Seasonal Setpoints Optimization of WWTP DO Control Based on Artificial Neural Networks Performance Indices Prediction

Norbert B. Mihálya, Vasile M. Cristeaa\*

aBabeş-Bolyai University of Cluj-Napoca, 1 Mihail Kogalniceanu Street, 400028 Cluj-Napoca, Romania

mircea.cristea@ubbcluj.ro

Abstract

Adaptive and optimal setpoints for the aeration control system are necessary to maintain the high performance of wastewater treatment plant operation under generally variable seasonal weather conditions. By effectively achieving the optimization aims, models with shorter computation times and more dependable forecasts are highly valued components for real-time optimization activities. In order to forecast the wastewater treatment plant's Greenhouse Gas Emissions and Effluent Quality performance indicators, artificial neural network models were designed, trained, and evaluated. We took into consideration the nonlinear autoregressive network with exogenous inputs network type. The models of artificial neural networks were developed using data particular to each season. Using evolutionary algorithm optimizations and two distinct selection techniques based on the Pareto fronts of the two considered performance indicators, the optimal artificial neural network architecture and hyperparameters were identified for each of the four seasons. When tested, the trained network models showed high forecast accuracy for all seasons, with mean absolute percentage error values for the greenhouse gas emissions reaching 2.88% and the effluent quality index up to 4.25%. The optimization of aeration led to improvements in Effluent Equality, Greenhouse Gas Emissions, and Operational Cost performance throughout all seasons. The improvements ranged from 0.40% for Greenhouse Gas emissions to 13.31% for Effluent Quality Index.

**Keywords**: seasonal artificial neural network, genetic algorithm, aeration control, greenhouse gas emissions, wastewater treatment plant, performance indices.

* 1. Introduction

A rapidly expanding and growing important area of study for wastewater treatment plants (WWTPs) is greenhouse gas (GHG) emission reduction (Mannina et al., 2016). It was demonstrated to be advantageous to include these emissions in the evaluation of the environmental effects (Nguyen et al., 2020). Many models and tools for estimating greenhouse gas emissions have been created and used in various WWTP investigations, such as analyzing the effects of cutting-edge treatment techniques (e.g. thermal drying of sludge) on greenhouse gas emissions (Szypulska et al., 2021).

The nonlinear autoregressive network with exogenous input (NARX), a dynamic network that makes predictions based on historical data, is the best kind of network to handle sequential and complicated tasks. NARX has been shown to be an effective tool for predicting gaseous emissions in the influent chamber of WWTPs (Zounemat-Kermani et al., 2019). Simultaneously, few studies focused on the use of NARX models to dynamically analyze the performance of WWTP operation. Successful applications of artificial neural network (ANN)-based GHG modeling include estimating GHG emissions in Europe (Antanasijević et al., 2014) and predicting the impacts of climate change on GHG emissions (Guo et al., 2021). Nevertheless, research has not yet been done on the modeling of a complete WWTP's GHG emissions using these models.

Optimizing controller settings can lead to the optimization of WWTP operations. The dissolved oxygen (DO) and nitrate (NO) controllers are common examples. Tejaswini et al. optimized the gain and integral time values of the controllers using simulated data, which resulted in a reduction in the effluent quality and total cost indices (Tejaswini et al., 2021). While looking at ways to optimize the operation of the WWTP through the use of aerated bioreactors, it is necessary to take GHG emissions into account.

The objective of the current study is to optimize the WWTP seasonal operation while accounting for the majority of intrinsic biological processes. To accomplish it, the dynamic ANN-based modeling of the complex Activated Sludge Model No. 2d (ASM2D) will be used. The novelty lies in the utilization of ANN models to assess the effluent quality index (EQI) and greenhouse gas emissions of the WWTP. These models are further employed in optimization with genetic algorithms (GAs) of the WWTP seasonal operation by finding the optimal setpoint of the DO control loop.

* 1. Methodology
		1. Data Generation

The Benchmark Simulation Model no. 2 (BSM2) was used to generate the simulated data sets used in this work, with model characteristics being outlined in the corresponding technical report (Alex et al., 2018). The model used was an extended version of the BSM2, which is detailed in (Flores-Alsina et al., 2016; Solon et al., 2017). Besides C and N compounds, it further describes P, S, and Fe transformations. The ideal treatment is hard to forecast during times of changeable temperature since temperature affects a number of processes involved in wastewater treatment, such as the impact on the metabolic activity of microorganisms. Consequently, a one-year period of 364 days, beginning on day 45, was selected from the 609 days of BSM2 dynamic inputs. The 364 days of data were evenly divided into 4 sections, with each season being 91 days long.

* + 1. GA-NARX models development

The 13 input features of the ANN consisted of influent and operational variables, while the two output features were the EQI and GHG emissions performance indices. To find the appropriate network hyperparameters that are: the training algorithm (TA), the tapped delay lines horizon (TD), the number of hidden layers, the number of neurons in each hidden layer, and the kind of transfer functions, the models were developed using a genetic algorithm. The three most commonly used backpropagation algorithms in the field of study were considered, i.e., Levenberg-Marquardt (LM), Quasi-Newton (BFGS), and scaled conjugate gradient (SCG) (Bahramian et al., 2023). The training process utilized 70% of the dataset, while two sets of 15% each were used for validation and testing. The number of sampling time delays for the input and output was searched from 2 to 20, and logistic sigmoid (log) and tangent sigmoid (tan) transfer functions (TF) were considered.

The most accurate GA-NARX networks were saved after all developed networks were assessed using three distinct assessment criteria to guarantee that the GA optimization produced the best-performing models. The mean squared error (MSE), mean absolute percentage error (MAPE), and coefficient of determination (R2) were the assessment criteria used to choose the most accurate ANN models (Mihály et al., 2022).

* + 1. Effluent quality index and GHG emissions estimation
			1. Effluent quality index

The daily emitted mass of pollution, measured in kilograms of pollution units per day (kg PU/d), is described by the EQI. An extended version of the criterion was employed, as shown by Eq. (1) (Solon et al., 2017), in order to also account for pollution caused by P delivered to the receiving water bodies.

 (1)

* + - 1. GHG emissions

The on-site emissions of CO2 and N2O by the aerobic biological processes, as well as the off-site, downstream N2O emissions were taken into account as described in (Mihály et al., 2023), while the CO2 and CH4 emissions due to the anaerobic digestion were calculated as shown in Eq. (2) and (3).

 (2)

 (3)

It was assumed that of the generated methane (*MP*) 99% would burn in a gas engine and the remaining 1% would escape into the atmosphere. is the global warming potential relative to CO2 for CH4.

Utilizing a factor for the emission intensity of power generation, the GHG emissions (kg CO2 eq./d) resulting from the net energy consumption were calculated as shown in Eqs. (4) and (5). The difference between the daily energy demand (*eD*) and energy recovery (*eR*) was used to compute the WWTP's net energy consumption (kWh/d).

 (4)

 (5)

 (6)

here, *EFenergy*, with a value of 0.275 kg CO2 eq./kWh in 2021, represents the GHG emission intensity of electricity generation for the EU (EEA, 2022). Calculations of the *AE*, *PE*, *ME*, *HEnet*, and *MP* components were performed as described in (Gernaey, 2014).

The GHG emission due to sludge disposal was calculated as the CO2 (kg CO2/d) generated from the combustion of biogas in landfills:

 (7)

where, *WS,landf* is the amount of disposed sludge to landfills.

* 1. Results and discussion

Taking the concept of the most accurate model into consideration, two distinct selection scenarios were examined. If all three assessment criteria performed better than the best results that had been previously achieved in the selection process, the model was saved, and this was considered as Case 1 selection approach. While in Case 2 when any of the three measurements produced better outcomes than the prior top result of that metric in the selection process, the network was saved. Tables 1 and 2 contain these results.

The most effective networks for EQI modeling showed R2 values ranging from 0.9930 to 0.9950. In contrast, the MAPE values were within the range of 3.53% and 4.25%. The ranges for these values, with regard to the GA-NARX modeling of GHG emissions, were 0.9867 to 0.9872 and 2.79% to 2.88% for R2 and MAPE, respectively. The 8 GA-NARX models, whose predictions were highlighted in the tables, were found to have reliable accuracy to be further applied in the operation optimization of the WWTP operation.

Table 1. GA-NARX models for EQI and GHG emissions predictions in Case 1

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Season | Out | TA | TD | Neurons | Functions | Evaluation on testing data |
| Layer 1 | Layer 2 | TF 1 | TF 2 | R2 | MSE∙105 | MAPE |
| Winter | **EQI** | **SCG** | **14** | **8** | **6** | **tan** | **tan** | **0.993** | **3.64** | **3.53** |
| **GHG** | **BFG** | **12** | **14** | **9** | **tan** | **tan** | **0.987** | **2.67** | **2.83** |
| Spring | **EQI** | **LM** | **3** | **4** | **4** | **tan** | **tan** | **0.994** | **5.69** | **3.82** |
| GHG | BFG | 2 | 12 | - | log | - | 0.986 | 2.59 | 2.88 |
| Summer | **EQI** | **LM** | **2** | **15** | **-** | **tan** | **-** | **0.993** | **5.32** | **4.25** |
| GHG | BFG | 9 | 14 | 9 | log | log | 0.987 | 2.69 | 2.85 |
| Autumn | EQI | SCG | 14 | 5 | - | tan | - | 0.995 | 5.06 | 3.98 |
| **GHG** | **LM** | **17** | **4** | **-** | **tan** | **-** | **0.987** | **2.51** | **2.87** |

Table 2. GA-NARX models for EQI and GHG emissions predictions in Case 2

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Season | Out | TA | TD | Neurons | Functions | Evaluation on testing data |
| Layer 1 | Layer 2 | TF 1 | TF 2 | R2 | MSE∙105 | MAPE |
| Winter | EQI | LM | 14 | 14 | - | tan | - | 0.991 | 4.79 | 3.96 |
| GHG | SCG | 5 | 15 | 10 | tan | tan | 0.984 | 3.14 | 2.96 |
| Spring | EQI | SCG | 16 | 12 | - | tan | - | 0.993 | 7.82 | 4.38 |
| **GHG** | **BFG** | **6** | **8** | **-** | **log** | **-** | **0.987** | **2.68** | **2.79** |
| Summer | EQI | LM | 8 | 14 | - | tan | - | 0.993 | 5.07 | 4.32 |
| **GHG** | **LM** | **6** | **6** | **-** | **log** | **-** | **0.987** | **2.45** | **2.88** |
| Autumn | **EQI** | **BFG** | **14** | **8** | **-** | **tan** | **-** | **0.995** | **4.90** | **3.80** |
| GHG | SCG | 6 | 4 | 12 | log | tan | 0.985 | 2.90 | 2.92 |

The multi-objective method using GA yielded the best values of the DO control loop setpoint for each of the four seasons, utilizing the best GA-NARX models. From the non-dominated solutions represented by the Pareto front, the optimal DO values to be tested on the first-principle model were selected as: 1.373 mg O2/L for winter, 1.911 mg O2/L spring, 1.553 mg O2/L summer, and 1.837 mg O2/L for autumn. Each of the aforementioned values were applied as setpoints of the DO controller for the core 30-day period of each season.

The obtained EQI, GHG emissions, and overall cost index (OCI) were compared to the results obtained in the base case, which considers the setpoint for the DO control loop as 2.0 mg O2/L. These results are presented in Table 3. The relative differences (Relative diff.) between the two cases were also calculated to better display the change that the optimized case brought relative to the base case. All seasonal data showed a simultaneous drop in both EQI and OCI as a consequence of operation optimization, indicating the achievement of a more effective treatment procedure in terms of kg PU per OCI units.

Overall, the findings showed that in order to get better WWTP functioning, the various seasonal conditions needed varied settings. At the same time, reduction of GHG emissions was also achieved throughout the 4 seasons.

It is also crucial to highlight that the application of GA-NARX models significantly lowered the processing time to around 600 seconds and reduced the computational resources for the multi-objective optimization job. At the same time, a single 30-day simulation with the first-principle mathematical model required more than 630 seconds. It would take around 73 days of calculation if the optimization would use the first principle mathematical model for the objective function computation, if required to complete the same number of iterations as the ANN based optimization. This optimization task is performed by the developed GA-NARX models in 10 minutes.

Table 3. EQI, GHG, and OCI results obtained from the base and optimized cases

|  |  |  |
| --- | --- | --- |
| Case | Winter | Spring |
| EQI | GHG | OCI | EQI | GHG | OCI |
| kg PU/d | kg CO2 eq./d | - | kg PU/d | kg CO2 eq./d | - |
| Base case | 13158 | 11037 | 9256 | 12555 | 11116 | 9544 |
| Optimized | 12252 | 10979 | 9226 | 12355 | 11098 | 9518 |
| Relative diff | -6.88 | -0.53 | -0.33 | -1.60 | -0.17 | -0.26 |
|  |  |  |  |  |  |  |
| Case | Summer | Autumn |
| EQI | GHG | OCI | EQI | GHG | OCI |
| kg PU/d | kg CO2 eq./d | - | kg PU/d | kg CO2 eq./d | - |
| Base case | 13034 | 11137 | 10384 | 12961 | 11146 | 10275 |
| Optimized | 11299 | 11039 | 10290 | 12375 | 11112 | 10249 |
| Relative diff | -13.31 | -0.87 | -0.90 | -4.52 | -0.30 | -0.25 |

* 1. Conclusions

In the current work, the seasonal WWTP performance indices were predicted using NARX type models with their associated hyperparameter values found through GA optimization. The resulting neural network models were highly accurate, with MAPE values less than 4.25%. The utilization of these models in the multi-objective optimization of seasonal setpoints for the DO control loop resulted in operation performance enhancements regarding the EQI, GHG emissions, as well as the OCI. Effluent pollution was reduced by up to 13.31%, while GHG emissions and OCI were decreased in all cases with less than 1%.

In summary, an adaptable and workable solution for enhanced and sustainable functioning of the WWT process in each seasonal situation was produced by the suggested modelling and optimization proposed methodologies. However, the unique optimal solutions identified for the various seasons imply that every season has its own best parameters and operation conditions. As a result, the operation optimization should be examined seasonally when the yearly comprehensive WWTP optimization is considered.

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