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Neural Network ABAC with Dropout Layer for Activated Sludge System

Maimun Huja Husin, **Mohd Fua'ad Rahmat***, **Norhaliza Abdul Wahab** and **Mohamad Faizrizwan Mohd Sabri**

[1]Department of Electrical and Electronic Engineering, Faculty of Engineering, Universiti Malaysia Sarawak, Malaysia.
[2]School of Electrical Engineering, Universiti Teknologi Malaysia, 81310 UTM Skudai, Johor, Malaysia.

*Corresponding author: fuaad@fke.utm.my, Tel: 607-5557216, Fax: 607-5566272

Abstract: Due to the expensive operation of the activated sludge process and more stringent effluent requirements of wastewater treatment plant (WWTP), the wastewater treatment operator has been forced to find an alternative to improve the current control strategy, especially for those operating using an activated sludge system. The study aims to reduce the energy usage of a WWTP and to increase the effluent quality to meet the requirements of state and national laws by using the aeration control technique. The goals are achieved by varying the dissolved oxygen concentration in the benchmark plant's fifth tank according to the real ammonium measurement, a technique known as Ammonium-based aeration control (ABAC), which produced less nitrogen, resulting in better effluent and lower energy consumption. The simulation model Benchmark Simulation Model No. 1 (BSM1) was used to analyze ABAC in this study. The neural network (NN) model is used to design the ABAC controller, and simulation results were compared to the Proportional Integral (PI) controller of the BSM1 and PI ABAC control configurations. A dropout layer was added during the training process to improve neural network generalization. The dropout layer in the NN ABAC has improved the performances in terms of total nitrogen effluent violations by 4 percent less than the PI-ABAC and by 36 percent less than the PI. The NN ABAC LM dropout has been proven to be more effective in terms of energy efficiency by significantly reduced by 25 percent, effluent quality by successfully improved by 1 percent, and successfully reduced the total overall cost index by 5 percent when compared to PI-ABAC control. The study has illustrated that the NN ABAC could be used to improve the performance of the activated sludge system.

Keywords: ABAC, activated sludge, aeration control, BSM1, wastewater.

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1. INTRODUCTION

Wastewater treatment plant (WWTP) is the key infrastructures for protecting public health by preserving water resources and protecting the environment for a sustainable future. It is frequently defined as a complex system with nonlinear dynamics and has strong interactions with the multivariable system [1]. The influent of the WWTP exhibits oscillating behavior which subjects to large disturbances in the flowrate and uncertainties concerning the composition of the influent, thus making them hard to control [2].

Studies have shown that the energy consumption in biological systems such as the ASP, biological trickling filters, and membrane bioreactors can be curbed through good control of the aeration system. The issue of energy consumption has been investigated by various researchers and the findings suggest that the aeration section which is needed in the WWTP to detract nitrogen and natural or inorganic carbon in the biological process, contributes to 50-90% of the overall energy requirement of the WWTP [3]–[5].

In the last decade, there have been various studies investigating the effectiveness of various controller designs utilizing dissolved oxygen (DO) control in lowering the aeration cost. This control configuration is the highlight during that time due to the availability of a DO sensor probe that can continuously measure the DO concentration in the tank. The fundamental of using the DO sensor probe is to control the DO supply according to the oxygen demand of the microorganism in the tank. However, this solution has weakness due to the difficulty in getting the exact value of the actual oxygen demand by the microorganism at a specific time, thus, most of the proposed DO control strategies implemented an elevated DO set point to avoid nitrification failure. The DO control strategy has been extensively studied and many viable solutions have been developed and proposed, for example, model predictive control (MPC) [6], [7], Proportional Integral Derivative (PID) [1], [8], [9], fuzzy and neural network (NN) control [10].

However, even with the DO control strategy, the aeration cost issues persist as DO control requires aerators and turbines which are operated by electrically powered motors that add extra cost to the system. This calls for a paradigm shift in the choice of methodology to solve the problems of energy consumption and the cost of aeration control. This issue was explored and it is suggested that the aeration process can be regulated either using the aeration concentration control or tweaking the DO setpoint level corresponding to the ammonium (S_{NH}) concentration in the effluent [11]. During the last ten years, the ion-selective electrodes (ISEs) S_{NH} sensor probe has become available for online process. This is developing technology and has led to the introduction of ammonium-based aeration control (ABAC).

ABAC is an approach that utilizes the S_{NH} concentration level in the effluent flow to decide on the DO set point for the controller of the aerated zone. The ABAC has a variation of the DO concentration based on the ammonia (S_{NH}) concentration in the effluent and the aeration intensity is changed according to the process requirement which helps to lessen the energy consumption without raising the effluent S_{NH} load.

ABAC is a control strategy that uses S_{NH} as a response variable in addition to or in place of DO. ABAC has been introduced to overcome some of the inherent limitations of the DO control strategy and it is used mainly to restrict aeration and shrink effluent S_{NH} peaks. Several techniques have been recently proposed regarding ABAC, ranging from a conventional Proportional Integral (PI) ABAC control [11]–[15] to advanced MPC ABAC [16]–[18]. From the literature, it is observed that most pilot or real plants are using the PI control in their ABAC configurations. The PI controllers used are of decentralized configuration. This configuration is favorable because there is no need to deal with the coupling problem in a multi-input multi-output (MIMO) system. However, a PI controller is notorious for its susceptibility to disturbances and/or variations in the state of the operation.

On the other hand, advanced control scheme like MPC is proven to be able to produce better results compared to PI controllers but MPC is also known to be computationally complex [19] and it is difficult to be applied online in a real plant. All the studies in the literature indicated that the MPC is implemented in Benchmark Simulation Model No. 1 (BSM1) and BSM2. Another observation into the recent research trend is the emphasis on aeration energy cost problem but less towards the pragmatic benefits brought by ABAC control strategy on effluent quality which has not been extensively explored by researchers. Some of the recent proposals are summarized in Table 1.

Considering the advantages and disadvantages levied by these publications, an alternative control strategy that is more streamlined with lower complexity is desirable especially if the aim is to apply the controller in the real or pilot plant. The study aims to develop a direct feedback ABAC control of a biological WWTP that focuses on the reduction in the number of violations in total nitrogen (N_{tot}) and S_{NH} concentration, which are considered the two most important effluent pollutants. Direct feedback configuration will only require one controller to control the airflow to the basin. With this aim in mind, a new NN-ABAC is proposed to be applied in the BSM1. NN is chosen due to its simplicity and non-linear approximation ability. In this study, a two-input single-output (TISO) system is used. A strong coupling problem might arise as the S_{NH} and DO concentration are applied as separate inputs for the system, but the proposed NN method will function as a decoupling control of the MIMO system because it has a commendable nonlinear approximation ability.

Table 1. Summary of recent research trend using ABAC.

	Author	Methods	Results
PI ABAC	[13]	Feedback PID controller for ABAC to adjust DO in all aeration basins and zones	Decrease in supplemental carbon used for denitrification by 53% and overall decrease in energy consumption by 10%
PI ABAC	[14]	DO cascade, ABAC and combination of ABAC with the control of nitrate and return activated sludge recycles	ABAC combination is the most cost-saving methods (reduction of about 43%)
MPC ABAC	[17]	Fuzzy Control and MPC (Feedforward ABAC)	Total Nitrogen (N_{tot}) violations reduced by 11.04% and 100% elimination of S_{NH} violations
MPC ABAC	[18]	Risk detection of the effluent violation using artificial NN, fuzzy controller to improve denitrification / nitrification and MPC to improve DO tracking.	N_{tot} violations reduced up to 97.63% and S_{NH} violations reduced up to 68.29% (N_{tot} violation strategy) N_{tot} violations reduced up to 78.81% and 100% elimination of S_{NH} violations (S_{NH} violation strategy)

2. METHODOLOGY

One proposed method of using NN in nonlinear dynamic process control is to adjust the NN structure. The structure can be the number of hidden neurons and the parameters like node weights. In the previous section, the NN structure is fixed. Whereby in this section, the dropout layer is added to the NN architecture during training phases so that the NN structure can be adjusted. The literature study has confirmed that the non-fixed structure of NN has better performances in terms of computation time and testing error.

Figure 1 shows the flowchart of the NN training process with the additional dropout layer. From this flowchart, the dropout layer algorithm is added before the weight and input multiplication. Dropout lets the NN learn only a fraction of the weights in the network in each training iteration. What happened in the dropout layer is the dropout mask is generated which is according to the probability set by the user and then applied to the input. Finally, a multiplication between input and weight is based on this new layer configuration. The other steps after the multiplication process are the same as in the previous section.

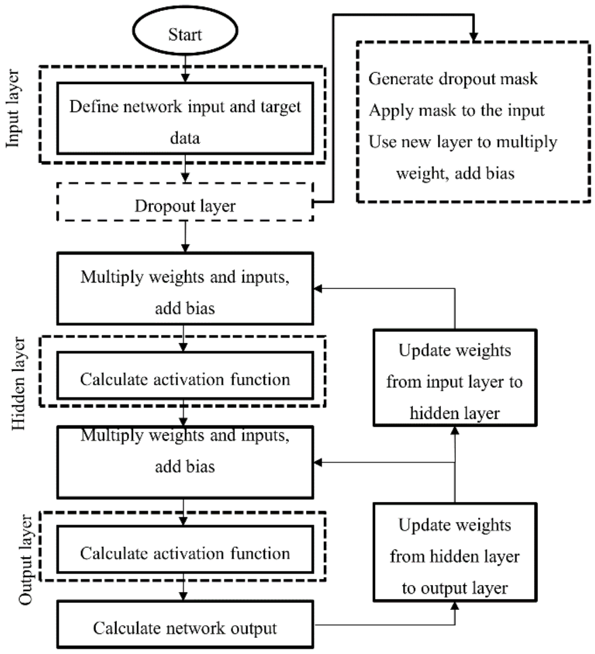

Figure 1. Flowchart of the NN training process with a dropout layer

The feedforward operation of a standard NN is shown in Equations (1) and (2). The dropout network is shown in Equations (3) to (6).

$$z_i^{(l+1)} = w_i^{(l+1)} y^l + b_i^{(l+1)} \quad (1)$$

$$y_i^{(l+1)} = f\left(z_i^{(l+1)}\right) \quad (2)$$

$$r_j^{(l)} \sim \text{Bernoulli}(p) \quad (3)$$

$$\tilde{y}^{(l)} = r^{(l)} * y^{(l)} \quad (4)$$

$$z_i^{(l+1)} = w_i^{(l+1)} \tilde{y}^{(l)} + b_i^{(l+1)} \quad (5)$$

$$y_i^{(l+1)} = f\left(z_i^{(l+1)}\right) \quad (6)$$

Figure 2 illustrates how the mask is done in the dropout layer. It is a random choice, based on Bernoulli(p).

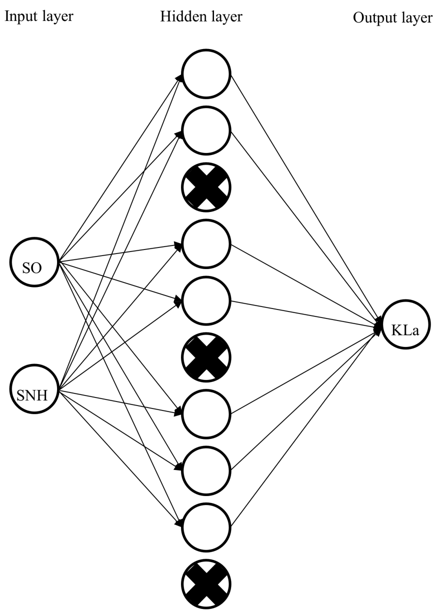

Figure 2. The topological structure of the dropout layer feed forward NN

3. RESULT

To verify the result, a comparison between NN-ABAC with LM dropout algorithm, PI, and PI-ABAC is performed.

The effluent quality limit comparison is illustrated in Table 2 for dry weather. In this table, the N_{tot} limit in NN-ABAC with the dropout is better by 3 percent when compared to PI-ABAC, and by 9 percent better compared to PI.

Table 2. The effluent quality limit in dry weather

Effluent average	PI	PI-ABAC	NN-ABAC LM Dropout
S_{NH} ($gN.m^{-3}$)	2.4783	2.5481	2.8869
T_{SS} ($gSS.m^{-3}$)	13.0248	13.0244	**13.0233**
N_{tot} ($gN.m^{-3}$)	16.8908	15.8626	**15.3938**
COD_t ($gCOD.m^{-3}$)	48.2470	48.2736	48.2876
BOD_5 ($gBOD.m^{-3}$)	2.7587	2.7654	2.7686

The results illustrated in Table 2 can be furthered detail up using data on effluent violation as shown in Table 3. According to the findings, the NN-ABAC using LM-dropout reduces the percentage of operating time during which N_{tot} violations occurred by 4 percent less than the PI-ABAC, and by 36 percent less than the PI.

Table 3. The effluent violations under dry influent

	PI	PI-ABAC	NN-ABAC LM Dropout
Ntot violations (% of operating time)	17.86	11.90	**11.46**
Ntot violations (Occasions)	7	5	5
SNH violations (% of operating time)	16.82	16.52	16.67
SNH violations (Occasions)	5	5	5

The results can be further depicted using effluent performances over one week simulation. N_{tot} violations are depicted in Figure 3 and S_{NH} violations are shown in Figure 4.

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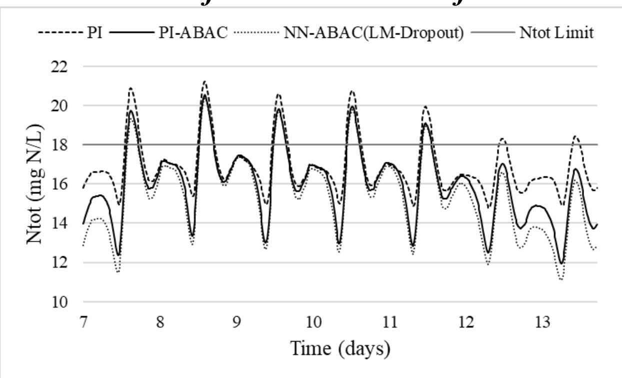

Figure 3. N_{tot} performances of one-week simulation

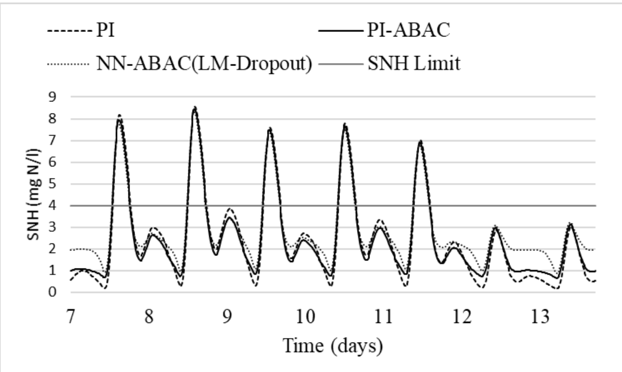

Figure 4. S_{NH} performances of one-week simulation

Figure 3 clearly illustrates that N_{tot} violation is remarkably reduced in NN-ABAC LM Dropout, despite the fact that the number of times N_{tot} violation exceeds the allowable limit is the same as in PI-ABAC. The differences are most noticeable between days 12 and 14 of the evaluation. The S_{NH} performance is almost identical to the PI-ABAC, as illustrated in Figure 4.

The average effluent quality (EQ), aeration energy (AE), and total overall cost index (OCI) consumed in the ASP process are displayed in Table 4.

Table 4. The comparison of EQ, AE, and OCI in dry weather

	PI	PI-ABAC	NN-ABAC LM-Dropout
IQ (kg/d)	52081.3952	52081.3952	52081.3952
EQ (kg/d)	6096.71	5938.3021	5970.799
AE	3697.57	3769.517	**2833.56**
Total OCI	16366.30	16500.995	**15685.1203**

The results reveal that employing the NN-ABAC LM dropout increases the EQ marginally over PI-ABAC but decreases it by roughly 3 percent when compared to PI. In terms of AE, the NN-ABAC LM dropout has the lowest score, which is 25 percent lower than PI-ABAC and 23 percent lower than PI. Finally, as compared to PI, the overall OCI has decreased by 4 percent, and by 5 percent when compared to PI-ABAC. The best control technique is the one with the lowest OCI, which is the NN-ABAC LM-Dropout in this study.

4. CONCLUSION

The study has illustrated that the NN ABAC could be employed to increase the performance of the activated sludge system. The NN-ABAC utilizing LM-dropout reduces the proportion of operating time during which total nitrogen violations occur by 4 percent, and by 36 percent compared to the PI-ABAC. When compared to the PI-ABAC control, the NN ABAC has been shown to be more effective in terms of energy efficiency, effluent quality, and overall cost index.

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