Real-time model predictive control of a wastewater treatment plant based on machine learning


ABSTRACT

Two separate goals should be jointly pursued in wastewater treatment: nutrient removal and energy conservation. An efficient controller performance should cope with process uncertainties, seasonal variations and process nonlinearities. This paper describes the design and testing of a model predictive controller (MPC) based on neuro-fuzzy techniques that is capable of estimating the main process variables and providing the right amount of aeration to achieve an efficient and economical operation. This algorithm has been field tested on a large-scale municipal wastewater treatment plant of about 500,000 PE, with encouraging results in terms of better effluent quality and energy savings.

Key words | Artificial Intelligence, machine learning, model predictive control, neuro-fuzzy computing, nutrient removal, real-time control

HIGHLIGHTS

- Artificial Intelligence helps improve the energy efficiency of a wastewater treatment plant.
- Model predictive control produces a better effluent quality in a wastewater treatment plant.
- A neuro-fuzzy controller improves the reliability of a wastewater treatment plant.

NOMENCLATURE

<table>
<thead>
<tr>
<th>Acronyms</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>AI</td>
<td>Artificial Intelligence</td>
</tr>
<tr>
<td>AIE</td>
<td>Artificial Intelligence Engine</td>
</tr>
<tr>
<td>ANFIS</td>
<td>Adaptive Neuro-Fuzzy Inference System</td>
</tr>
<tr>
<td>CC</td>
<td>Conventional Controller</td>
</tr>
<tr>
<td>DO</td>
<td>Dissolved Oxygen (mg/l)</td>
</tr>
<tr>
<td>DO_sp</td>
<td>Dissolved Oxygen set-point (mg/l)</td>
</tr>
<tr>
<td>EW</td>
<td>Energy Way</td>
</tr>
<tr>
<td>FL</td>
<td>Fuzzy Logic</td>
</tr>
<tr>
<td>GA</td>
<td>Genetic Algorithm</td>
</tr>
<tr>
<td>MPC</td>
<td>Model Predictive Control</td>
</tr>
<tr>
<td>N_tot</td>
<td>Total Nitrogen (mgN/l)</td>
</tr>
<tr>
<td>PID</td>
<td>Proportional-Integral Derivative controller, equivalent to CC</td>
</tr>
<tr>
<td>Q_in</td>
<td>Input recycle flowrate (m³/s)</td>
</tr>
<tr>
<td>Q_r</td>
<td>Internal recycle rate (percentage of maximum)</td>
</tr>
<tr>
<td>Q_ras</td>
<td>External recycle rate (percentage of Q_in)</td>
</tr>
<tr>
<td>Q_w</td>
<td>Waster rate (percentage of Q_in)</td>
</tr>
<tr>
<td>U_a</td>
<td>Air flow rate (Nm³/h)</td>
</tr>
<tr>
<td>WWTP</td>
<td>Waste Water Treatment Plant</td>
</tr>
</tbody>
</table>

Symbols

- $NH_4^+$ Ammonium-N concentration (mgN/l)
- $NO_3^-$ Nitrate-N concentration (mgN/l)
- $NO_2^-$ Nitrite-N concentration (mgN/l)
- $\gamma_1$, $\gamma_2$, $\gamma_3$ Unconstrained optimisation coefficients
- $\rho_1$, $\rho_2$, $\rho_3$ Constrained optimisation coefficients
- $\delta$ Control sampling time (min)
- $\alpha$, $\beta$ Prediction and control horizons, as multiples of $\delta$

This is an Open Access article distributed under the terms of the Creative Commons Attribution Licence (CC BY-NC-ND 4.0), which permits copying and redistribution for non-commercial purposes with no derivatives, provided the original work is properly cited (http://creativecommons.org/licenses/by-nc-nd/4.0/).

doi: 10.2166/wst.2020.298
INTRODUCTION

A wastewater treatment plant (WWTP) is a complex process that uses microbiological reactions to remove pollutants from wastewater. In its operation, this energy-intensive process must reconcile two partially conflicting objectives: pollution abatement and energy conservation. It appears that a balance between these two diverging goals can be achieved through automatic control based on Artificial Intelligence (AI).

In the last two decades, as recently documented, there has been a growing integration between Artificial Intelligence and wastewater treatment processes (Mannina et al. 2019; Zhao et al. 2020). Biological treatment processes are intrinsically complex, involving a variety of microbial communities, of natural conditions, of influent characteristics, each with inherent uncertainties and time changes. On the other hand, governing legislation demands consistent effluent standards, while financial constraints call for energy savings. Reconciling effluent quality and economical operation, given the time-varying and uncertain nature of the process, requires advanced control solutions, which can be provided by Artificial Intelligence. This powerful tool can cater for both of the process operational requirements previously defined.

Artificial Intelligence is a universe of differing mathematical tools, which can be roughly grouped into Artificial Neural Networks (Kosko, 1992; Hagan et al. 1996), Fuzzy Logic (Yager & Zadeh 1994; Babuska 1998), and Genetic Algorithms (Goldberg 1989; Holland 1998), each with varied sub-categories, as aptly analysed in Zhao et al. (2020). Often these techniques are combined to produce high-level supervisory systems, generally referred to as Expert Systems (Castillo et al. 2016; Torregrossa et al. 2018; Judson 2019; Nikolopoulos 2019) or Decision Support Systems specifically aimed at harmonising conflicting objectives in the design of WWTP (Iglesias et al. 2007; Snip et al. 2014; Corominas et al. 2018), as later reviewed by Mannina et al. (2019). AI tools have also been used in WWTP to develop soft sensors to provide a double-check, or even substitute for hard sensors (Haimi et al. 2013, 2016; Mulas et al. 2015; Fernandez de Canete et al. 2016).

The application of Artificial Intelligence to the wastewater treatment area has been documented in many successful applications. Unlike many industrial processes where an approximating linear model can be used to implement a model predictive controller (MPC) (Borrelli et al. 2017; Rawlings et al. 2017), WWTP is a highly nonlinear, time-varying process and ad-hoc versions of MPC must be designed. A carbon-dosing system based on a fuzzy model predictive controller was proposed by Marsili-Libelli & Giunti (2002) to improve the nitrification performance. An evolutionary self-organising model of a municipal WWTP based on genetic programming was designed by Hong & Bhamidimarri (2003) to successfully model the many process nonlinearities. The primary aspect of WWTP management is the harmonisation of the effluent quality requirements with the energy conservation. This challenge has produced many studies in which the multi-objective nature of the problem was approached with AI tools and solved by the application of MPC, resulting in a multi-loop structure, as surveyed by Qiao et al. (2018). Differing nitrogen control strategies were proposed by Stare et al. (2007), while the specific problem of dissolved oxygen (DO) control using an MPC was considered by Holenda et al. (2008). O’Brien et al. (2011) used an MPC to reduce the plant power consumption by a quarter. A multivariable MPC for improving the nitrogen removal and reducing the operational costs was proposed by Dainotto et al. (2012) and Mulas et al. (2013), to be later extended to the control of a full-scale WWTP (Han & Qiao 2014; Mulas et al. 2015; Foscoliano et al. 2016). Francisco et al. (2015) described a procedure to determine the most economically viable controlled variable in the WWTP and proposed a nonlinear MPC integrated with a PI to monitor the process constraints. A similar approach was used by Goldar et al. (2016) to design a decentralised nonlinear MPC combined with a PI controller, which compared favourably to the previous centralised controller based on PI alone.

MATERIAL AND METHODS

Description of the plant and the information technology

The WWTP from which the data were acquired, and which is being used as a test plant, is the municipal plant of the city of Modena, in Northern Italy. It consists of a conventional biological treatment plant for nutrient removal with pre-denitrification, with a capacity of approximately 500,000 PE.

The process instrumentation consists of a Dissolved Oxygen meter and a nutrient sensor (Hach, Endress + Hauser). These field measurements are routed to the plant SCADA for real-time operation. An encrypted connection between the plant and the Energy Way centre was created to allow prototypical testing. This arrangement enables specific clients to access the controller through a LAN. Through VPN encrypted tunnelling, clients can mount directories on the controller as NFS folders and obtain
services directly from the controller, enabling fast analysis iteration and maintenance.

Communication between the centre and the plant SCADA is based on the Modbus protocol over TCP/IP, physically linking the controlling machine to the PLC-front-end with an Ethernet patch cable, enabling peer-to-peer IP communication.

The AI components of the MPC were trained and validated using plant data spanning over one year of operation of the same plant.

Before this MPC was designed, the plant automation consisted of conventional Proportional-Integral-Derivative (PID) control loops, which are now used as yardsticks to assess the performance of the new controller.

**ANFIS – a systematic approach to neuro-fuzzy modelling**

The AIE applied in this study is based on an Artificial Neuro-Fuzzy Inference System (ANFIS). This structure, shown in Figure 1, was originally proposed by Jang (1993) and was later used, among other applications, to model wastewater treatment processes (Tay & Zhang 1999, 2000), drinking water processes (Wu et al. 2004), composting (Giusti & Marsili-Libelli 2010), irrigation management (Giusti & Marsili-Libelli 2015), flood forecasting (Bartoletti et al. 2016) and in the context of soft-sensors development (Dürrenmatt & Gujer 2014; Haimi et al. 2017). ANFIS, which is thoroughly described in Marsili-Libelli (2016), is a composite neuro-fuzzy structure that implements Sugeno-type fuzzy logic (Takagi & Sugeno 1985)

\[
R_i: \text{if } (x_1 \text{ is } A_i^{(1)}) \ldots \text{ and } (x_n \text{ is } A_i^{(n)}) \text{ then } f_i = a_i^T \cdot x + b_i
\]

where \((x \in \mathbb{R}^n)\) is the vector of inputs, and \((a_i, b_i)\) are the coefficients of the linear Sugeno consequents.

The improvement of ANFIS with respect to the classical Sugeno fuzzy models is in its ability to adjust both the antecedent membership functions and the linear consequents to minimise the sum of squared differences between the ANFIS output and a training data set. As explained later, this structure has been used repeatedly to develop the MPC.

**Development of the model predictive controller**

The present real-time MPC was designed to improve the energy efficiency of the nutrient removal process in the full-scale municipal WWTP described earlier. The process control scheme is shown in Figure 2, where the set-points for the dissolved oxygen DO\(_{sp}\) and the recycle flow Q\(_{r,sp}\) are determined on the basis of the forecasted future nutrient loading provided by the artificial intelligence engine (AIE). These set-points are fed to local controllers to deliver the proper amount of air flow (U\(_a\)) and internal recycle (Q\(_r\)). The grey boxes indicate the low-lever controllers/actuators.

The observed variables used to train the ANFIS are the DO, oxidation reduction potential (ORP), temperature, the nitrogen species (NH\(_4\) and NO\(_3\)) in the oxidation tank, and the output total nitrogen (N\(_{tot}\)). The manipulated variables are the airflow rate (U\(_a\)) and the internal recycle Q\(_r\), the latter expressed as a percentage \((0\% - 100\%)\) of the maximal allowable flow. This reflects the fact that the recycle pump operates at a fixed regime, so the percentage represents the fraction of the ON time in each time frame.

It is assumed that the controlled variables (DO and Q\(_r\)) can track their set-points without appreciable error, being
locally controlled by low-level PID regulators. They act on
the blowers delivering the air flow $U_a$ and on the recycle
pump providing the internal recycle ($Q_r$). The MPC aims
to reduce the amount of output total nitrogen ($N_{tot}$), while
at the same time minimising the energy consumption.

All of the process variables are sampled at regular inter-
vals $\delta = 5$ min, which represents the MPC time-base, of
which the control ($\beta$) and prediction ($\alpha$) horizons are mul-
tiples. The control horizon is equal to the sampling time,
so $\beta = 1$, while the prediction horizon $\alpha > \beta$ was suitably
defined as a multiple of $\beta$, which cannot be further specified
here because of industrial confidentiality.

The purpose of the MPC is the minimisation of the
following performance function, which takes into account
both the predicted nitrogen species and the energy
consumption, represented by the blower energy consump-
tion $E$.

$$DO_{sp}^i(t + \beta) = \arg \min_{DO_{sp}} \left[ \gamma_1 \frac{N_{H_4}(t + \alpha) + N_{O_3}(t + \alpha)}{N_{tot}} + \gamma_2 \frac{E(t + \beta)}{E} + \gamma_3 \frac{DO_{sp}(t + \beta) - DO_{sp}(t)}{DO_{sp}} + \gamma_4 \frac{N_{H_4}(t + \alpha) + \beta}{N_{H_4}} + \rho_2 \frac{N_{O_3}(t + \alpha) + \beta}{N_{O_3}} \right]$$

where $N_{tot} = N_{H_4} + N_{O_3}$
$\gamma_1, \gamma_2, \gamma_3, \rho_1, \rho_2, \rho_3 =$ weighting factors;
$E =$ blower energy
$\gamma =$ average value; $\alpha =$ prediction horizon;
$\beta =$ control horizon.

While the $\gamma$ weights are always active, the $\rho$ coef-
cients can be regarded as ‘soft constraints’ because they
are activated whenever each variable reaches its upper bound

$$\rho_1 = 0 \quad \text{if } N_{H_4}(t + \alpha) \geq N_{H_4}$$
$$\rho_2 = 0 \quad \text{if } N_{O_3}(t + \alpha) \geq N_{O_3}$$
$$\rho_3 = 0 \quad \text{if } N_{tot}(t + \alpha) \geq N_{tot}$$

with $N_{H_4}, N_{O_3}, N_{tot}$ fixed threshold values.

The following feedforward control generates the next
recycle flowrate $Q_r(t + \beta)$ by updating the current value
$Q_r(t)$ according to the forecasted NO3 value

$$Q_r(t + \beta) = Q_r(t) + \frac{N_{O_3}(t + \alpha) - N_{O_3}(t)}{N_{O_3}(t)}$$

Then $Q_r(t + \beta)$ is constrained between 60% and 100%
of the allowable range, namely

$$Q_r(t + \beta) = \begin{cases} \min (Q_r(t + \beta), 100) \\ \max (60, Q_r(t + \beta)) \end{cases}$$

Equation (4) indicates that for operational reasons the
internal recycle must remain inside the range [60, 100]%
of its nominal value, in other terms it can only be
decreased down to nearly half its nominal value, but not
increased beyond that limit. The inner structure of the
MPC is shown in Figure 3, and consists of two parts.
represented by the dashed boxes: the optimisation in the upper block implements Equations (2) and (3), while the lower block produces the forecasts on which the optimisation is based. The purpose of the upper block is to determine the best $DO_{sp}$ by testing all of the possible $DO_{sp}(t + \beta)$ values, within a predefined grid of values, on the basis of the forecasts of the lower block. The current $DO_{sp}(t + \beta)$ under test is also fed into the inverse ANFIS, which yields the corresponding value of air flow $U_a(t + \beta)$. From the blower rating curve, this value is converted into the energy consumption $E(t + \beta)$, which is returned to the upper block. The lower block also computes the next recycle flow $Q_r(t + \beta)$ according to Equations (4) and (5).

The prediction accuracy is assessed through the following performance indexes computed over $n$ samples:

$$
MAE \ (\text{Mean Absolute Error}) = \frac{1}{n} \sum_{i=1}^{n} |\hat{y}_i - y_i| \\
RAE \ (\text{Relative Absolute Error}) = 100 \times \frac{1}{n} \sum_{i=1}^{n} \frac{|\hat{y}_i - y_i|}{y_i},
$$

where $y$ represents the actual generic variable and $\hat{y}$ its estimate. Figure 4 shows the performance of the trained neuro-fuzzy predictors in estimating the process variables $\alpha$ steps ahead for the nitrogen species and $\beta$ steps ahead for the airflow.

![Figure 3](image1.png)  
Figure 3 | General scheme of the neuro-fuzzy MPC. The prediction is made $\alpha$ steps ahead, while the control is applied at $\beta$ steps ahead. The grey boxes represent the manipulated variables to be applied to the plant at the next step $t + \beta$.

![Figure 4](image2.png)  
Figure 4 | Performance of process variables prediction, at time $t + \alpha$ for the nutrients and at $t + \beta$ for the airflow provided by the trained neuro-fuzzy networks. Normalised values are shown to preserve confidentiality.
A sensitivity assessment was also performed on the model by considering the percentage variations of the output variables ($NH_4^+$, $NO_3^-$) caused by a ±20% variation in DO. Figure 5(a) shows that a positive DO variation of 20% produces a $NH_4^+$ decrease in 95.8% of the cases (red bars), while a −20% DO variation results in an increase of $NH_4^+$ in 96.1% of the times (blue bars). Likewise, Figure 5(b) shows that a +20% DO increase is followed by an $NO_3^-$ increase in 91.7% of the cases, while a −20% DO decrease results in a lower $NO_3^-$ in 92.3% of the times. The spread in the response is due to the influence of other process conditions.

RESULTS AND DISCUSSION

After testing the consistency of the predictions via error assessment of Equation (6) and the sensitivity analysis, the proposed EW controller has been compared to the conventional controller (CC) that was previously in operation. The preliminary test shown in Figure 6 consists of three time-windows and compares the total output nitrogen ($N_{tot}$) produced by the two controllers, only one of which is engaged at any one time. The total output nitrogen follows the reference value produced by the active controller within the model error tolerance. In the first and third time-window, the conventional controller (CC) is active, yielding a higher value of $N_{tot}$, while in the central grey window, the EW controller is engaged and produces a lower output $N_{tot}$. However, since both controllers are always updated, they continue to produce a reference output even when disengaged. Hence, in the grey slot, the CC controller still produces a higher reference, which, however, has no effect on the output because it is disconnected, being disengaged.

A further test was then carried out to test the EW controller’s adaptability to differing operational situations,
putting the emphasis either on the effluent quality, or on the energy conservation, as the conditions required. Figure 7 shows the average relative weights of the performance function Equations (2) and (3) during two different periods in which the EW controller was operating. The left bar corresponds to a high-load condition, when the effluent quality is the primary concern. The blue bar, corresponding to the unconstrained NH₄ term \( \gamma_1 \), is predominant because the premium is set on limiting the ammonium-N discharge. For the same reason, the constrained weight on N₉₀₅ (\( \rho_3 \)) is the second largest coefficient, while the energy weight \( \gamma_2 \) is comparatively much smaller. The severity of the loading is also apparent in the comparatively large activation of the constrained terms \( \rho_1 \), \( \rho_2 \), and \( \rho_3 \), indicating that both Nitrogen species are approaching their limit.

The right bar, by contrast, shows the weights distribution during a mild load period, during which energy saving becomes the primary concern. It can be seen that while the constrained weights \( \rho_1 \), \( \rho_2 \), and \( \rho_3 \) are not activated, the energy weight \( \gamma_2 \) is now the dominant one.

This performance assessment shows that the EW controller is able to combine the two operational modes and selects the overall goal to be pursued, depending on the incoming load, by dynamically adapting its performance function Equations (2) and (3), depending on the present and predicted loading conditions.

After the goal-shifting experiments of Figure 7, the two controllers were run on alternate weeks from 10 June to 9 September 2019. To compare their performance over this period, the influent NH₄ was divided into three classes based on percentiles, as shown in Table 1, and the corresponding effluent NH₄ was observed.

Table 2 summarises the performance of the two controllers during this period. It shows that while the average input NH₄ is nearly the same for both controllers, indicating two comparable operational periods, their process management is very different: looking at the values of the DOₙ₉₀ and actual DO value, they are both higher in the CC case, indicating a larger energy consumption. Conversely, the EW controller keeps the DO lower, but still at a safe level, to ensure adequate NH₄ oxidation. It is not surprising that the air flow is highest for both controllers in the Medium input range, because in this segment the oxidation...
needs are highest, while in the High range of NH₄, the airflow can be safely decreased without exceeding the effluent allowable limit.

The EW controller achieves a better overall performance, though the output ammonium-N is higher, but still within the regulatory limit. This is due to the fact that the EW controller lowers the DOₜₐ in order to save energy and avoid an excessive nitrate-N build-up, which would then be difficult to eliminate in the denitrification phase because of the limited availability of organic carbon. In fact, although the ammonium-N output is slightly higher than that produced by the CC controller, it still remains well within the prescribed limit, so any further reduction in output NH₄ would only imply a larger energy expenditure, without any benefit in effluent quality.

**Table 2** Weekly averages of the main process variables over the period 10 June – 9 Sept. 2019

<table>
<thead>
<tr>
<th>NH₄ class</th>
<th>Input NH₄</th>
<th>DO</th>
<th>DOₜₐ</th>
<th>Air flow</th>
<th>Output NO₃</th>
<th>Output NH₄</th>
<th>Output Ntot</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CC</td>
<td>EW</td>
<td>CC</td>
<td>EW</td>
<td>CC</td>
<td>EW</td>
<td>CC</td>
</tr>
<tr>
<td>Low</td>
<td>5.23</td>
<td>8.63</td>
<td>0.95</td>
<td>0.49</td>
<td>0.48</td>
<td>0.51</td>
<td>1,194.42</td>
</tr>
<tr>
<td>Medium</td>
<td>25.14</td>
<td>24.05</td>
<td>0.56</td>
<td>0.47</td>
<td>0.49</td>
<td>0.42</td>
<td>1,425.83</td>
</tr>
<tr>
<td>High</td>
<td>32.47</td>
<td>31.99</td>
<td>0.54</td>
<td>0.44</td>
<td>0.50</td>
<td>0.38</td>
<td>1,135.97</td>
</tr>
</tbody>
</table>

**Table 3** Performance improvement of EW over CC during the period 10 June – 9 Sept. 2019

<table>
<thead>
<tr>
<th>Measured averages over the three input classes</th>
<th>Effluent Ntot</th>
<th>Air flow (Uₐ)</th>
<th>DO</th>
<th>Energy saving</th>
</tr>
</thead>
<tbody>
<tr>
<td>Δ(EW-CC) %</td>
<td>–8.1%</td>
<td>–16.7%</td>
<td>–29.0%</td>
<td>–16.0%</td>
</tr>
</tbody>
</table>

**Figure 8** Box plots of the controller performances over the period 10 June – 9 Sept. 2019. The band width represents the amount of data in the 5th, 25th, 50th, 75th, and 95th percentiles, while the mean value is represented by the white segment. (a) Distribution of input NH₄; (b) distribution of output NO₃; (c) distribution of output NH₄; (d) distribution of Ntot; (e) distribution of airflow; (f) distribution of DO.
From the values of Table 2, the percentage improvements of the EW controller are computed in Table 3, assessing the improvement of EW over CC.

To better appreciate the differing behaviour of the two controllers over the test period of weekly switching, several box plots were produced, as shown in Figure 8. As noted, the NH4 input ranges were about the same for both controllers (Figure 8(a)), and the thickness of the Low plot shows that the low loading was the most common situation. Conversely, Figure 8(b), 8(c), and 8(d) show that the effluent quality obtained by the EW controller was consistently lower than in the CC case, save for the output Ntot that was slightly higher obtained by the EW controller was consistently lower than in the CC case. Further, Figure 8(e) shows that under the EW controller management the aeration was consistently lower than in the CC case. Further, the wider box of the Low percentiles in the High input case indicates a net energy saving for the EW controller. This is also reflected in the lower DO values shown in Figure 8(f), particularly evident in the Low input case, when the CC produced a higher DO, with the risk of adversely affecting the sedimentation characteristics of the sludge.

CONCLUSIONS

This paper has described the design and field testing of the EW MPC based on neuro-fuzzy networks and heuristic search. Its main asset is the ability to predict the N tot peaks sufficiently in advance ($\alpha > 30 \text{ min}$) to adapt the air low and secure safe effluent standards while saving energy.

During the initial test, the two controllers (EW and CC) were alternatively engaged as shown in Figure 6. The flexibility of the EW controller is further demonstrated by comparing the average relative weights of the cost function Equations (2) and (3) in two periods with differing treatment requirements, as demonstrated in Figure 7.

Further tests obtained by alternating the two controllers on a weekly basis have confirmed the improved reliability of the EW controller in achieving a better effluent quality while conserving energy, particularly by decreasing the air flow during the low load periods, but also by limiting the oxidation during high load peaks, provided that the nutrients limit is never reached. In all cases, the effluent is kept well within the regulatory limit. This aspect is demonstrated in statistical terms in Figure 8, where the EW controller compares favourably to the previous scheme, being able to consistently shift the percentile plots towards lower values of each output indicator and of the air flow.

The system is presently in operation at the previously mentioned plant, where its testing against the conventional controller continues.

ACKNOWLEDGEMENT

The authors gratefully acknowledge the collaboration of HERA SpA for supporting this research and for consenting to the present publication.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

REFERENCES


