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Artificial Neural Networks Based Model Predictive Control of the Wastewater Treatment Plant

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Abstract

A statistical model, using Artificial Neural Networks (ANN), has been developed for the aerobic suspended growth Wastewater Treatment (WWT) plant. The paper presents the way ANN model has been designed and trained. The emerged recurrent ANN model has been used to perform WWT control using Model Predictive Control (MPC) algorithm. Model Predictive Control of the WWT soluble substrate and dissolved oxygen concentration has been investigated in the presence of setpoint changes and disturbance action. Cases of feedback provided by direct measurement of the soluble substrate concentration but also by using a special trained ANN soluble substrate estimator based on dissolved oxygen concentration measurement are shown. Incentives of the ANN model and ANN estimator based MPC are presented.

Keywords: Biological wastewater treatment, Model Predictive Control, Artificial Neural Networks.

1. Introduction

The importance of the biological WWT is continuously growing, as sustainable development of the modern society is concerned on the health of the environment. The biological treatment converts soluble organic or inorganic contaminants to insoluble organic and inorganic constituents or to CO_2 and

H_2O. Aerobic or anaerobic processes are based on enzymes that transform hydrocarbons into food for bacteria, removing the hydrocarbons [1].
Suitable conditions have to be achieved for bacterial growth, death phase and endogenous respiration in order to get optimal pollutant removal. Requirements may be obtained by appropriate control techniques intended to keep the operation of the unit at the most efficient working regime. MPC is a perfect fitted control strategy for fulfilling the demanding control tasks as the process features large time lags and nonlinear behaviour.

2. Model description and model predictive control approach

The aerobic activated sludge WWT system is presented in Fig 1. First, organic wastes are introduced together with the nutrients in a mixing basin. The mixture is then sent to the aeration basin (reactor) where the bacterial culture is held in suspension. Bacteria in activated sludge are capable of performing hydrolysis and oxidation reactions. Oxidation is conducted by aerobic organisms which use dissolved oxygen present in the biological system. Aerobic environment is achieved through diffused or mechanical aeration. For the completely mixed continuous-flow aeration unit, presented in Fig. 1, the influent is fed uniformly along the entire length of the basin.

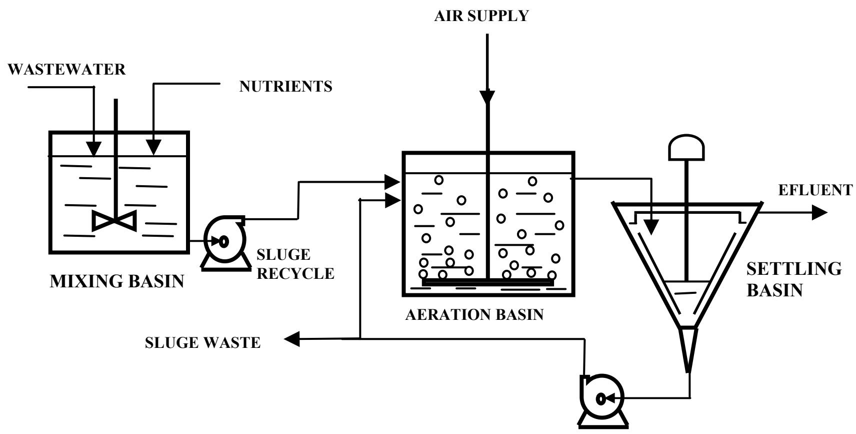

Figure 1: Schematic representation of the continuous-flow aeration unit.

The aeration is essentially homogenous, resulting in uniform oxygen demand throughout the basin. This results in a homogeneous concentration of solids and substrates in the basin. A recurrent Artificial Neural Networks model of the WWT has been developed in order to describe the dynamic behaviour of the unit and for building the soluble substrate concentration estimator on which the model based control strategies have been studied.

3. ANN model development

In order to achieve the first goal of building a ANN dynamic model of the WWT plant, the design started with setting up the process variables considered as inputs and outputs for the ANN. Since the analytical model of the WWT served as a basic source of data for training the ANN, the network inputs have been taken as the set of the states (process outputs) appended to the set of manipulated variables, all considered at the current moment of time *t,* [2, 3]. The ANN outputs (targets) have been selected as consisting in the set of the (subsequently) controlled variables but considered at the next sampling moment $t+\Delta t$, ($\Delta t=1h$). The set of the states consist in the following four variables: biomass effluent concentration $X(t)$, soluble substrate (pollutant) concentration $S(t)$, dissolved oxygen concentration $DO(t)$ and recycled biomass concentration $X_r(t)$. The manipulated variables are: air flowrate, considered indirectly by the ratio of air flowrate to basin volume W, and the ratio of recycled flowrate to influent flowrate r. The controlled outputs are: effluent soluble substrate (pollutant) concentration $S(t)$ and dissolved oxygen concentration $DO(t)$. Summarizing, the six inputs/two outputs ANN has been trained to predict the values of the change in the controlled variables, from one sample time to the next one, based on the current values of the states and manipulated variables. The employed ANN architecture was a two-layer feed-forward one (sigmoid and linear transfer functions) and the back-propagation training algorithm was used for computing the network biases and weights. The quasi-Newton Levenberg-Marquardt algorithm was used for training the ANN.

The entire set of input and output data has been divided into a bulk set of input/target pairs of data (*90%*), used for training the ANN, and a smaller set (*10%*), later used for testing the quality of the learning process. The set of *900* data has been presented to the ANN in order to carry out the learning procedure. Good training performance has been obtained as it is proved by the close to unity correlation coefficients between targets and ANN response. The *100* testing set of data, completely different of the training one and not yet seen by the ANN, preserves the same favourable adequacy between targets and ANN outputs demonstrating a very good generalization property of the designed ANN. As a second test for proving the quality of the training process, randomly changing sequence has been generated for both considered manipulated variables (with changes equally distributed in time at multiples of ten hours). The comparative dynamic simulation results between the WWT response of the analytical model and the response of the trained ANN model are presented in Fig. 2 and Fig. 3, for the controlled variables of interest, effluent soluble substrate concentration $S(t)$ and dissolved oxygen concentration $DO(t)$.

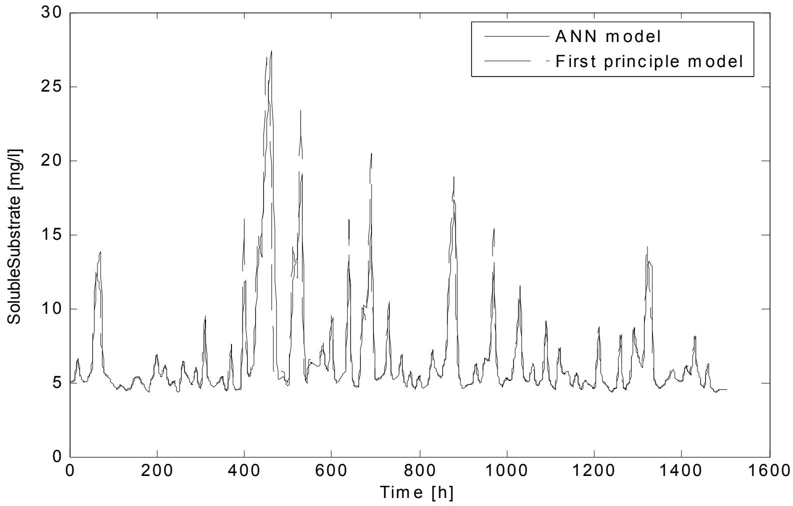

Figure 2: ANN (dashed line) and first principle (solid line) model simulation results for soluble substrate concentration *S*.

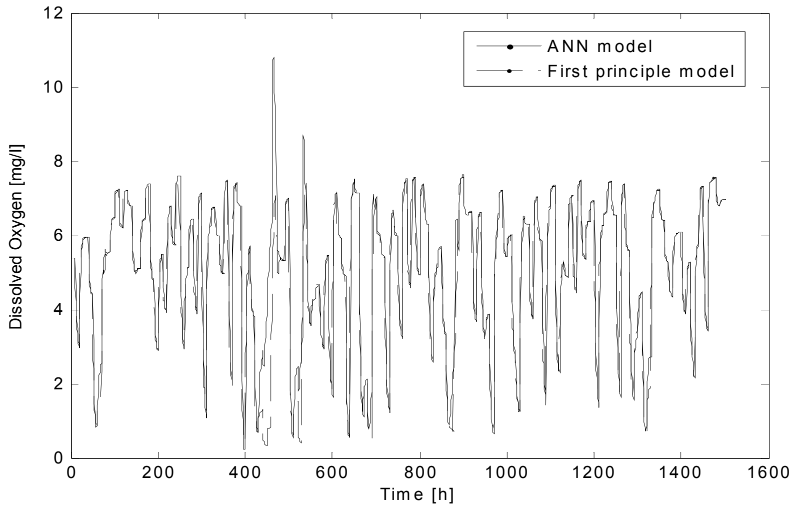

Figure 3: ANN (dashed line) and first principle (solid line) model simulation results for dissolved oxygen concentration *DO*.

As it may be noticed in Fig. 2 and Fig. 3, the ANN dynamic model has an almost identical behaviour with the first principle one, succeeding to capture the main dynamic features of the WWT. The ANN model will be further used for MPC.

4. Results of the ANN model based MPC approach

The main control objective of the WWT unit is to maintain the effluent soluble substrate concentration *S(t)* at *0.5018 mg/l*. Feedback is needed but measurement is either expensive or time consuming, making it difficult and/or infeasible. An ANN based estimator was developed based on dissolved oxygen process measurement, available from reliable instrumentation. For training the ANN based estimator of the soluble substrate concentration the following ANN structure has been chosen. As ANN estimator inputs have been considered the set of the manipulated variables appended to the dissolved oxygen variable, all considered at the current and *17* past moments t, $t-\Delta t$, $t-2\cdot\Delta t$, … , $t-17\cdot\Delta t$. The soluble substrate concentration *S* was taken as ANN estimator output (target), considered at the sampling moment $t+\Delta t$. Results of ANN estimator training were investigated by simulation. Using randomly varying inputs, the ANN estimator predictions and the first principle soluble substrate results have been compared and presented in Fig. 4. Showing relative errors within the range of ±*2.5%*, the simulation results prove the quality of the ANN estimator, proposing

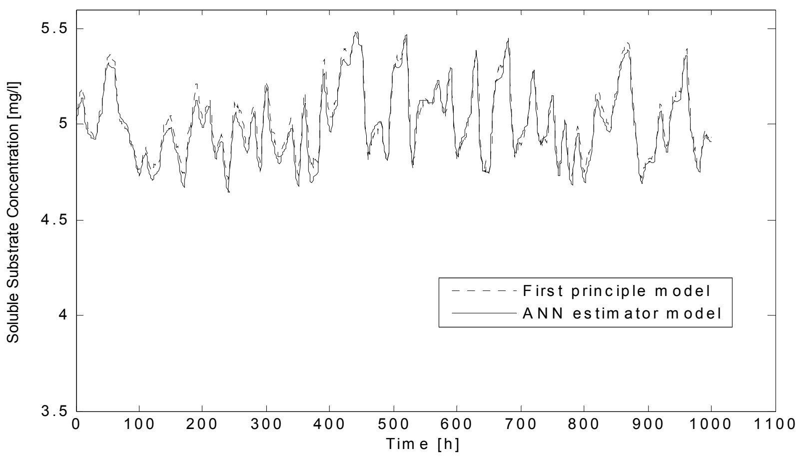

Figure 4: ANN estimator and first principle model simulation results for random varying inputs.

it for the observer based MPC. Using the developed ANN estimator and based on the dissolved oxygen feedback measurement, MPC of both soluble substrate and dissolved oxygen concentration have been tested by simulation. Results are presented in Fig. 5, for *+10%* setpoint change of soluble substrate, acting stepwise at the moment *t=500 h*. Fig. 6 presents the control performance for the case of the inlet soluble substrate concentration disturbance change of *+10%*, acting stepwise the at the moment *t=500 h*. MPC results presented in Fig. 5 and Fig. 6 reveal good setpoint following performance, zero offset and rejection of inlet soluble substrate concentration disturbance.

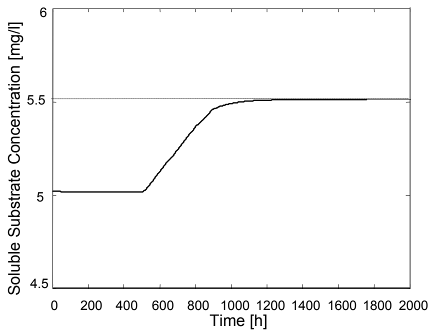

Figure 5: Soluble substrate change for MPC control of *S* and *DO* for *+10%* step increase of the soluble substrate concentration, using ANN model and estimator.

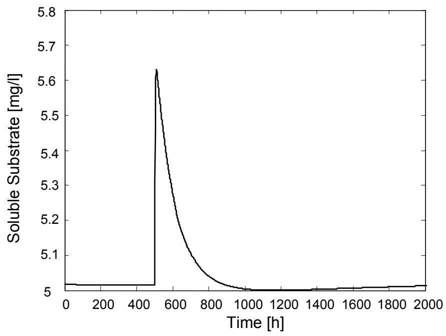

Figure 6: Soluble substrate change for MPC control of *S* and *DO* for *+10%* step increase of inlet soluble substrate conc. S_{in} disturbance, using ANN model and estimator.

5. Conclusions

The presented results demonstrate the way recurrent ANN may be successfully designed and trained to subsequently perform MPC of the WWT plant. The ANN model and the ANN estimator of the soluble substrate concentration based on dissolved oxygen concentration measurement make the soluble substrate control efficient for both setpoint tracking and disturbance rejection. Incentives of the ANN based MPC approach consist in the capability of building the model of the WWT plant based on process data and avoiding complex first principle model development. The computation effort is also reduced, as ANN models require less calculation time than models based on solving sets of differential equations. The ANN based estimator of the soluble substrate concentration eliminates the need for special measuring instrumentation. They all motivate the development of the presented ANN based MPC for industrial implementation.

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