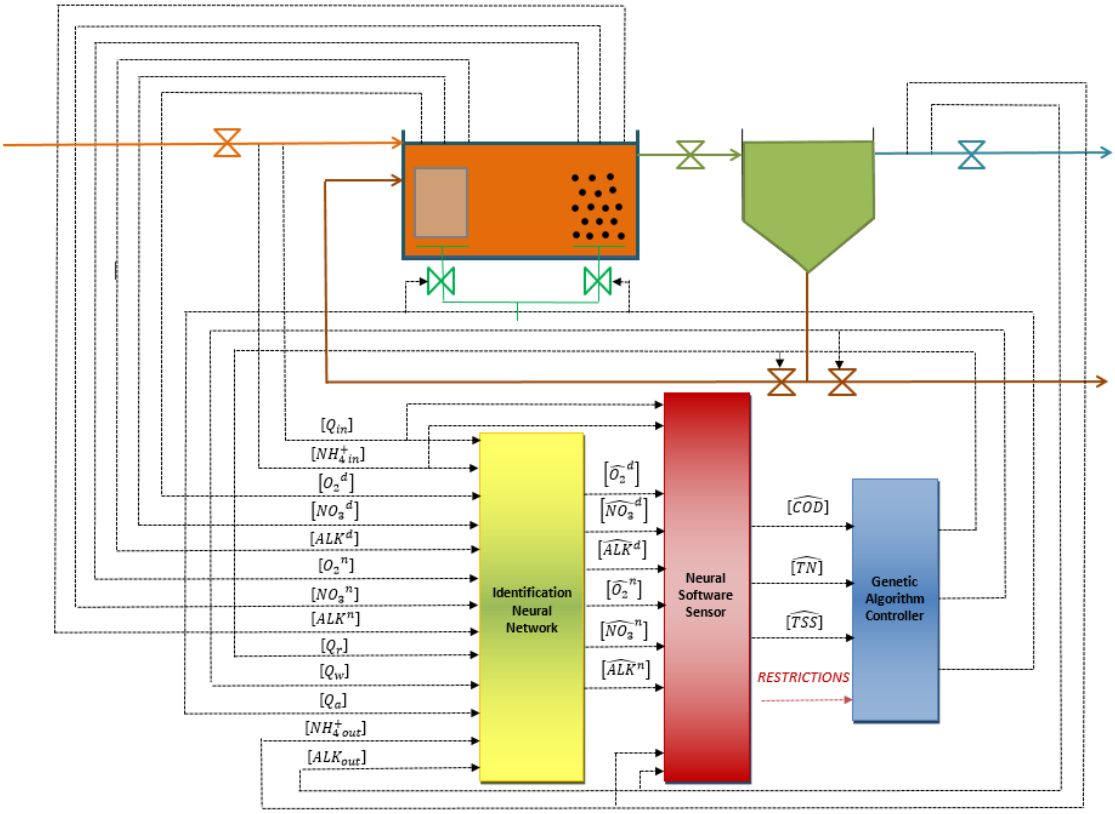
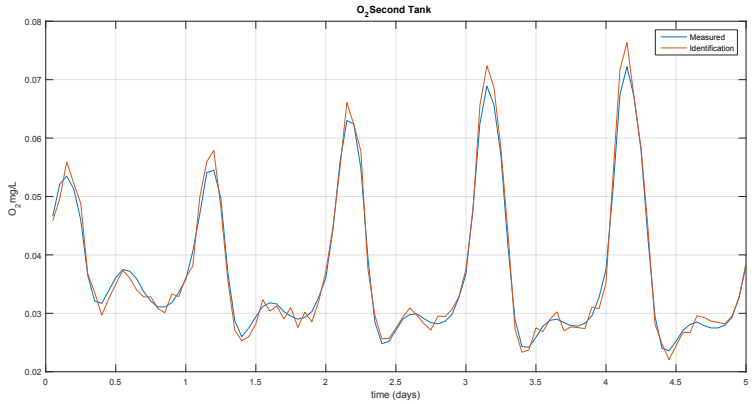

$[Q_{in}]$
$[NH_{4\,in}^{+}]$
$[O_2{}^{d}]$
$[NO_3{}^{d}]$
$[ALK^{d}]$
$[O_2{}^{n}]$
$[NO_3{}^{n}]$
$[ALK^{n}]$
$[Q_r]$
$[Q_w]$
$[Q_a]$
$[NH_{4\,out}^{+}]$
$[ALK_{out}]$
Identification Neural Network
$[\widehat{O_2}^{d}]$
$[\widehat{NO_3}^{d}]$
$[\widehat{ALK}^{d}]$
$[\widehat{O_2}^{n}]$
$[\widehat{NO_3}^{n}]$
$[\widehat{ALK}^{n}]$
Neural Software Sensor
$[\widehat{COD}]$
$[\widehat{TN}]$
$[\widehat{TSS}]$
RESTRICTIONS
Genetic Algorithm Controller

Fig. 3


O2Second Tank
Measured
Identification
O2 mg/L
time (days)
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5

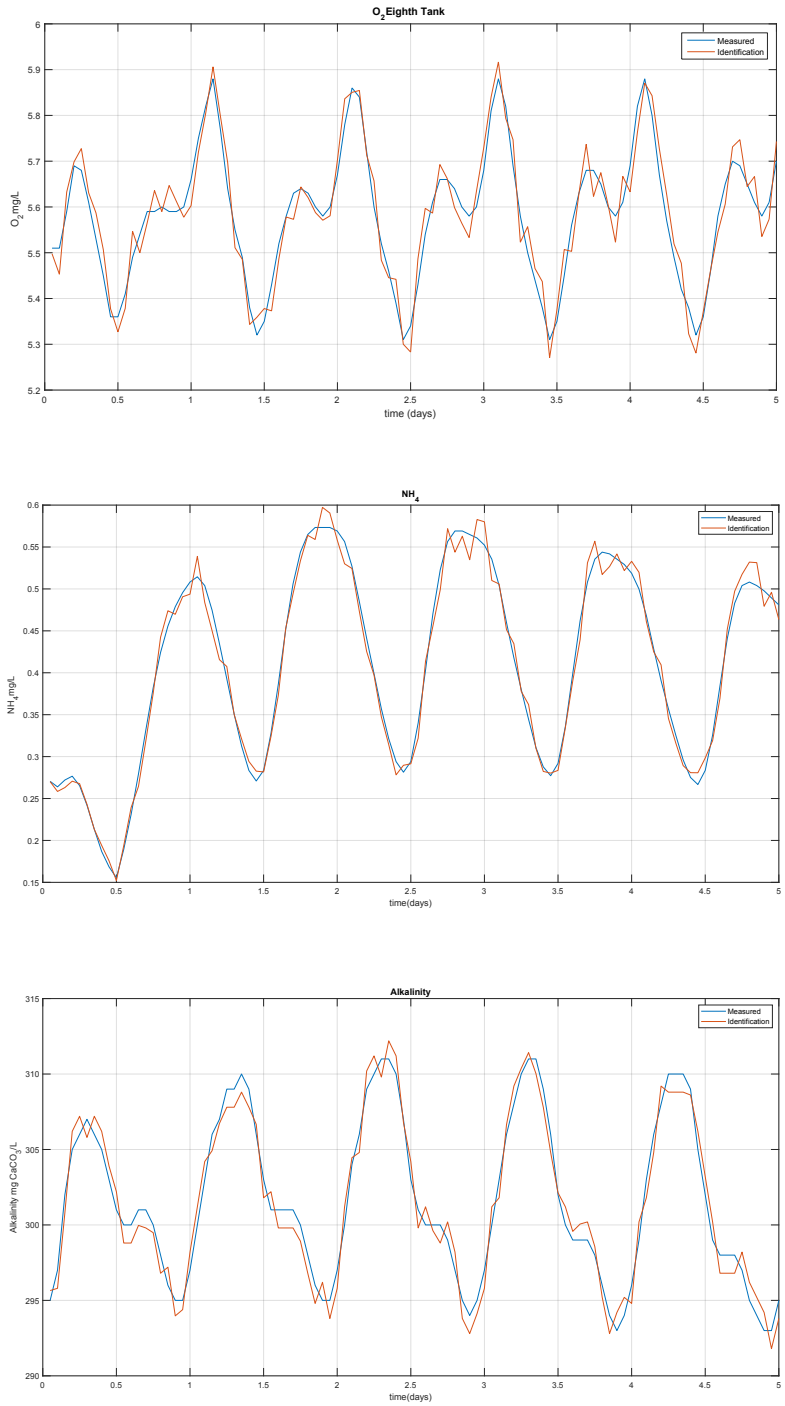
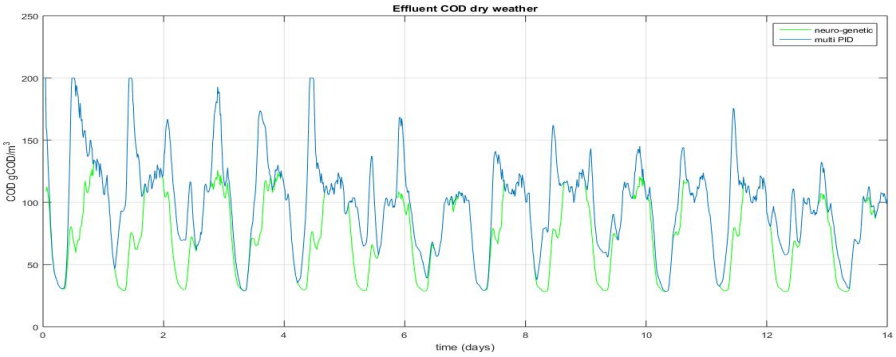
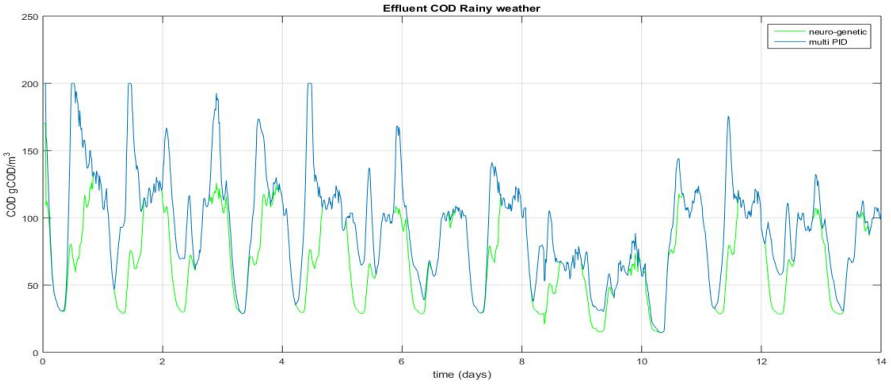

O2 Eighth Tank
Measured
Identification
O2 mg/L
time (days)
NH4
Measured
Identification
NH4 mg/L
time(days)
Alkalinity
Measured
Identification
Alkalinity mg CaCO3/L
time(days)

Fig. 4


Effluent COD dry weather
neuro-genetic
multi PID
COD gCOD/m3
time (days)


Effluent COD Rainy weather
neuro-genetic
multi PID
COD gCOD/m3
time (days)

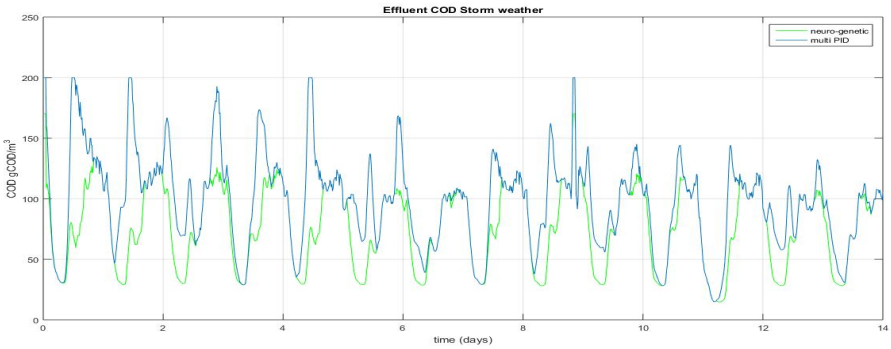

Effluent COD Storm weather
neuro-genetic
multi PID
COD gCOD/m3
time (days)

Fig. 5

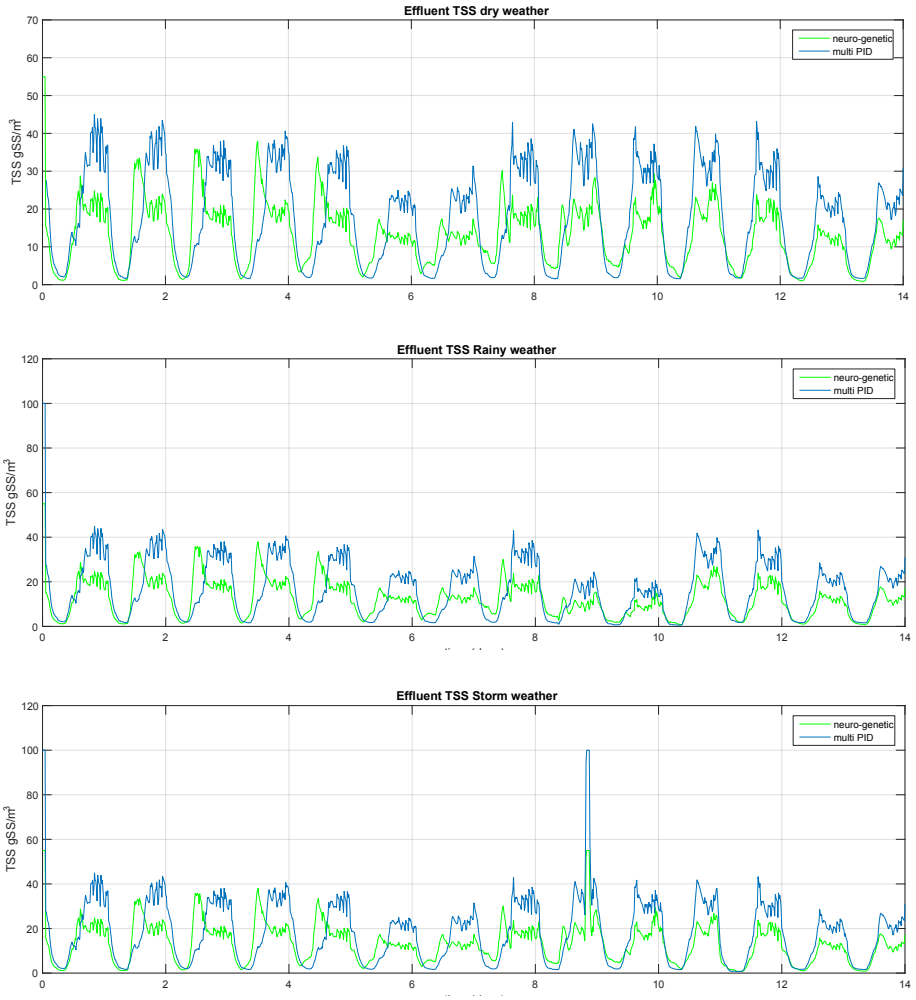

Effluent TSS dry weather
neuro-genetic
multi PID
TSS gSS/m3
Effluent TSS Rainy weather
neuro-genetic
multi PID
TSS gSS/m3
Effluent TSS Storm weather
neuro-genetic
multi PID
TSS gSS/m3

Fig. 6

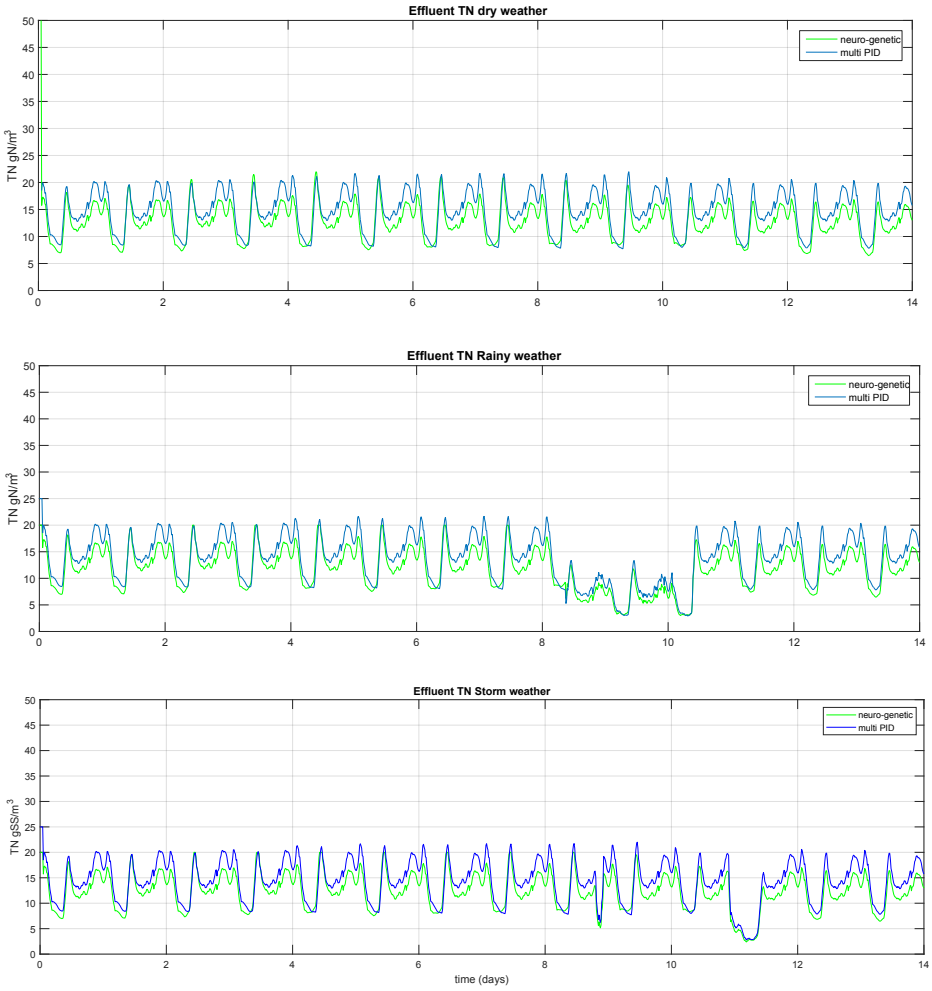
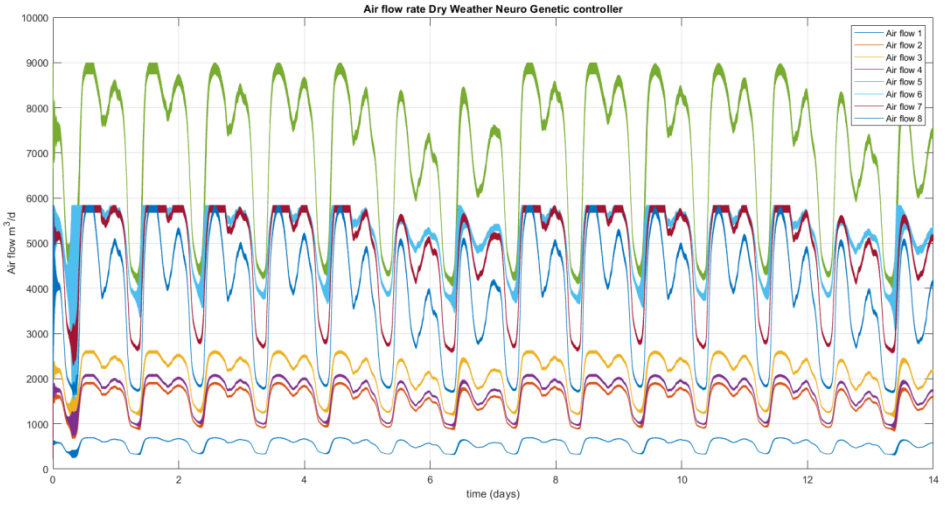
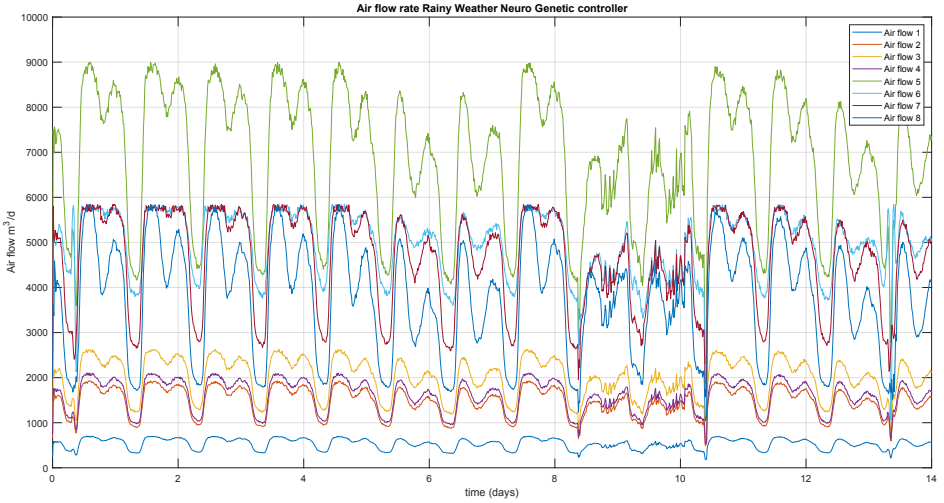
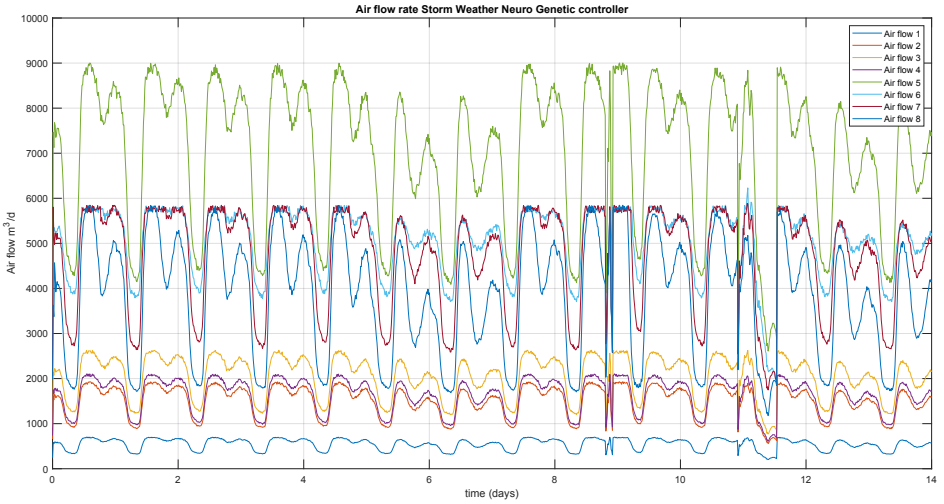
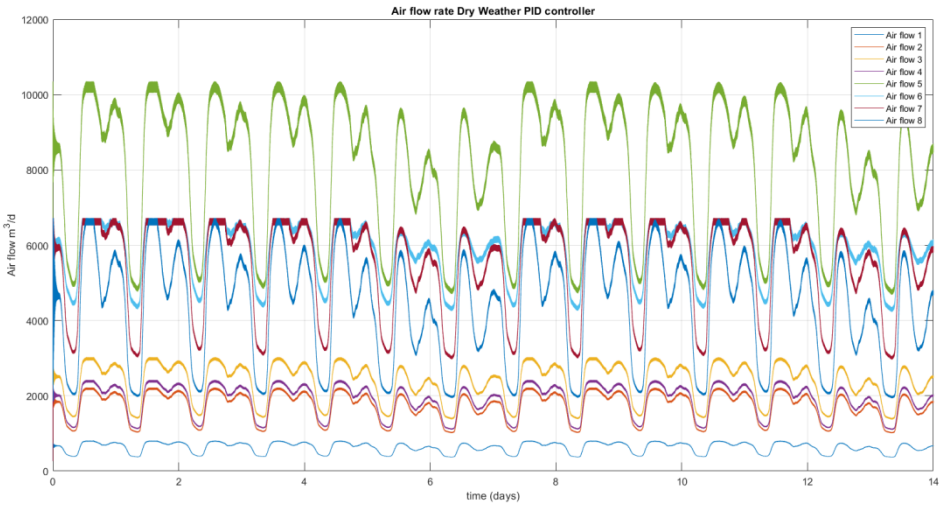

Effluent TN dry weather
neuro-genetic
multi PID
TN gN/m3
Effluent TN Rainy weather
neuro-genetic
multi PID
TN gN/m3
Effluent TN Storm weather
neuro-genetic
multi PID
TN gSS/m3
time (days)

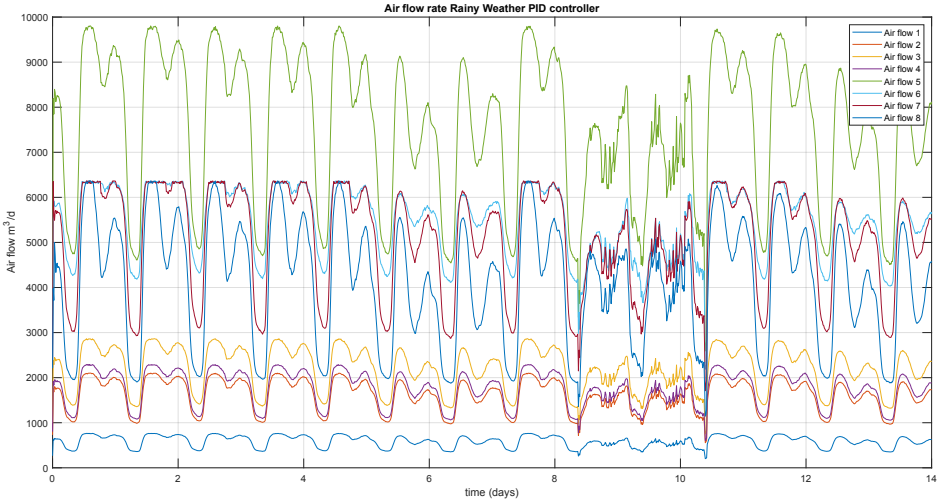
Fig. 7


Air flow rate Dry Weather Neuro Genetic controller
Air flow 1
Air flow 2
Air flow 3
Air flow 4
Air flow 5
Air flow 6
Air flow 7
Air flow 8
Air flow m3/d
time (days)


Air flow rate Rainy Weather Neuro Genetic controller
Air flow 1
Air flow 2
Air flow 3
Air flow 4
Air flow 5
Air flow 6
Air flow 7
Air flow 8
Air flow m3/d
time (days)


Air flow rate Storm Weather Neuro Genetic controller
Air flow 1
Air flow 2
Air flow 3
Air flow 4
Air flow 5
Air flow 6
Air flow 7
Air flow 8
Air flow m3/d
time (days)


Air flow rate Dry Weather PID controller
Air flow 1
Air flow 2
Air flow 3
Air flow 4
Air flow 5
Air flow 6
Air flow 7
Air flow 8
Air flow m3/d
time (days)


Air flow rate Rainy Weather PID controller
Air flow 1
Air flow 2
Air flow 3
Air flow 4
Air flow 5
Air flow 6
Air flow 7
Air flow 8
Air flow m3/d
time (days)

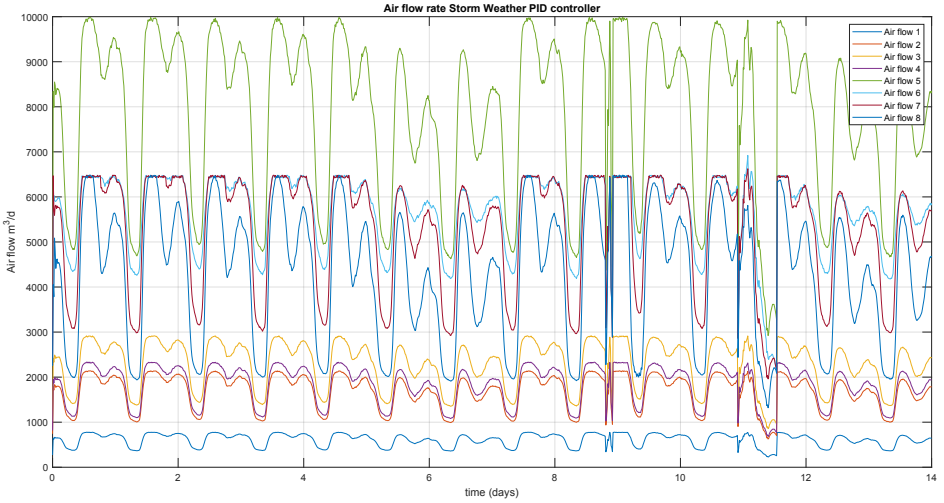

Air flow rate Storm Weather PID controller
Air flow 1
Air flow 2
Air flow 3
Air flow 4
Air flow 5
Air flow 6
Air flow 7
Air flow 8
Air flow m3/d
time (days)

Fig. 8

Table 1. Influent nominal conditions for the TecnoCasic Plant

		Dry Weather	Rainy Weather	Storm Event
Influent Flow Rate	Q_{in}	6152 m^3/d	7153 m^3/d	6585 m^3/d
Influent Chemical Oxygen Demand	COD_{in}	221 $gCOD/m^3$	190 $gCOD/m^3$	211 $gCOD/m^3$
Influent Total Suspended Solids	TSS_{in}	46 gSS/m^3	39.56 gSS/m^3	42.98 gSS/m^3
Influent Total Nitrogen	TN_{in}	22 gN/m^3	18.92 gN/m^3	20.55 gN/m^3
Influent Ammonia	NH_{4in}^{+}	13.8 gN/m^3	7.92 gN/m^3	11.2 gN/m^3

Table 2. Effluent contraints conditions

Effluent Chemical Oxygen Demand	$COD_{out}^{eff} \leq 125\ gCOD/m^3$
Effluent Total Suspended Solids	$TSS_{out}^{eff} \leq 35\ gSS/m^3$
Effluent Total Nitrogen	$TN_{out}^{eff} \leq 18\ gN/m^3$
Effluent Ammonia	$NH_{4out}^{+\,eff} \leq 0.6\ gN/m^3$

Table 3. Control pairs of manipulated-controlled variables

Airflow Q_{a1} in Tank 1	Oxygen O_{21}in Tank 1
Airflow Q_{a2} in Tank 2	Oxygen O_{22}in Tank 2
Airflow Q_{a3} in Tank 3	Oxygen O_{23}in Tank 3
Airflow Q_{a4} in Tank 4	Oxygen O_{24}in Tank 4
Airflow Q_{a5} in Tank 5	Oxygen O_{25}in Tank 5
Airflow Q_{a6} in Tank 6	Oxygen O_{26}in Tank 6
Airflow Q_{a7} in Tank 7	Oxygen O_{27}in Tank 7
Airflow Q_{a8} in Tank 8	Oxygen O_{28}in Tank 8
External recycle flowrate Q_r	Effluent ammonia $NH_{4_{out}}^{+}$
Waste sludge flowrate Q_w	Effluent alkalinity ALK_{out}

Table 4. Prediction errors in terms of MAPE, MaxAPE and R^2 for the software sensors in closed loop

Variable	**Neuro-genetic controller**			**Decoupled PID controller**		
	Dry	*Rainy*	*Stormy*	*Dry*	*Rainy*	*Stormy*
Effluent *COD*						
MAPE	1,85	1,77	1,70	1,84	1,76	1,72
MAPE_max	7,60	7,37	6,96	7,48	7,42	7,01
R^2	0,90	0,91	0,91	0,90	0,91	0,90
Effluent *TSS*						
MAPE	1,86	1,90	1,83	1,89	1,89	1,84
MAPE_max	7,22	6,90	7,01	7,24	6,82	6,99
R^2	0,88	0,89	0,89	0,88	0,89	0,88
Effluent *TN*						
MAPE	0,90	0,91	0,89	0,94	0,90	0,90
MAPE_max	5,84	5,61	5,51	5,81	5,70	5,60
R^2	0,91	0,90	0,92	0,91	0,90	0,92

Table 5. Comparison results with different climatic conditions for quality and economic performance

Variable	**Neuro-genetic control**			**Decoupled PID control**		
	Dry	*Rainy*	*Stormy*	*Dry*	*Rainy*	*Stormy*
Effluent *COD*						
% of limit violations *	2.64%	2,93 %	3,45%	16,74 %	17,65 %	18,81%
Mean (g*COD*/m^3)	78,06	74,81	77,26	99,11	93,25	98,45
Effluent *TSS*						
% of limit violations *	2,53%	2,39%	3,12%	9,22%	9,14 %	9,32%
Mean (g*SS*/m^3)	15,16	15,33	15,55	19,63	18,26	18,59
Effluent *TN*						
% of limit violations *	4,16%	3,49 %	4,08 %	24,24 %	20, 74%	22,60%
Mean (g*N*/m^3)	12,90	11,97	12,56	14,78	13,70	14,37
Effluent NH_{4out}^{+}						
% of limit violations *	5,82%	5,16 %	5,72 %	23,15 %	21, 12%	22,88%
Mean (g*N*/m^3)	0,35	0,31	0,33	0,53	0,48	0,51
* Measured in operational time						
Effluent Quality Index (g/day)	6251,04	7491,62	7307,81	7342.88	8547.15	8873.76
Total Costs (€/day)	**356**	**381**	**393**	**399**	**425**	**464**

Declaration of interests

 The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: