NEURAL NETWORK-BASED AMMONIUM AERATION CONTROL OF WASTEWATER TREATMENT PLANT

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ABSTRACT

Due to the expensive operation and stringent effluent requirements of wastewater treatment plants, the wastewater treatment operator has been forced to find an alternative to improve the current control strategy, particularly for those using conventional activated sludge systems. The goal of this research is to design a controller capable of reducing aeration energy while improving effluent quality. The objectives are met through a technique known as ammonium-based aeration control (ABAC). In this study, neural network (NN) – ABAC was designed and proposed for the Benchmark Simulation Model No. 1. The simulation results were compared to those of the proportional-integral (PI) controller and PI ABAC control configurations. During the NN training, a dropout layer was added to improve NN generalization. The simulation results show that the dropout layer successfully reduced the complexity of the NN while maintaining a good mean squared error and regression value. When compared to PI, the proposed NN – ABAC is more effective in terms of energy efficiency by lowering aeration energy by up to 23.86%, improving effluent quality by up to 1.94%, and lowering the total overall cost index by up to 4.61%. The findings suggest that the NN – ABAC has the potential to improve the performance of the activated sludge system.

ABSTRAK

Disebabkan oleh pengoperasian yang mahal dan keperluan efluen yang ketat bagi loji rawatan kumbahan, pengendali rawatan kumbahan terpaksa mencari alternatif untuk menambah baik strategi kawalan semasa, terutamanya bagi mereka yang menggunakan sistem enapcemar aktif secara konvensional. Matlamat penyelidikan ini adalah untuk mereka bentuk pengawal yang mampu mengurangkan tenaga pengudaraan di samping meningkatkan kualiti efluen. Objektif dicapai melalui teknik yang dikenali sebagai kawalan pengudaraan berasaskan ammonium (ABAC). Dalam kajian ini, rangkaian neural (NN) – ABAC telah direka bentuk dan dicadangkan untuk Model Simulasi Penanda Aras No. 1. Keputusan simulasi telah dibandingkan dengan pengawal kamiran berkadar (PI) dan konfigurasi kawalan PI ABAC. Semasa latihan NN, lapisan penciciran telah ditambahkan untuk meningkatkan pengitlakan NN. Keputusan simulasi menunjukkan bahawa lapisan penciciran berjaya mengurangkan kerumitan NN sambil mengekalkan nilai ralat min kuasa dua dan regresi yang baik. Jika dibandingkan dengan PI, NN – ABAC yang dicadangkan adalah lebih berkesan dari segi kecekapan tenaga dengan menurunkan tenaga pengudaraan sehingga 23.86%, meningkatkan kualiti efluen sehingga 1.94%, dan menurunkan jumlah indeks kos keseluruhan sehingga 4.61% . Penemuan menunjukkan bahawa NN – ABAC mempunyai potensi untuk meningkatkan prestasi sistem enapcemar aktif.

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LIST OF ABBREVIATIONS

ASP	-	Activated Sludge Process
ABAC	-	Ammonium-based Aeration Control
BSM1	-	Benchmark Simulation Model No. 1
BSM2	-	Benchmark Simulation Model No. 2
BOD	-	Biochemical Oxygen Demand
COD	-	Chemical Oxygen Demand
DO	-	Dissolved Oxygen
EQ	-	Effluent Quality
EQI	-	Effluent Quality Index
ISE	-	Ion Selective Electrodes
MIMO	-	Multi-Input Multi-Output
MPC	-	Model Predictive Control
NN	-	Neural Network
OCI	-	Overall Cost Index
PI	-	Proportional Integral
PID	-	Proportional Integral Derivative
SDG	-	Sustainable Development Goals
SISO	-	Single-Input Single-Output
TISO	-	Two-Input Single-Output
TSS	-	Total Suspended Solids
WWTP	-	Wastewater Treatment Plant

LIST OF SYMBOLS

t	-	time
S_I	-	Soluble inert organic matter
S_S	-	Suspended solids
X_I	-	Particulate inert organic matter
X_S	-	Slowly biodegradable substrate
X_{BH}	-	Active heterotrophic biomass
X_{BA}	-	Active autotrophic biomass
X_P	-	Particulate products arising from biomass decay
S_O	-	Dissolved oxygen
S_{NO}	-	Nitrate
S_{NH}	-	Ammonium and ammonia nitrogen
S_{ND}	-	Soluble biodegradable organic nitrogen
X_{ND}	-	Particulate biodegradable organic nitrogen
S_{ALK}	-	Alkalinity
Q_O	-	Input flowrate
N_{tot}	-	Total Nitrogen
g	-	Gram
l		Litre
kg		Kilogram
mg		Milligram
d		Day
Y_A		Autotrophic yield
Y_H		Heterotrophic yield
f_p		Fraction of biomass to particulate products
i_{XB}		Fraction of nitrogen in biomass
i_{XP}		Fraction of nitrogen in particulate products

K_{La}	Oxygen transfer coefficient
Q_{intr}	Internal recycle flow rate

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CHAPTER 1

INTRODUCTION

1.1 Research Background

Wastewater treatment plant (WWTP) is the key infrastructures for protecting public health by preserving water resources and safeguarding the environment for a sustainable future. Wastewater treatment is a combination of mechanical, biological, and chemical treatments which makes it considered a big-scale and complex process. Apart from that, WWTP is a complex system with nonlinear dynamics and has strong interactions with the multivariable system (Foscoliano et al., 2016; Roxana & Ioan, 2016). The influent of the WWTP exhibits oscillating behavior which subjects to large disturbances in the flowrate and uncertainties with reference to the composition of the influent, thus making them hard to control (Silvana Revollar et al., 2017).

For this research, the scope is on the biological treatment process which is a part of the secondary treatment. The wastewater entered the secondary treatment after it has gone through the mechanical treatment which are the filters that are committed to the removal of gross solids, sand, oil, and grease. In the biological treatment process, several organic components (i.e., soluble inert organic matter and particulate inert organic matter) and forms of nitrogen (i.e., nitrate and nitrite nitrogen, soluble biodegradable organic nitrogen, and particulate biodegradable organic nitrogen) are eliminated.

The activated sludge process (ASP) is the most widely used biological treatment process in WWTP to reduce the biochemical oxygen demand (BOD), nutrients, and some other micro-pollutants. In principle, all activated sludge systems consist of three main components which are aeration tank, settling tank, and a return activated sludge as shown in Figure 1.1. In the aeration tank, bacteria are used for nitrification, which is a process that converted ammonia to nitrite and denitrification which is a process that converted nitrite to nitrate which can be illustrated as in Figure 1.2. In this process, the bacteria need dissolved oxygen (DO) for growth. Normally, WWTP facility usually pretty 'dead' in the sense that minimum life exists and DO level is nearly zero. Therefore, aeration turbines are employed in wastewater treatment to give the bacteria with the required DO concentration in the aeration tank.

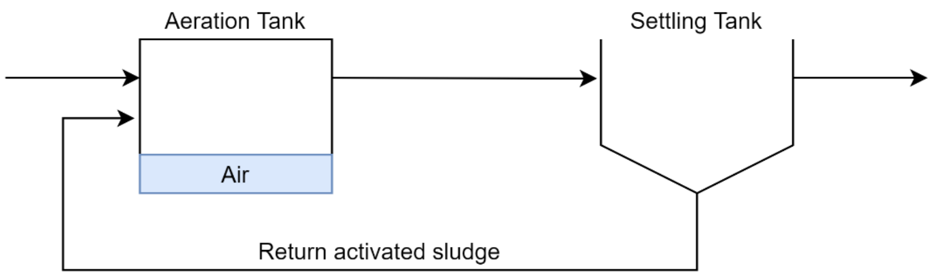

Figure 1.1 The activated sludge process

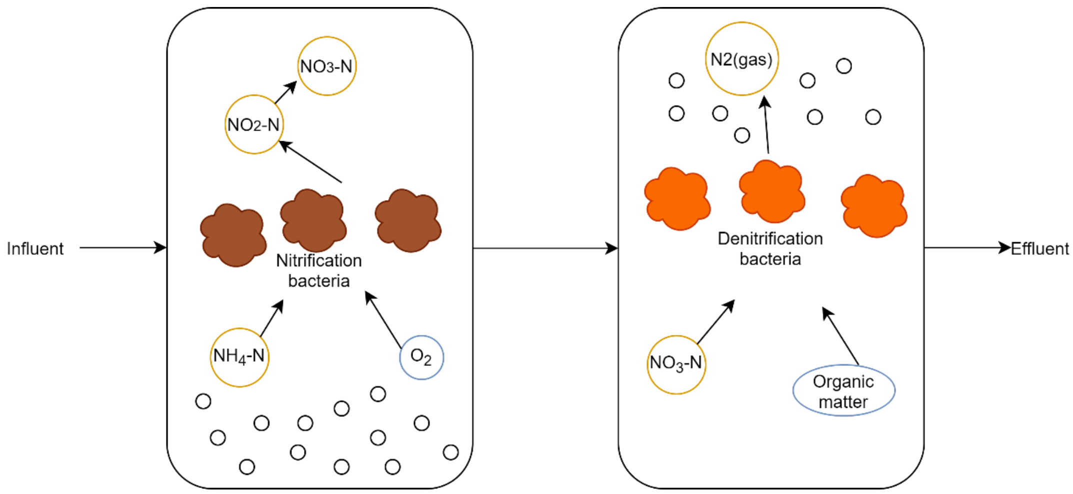

Figure 1.2 Nitrification and denitrification illustration

The ideal aeration control is highly important for the biological treatment process. The complex interaction in the biological phenomena in the ASP itself and the huge range of time constant e.g., oxygen transfer occurs within minutes; sludge properties changes over a period of days, has contributes to the difficulty in the operation and process control of WWTP (Amand & Carlsson, 2012; Nguyen et al., 2020). Apart from that, the DO concentration must be adequate to withstand the designated nitrogen removal rate. If the value of DO is set too high, however, it will result in higher costs and worse efficiency.

Table 1.1 shows an overview of the effects of various aeration rate circumstances. When the aeration rate is excessively high, not only is energy squandered, but so is the operational expense. Solids, which are waterborne particles larger than 2 microns in diameter, will also be increased. If too much DO is provided to the bacteria/microbe, a major operation problem known as activated sludge breakup occurs, causing the flocs to break up. Later on, this state will pose problems with the settling process.

On the other hand, if the aeration rate is too low, the process will operate poorly, and nitrification will be lost as a result of the lack of bacteria available to convert ammonia to nitrite. Apart from that, if the aeration rate is too low, a septic aeration tank situation might emerge, which is a condition in which there is no DO in the tank. If this happens, the bacteria will die, and the biological process would slow down, emit odours, and result in incomplete pollutants conversion. Bacterial death takes time and cost a lot of money to reestablish.

Table 1.1 The effect of the different condition of aeration rate

Aeration rate condition	Too high	Too low
Description	• Energy is wasted. • Operating cost is increased. • Solids are increased. • The breakup of activated sludge	• Septic aeration tank • Poor process (nitrification) performance • Loss of nitrification

WWTP is facing more stringent effluent standards which were formed for a safer ecosystem (Pisa et al., 2019). The WWTP industry must come up with a solution that abides by the stringent effluent requirements and is also economical.

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 electricity used by a WWTP depending on its size and the employed technological solution (Drewnowski et al., 2019; Ghoneim et al., 2016). The aeration section of the WWTP's biological reactors requires a lot of energy to ensure that the microorganisms in the activated sludge have optimal access to oxygen via aeration devices such as surface aeration (mechanical) and diffused aeration (coarse, medium, fine bubbles).

In the last decade, there have been various studies investigating the effectiveness of various controller designs utilizing 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 weaknesses 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) (Cheng et al., 2021; El bahja et al., 2018; H. Han, Liu, et al., 2019; Hassen & Asmare, 2018; Sheik et al., 2021), Proportional Integral Derivative (PID) (Du et al., 2018; Nguyen et al., 2020), fuzzy and neural network (NN) control (H. Han, Liu, et al., 2019).

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 cost of aeration control. This issue was explored in the publication by Linda Åmand et. al (2014) which has suggested that the aeration process can be regulated either using the aeration concentration control or tweaking the DO set point level corresponding to the ammonium (S_{NH}) concentration in the effluent (Åmand & Carlsson, 2014).

1.2 ABAC as a Alternative Solution to Aeration Cost Issue

During the last ten years, the ion-selective electrodes (ISEs) S_{NH} sensor probe has become available for online processes. 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 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 DO control strategy and it is used mainly for two reasons; to restrict aeration and to shrink effluent S_{NH} peaks. Several techniques have been recently proposed regarding ABAC, ranging from a conventional Proportional Integral (PI) ABAC control (Åmand & Carlsson, 2014; Uprety et al., 2015; Várhelyi et al., 2018), to advanced MPC ABAC (Santin et al., 2015b; Santín et al., 2015, 2016).

From the literature study, 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/PID controller is difficult to adjust to changing conditions, resulting in poor water quality (Y. Zhang & Wei, 2019). Apart from that, the nonlinearity and long time-delay characteristics of WWTP have a substantial influence on the PI/PID controller's parameters, so the control effect may be inadequate and the parameters are not self-adjusted (Du et al., 2018).

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 (Chistiakova, 2018) and it is difficult to be applied online in a real plant (Du et al., 2018). All the studies in the literature indicated that the MPC is implemented using simulation work only.

This thesis aims to focus on 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 N_{tot} and S_{NH} concentration, which are considered as 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 multivariable NN – ABAC is proposed to be applied in the chosen simulation platform which is Benchmark Simulation Model No. 1 (BSM1). BSM1 is the plant model and associated control strategy that serves as a baseline for simulation-based comparison of control strategies applicable to WWTP simulation studies. The International Water Association (IWA) Task Group on Benchmarking Control Strategies for WWTP developed BSM1. More information on BSM1 can be found in Chapter 2. NN is chosen to be used to design the controller due to its simplicity and non-linear approximation ability.

1.3 Problem Statement

The key objective of the ABAC control strategy is to lower aeration costs, lowering total WWTP costs while maintaining effluent quality below the permissible limit. The inconsistency between aeration cost and effluent quality is a serious problem in achieving this goal. More DO is needed to provide more oxygen to the bacteria, however this will result in higher aeration costs, but improved effluent quality. However, if the DO is severely limited, less nitrification and denitrification occurs, potentially resulting in poor effluent quality. As a result, the key to a successful ABAC development is finding the appropriate balance between effluent quality and aeration cost in order to achieve optimal performance. The existing controller, PI ABAC, has a limitation in that the operator must choose between effluent quality and cost. Aside from that, single input single output (SISO) controllers such as PI ABAC were chosen to avoid control parameter interaction in multivariable plants such as WWTP. According to studies, multivariable control for WWTP can produce good effluent quality while keeping operating costs low (Mulas et al., 2016). However, as previously stated, the main issue with multivariable control is the coupling problem, which can make tuning the multivariable controller difficult.

The main issue in the development of ABAC control strategy is to develop a control strategy that is more efficient with less complexity. NN offer many advantages if implemented in ABAC control strategy including simplicity and a good decoupling control due to its excellent nonlinear approximation ability. However, there are some drawbacks to using NN, such as the fact that in the presence of disturbance, the generalisation ability may struggle to maintain a consistent DO concentration when applied to highly nonlinear plants such as wastewater treatment (Y. Zhang & Wei, 2019). Furthermore, NN control necessitates a large number of computations, which increases computational time (Du et al., 2018; Y. Zhang & Wei, 2019).

Thus, for the NN – ABAC proposed in this study, a two-input single-output (TISO) NN system is designed with S_{NH} and DO concentrations are applied as independent inputs to the system and oxygen transfer coefficient (K_{La}) as output. A substantial coupling problem may occur; however, the proposed NN control will operate as a decoupling control of the MIMO system due to its excellent nonlinear approximation ability. In this study, a dropout layer is also added to the NN to improve the network's generalization capability and lower the computational complexity to solve the problem of generalization and computation time. The result is an NN – ABAC capable of producing a reduced aeration cost while maintaining permitted effluent quality.

1.4 Research Objectives

The objectives of this study are as follows:

(a) To design a multivariable NN – ABAC for BSM1 that capable of reducing the aeration cost and improve the effluent quality.

(b) To compare the performance of the NN – ABAC with and without the dropout layer in terms of mean square error, regression value, and computational time.

(c) To measure the performance of the NN-ABAC in terms of energy efficiency, EQ, and overall cost index (OCI) under different variations.

1.5 Research Scope

The scope and limitation of this study are as follows:

(a) The simulation work is performed using BSM1 described in (Alex et al., 2008) using MATLAB$^{(TM)}$ Simulink simulation platform, as shown in Appendix A.

(b) The sensor for S_{NH} is designed according to the description given in the BSM1 manual and the MATLAB$^{(TM)}$ Simulink block is shown in Appendix B.

(c) Five effluents are highlighted in the discussion which are: total nitrogen (N_{tot}) – maximum limit at 18 g/l, BOD – maximum limit at 100 g/l, chemical oxygen demand (COD) – maximum limit at 4 g/l, ammonia (S_{NH}) – maximum limit at 30 g/l and total suspended solids (TSS) – maximum limit at 10 g/l.

(d) Comparison is done between the proposed NN-ABAC and the BSM1 PI controller and PI ABAC.

1.6 Organization of the Thesis

After the brief introduction and research background in Chapter 1, Chapter 2 continues with literature on aeration control from its introduction to the current development in the subject. Aeration control and issues related to energy cost and stricter effluent standards will be thoroughly discussed. It includes the ABAC structure to emphasize the significant contributions to the problems by other researchers and to identify the research gap in which this study fits in and its significance to the subject. A further focus is put upon the use of NN in undertaking the problems. Finally, it ends with a critical review of the literature that motivates the implementation of the NN-ABAC.

Chapter 3 presents the implementation of the neural ABAC to manipulate the oxygen transfer coefficient in the BSM1. This is followed by an explanation of the criteria for the performance evaluation of the NN-ABAC.

In Chapter 4, the NN-ABAC is implemented in the BSM1 plant and is evaluated under various weather conditions (dry, storm, and rainy weather). The performance of the proposed controller in terms of the effluent violation, effluent quality, and total overall cost index are observed and calculated. The results are then compared with the results of the benchmark model to highlight the improvement brought forth by the proposed controller. Results are presented quantitatively with the use of graphs and charts to highlights the difference in performance between the benchmark and PI ABAC, which most other researchers used. Discussion on the results will be performed to highlight the outcomes from the simulations.

Chapter 5 will conclude the thesis. A thorough analysis is made regarding the findings from the simulations and a comparison to evaluate the outcome of the study. The performance of the NN-ABAC is summarized here, and further development potentials are highlighted. Reflections of the acquired results and the objectives are also discussed. Finally, the recommendation of future research work is included as the closure for the chapter and the thesis.

REFERENCES

Aguilar-López, R., López-Pérez, P. A., & Neria-González, M. I. (2016). Improvement of Activated Sludge Process Using a Nonlinear PI Controller Design via Adaptive Gain. *International Journal of Chemical Reactor Engineering*, *14*(1), 407–416. https://doi.org/10.1515/ijcre-2014-0129

Alex, J., Benedetti, L., Copp, J., Gernaey, K. V, Jeppsson, U., Nopens, I., Pons, M.-N., Rieger, L., Rosen, C., Steyer, J. P., Vanrolleghem, P., Winkler, S., Magdeburg, I. E. V, & Benedetti, G. L. (2008). Benchmark Simulation Model no. 1 (BSM1) Benchmark Simulation Model no. 1 (BSM1) Contributors. In *Benchmark Simulation Model* (Vol. 1, Issue 1BSM1). https://www.iea.lth.se/publications/Reports/LTH-IEA-7229.pdf

Amand, L., & Carlsson, B. (2012). Optimal aeration control in a nitrifying activated sludge process. *Water Research*, *46*(7), 2101–2110. https://doi.org/10.1016/j.watres.2012.01.023

Åmand, L., & Carlsson, B. (2014). Aeration Control with Gain Scheduling in a Full-scale Wastewater Treatment Plant. *IFAC Proceedings Volumes*, *47*(3), 7146–7151. https://doi.org/10.3182/20140824-6-ZA-1003.01892

Avilés, A. B. L., Del Cerro Velázquez, F., & Del Riquelme, M. L. P. (2020). Methodology for energy optimization in wastewater treatment plants. Phase II: Reduction of air requirements and redesign of the biological aeration installation. *Water (Switzerland)*, *12*(4). https://doi.org/10.3390/W12041143

Cheng, M., Han, G., Li, W., Wang, X., Sun, X., & Zheng, H. (2021). Fuzzy Model Predictive Control for Wastewater Treatment Process under Multi-Operating Conditions. *Chinese Control Conference, CCC*, *2021-July*, 2526–2531. https://doi.org/10.23919/CCC52363.2021.9550236

Chistiakova, T. (2018). *Ammonium Based Aeration Control in Wastewater Treatment Plants - Modelling and Controller Design*.

Drewnowski, J., Remiszewska-Skwarek, A., Duda, S., & Łagód, G. (2019). Aeration process in bioreactors as the main energy consumer in a wastewater treatment plant. Review of solutions and methods of process optimization. *Processes*, *7*(5). https://doi.org/10.3390/pr7050311

Dreyfus, S. E. (1990). Artificial neural networks, back propagation, and the kelley-bryson gradient procedure. *Journal of Guidance, Control, and Dynamics*, *13*(5), 926–928. https://doi.org/10.2514/3.25422

Du, X., Wang, J., Jegatheesan, V., & Shi, G. (2018). Dissolved Oxygen Control in Activated Sludge Process Using a Neural Network-Based Adaptive PID Algorithm. *Applied Sciences*, *8*(2), 261. https://doi.org/10.3390/app8020261

El bahja, H., Vega, P., Revollar, S., & Francisco, M. (2018). One layer nonlinear economic closed-loop generalized predictive control for a wastewater treatment plant. *Applied Sciences (Switzerland)*, *8*(5). https://doi.org/10.3390/app8050657

Fairbank, M., Li, S., Fu, X., Alonso, E., & Wunsch, D. (2014). An adaptive recurrent neural-network controller using a stabilization matrix and predictive inputs to solve a tracking problem under disturbances. *Neural Networks*, *49*, 74–86. https://doi.org/10.1016/j.neunet.2013.09.010

Foscoliano, C., Del Vigo, S., Mulas, M., & Tronci, S. (2016). Predictive control of an activated sludge process for long term operation. *Chemical Engineering Journal*, *304*, 1031–1044. https://doi.org/10.1016/j.cej.2016.07.018

Ghoneim, W. A. M., Helal, A. A., & Wahab, M. G. A. (2016, September 26). Minimizing energy consumption in Wastewater Treatment Plants. *2016 3rd International Conference on Renewable Energies for Developing Countries, REDEC 2016*. https://doi.org/10.1109/REDEC.2016.7577507

Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning - whole book. In *MIT Press*. http://www.deeplearningbook.org

Han, H.-G., Zhang, L., Hou, Y., & Qiao, J.-F. (2015). Nonlinear Model Predictive Control Based on a Self-Organizing Recurrent Neural Network. *IEEE Transactions on Neural Networks and Learning Systems*, *27*(2), 402–415. https://doi.org/10.1109/TNNLS.2015.2465174

Han, H. G., Qian, H. H., & Qiao, J. F. (2014). Nonlinear multiobjective model-predictive control scheme for wastewater treatment process. *Journal of Process Control*, *24*(3), 47–59. https://doi.org/10.1016/j.jprocont.2013.12.010

Han, H. G., Zhang, L., & Qiao, J. F. (2017). Data-Based Predictive Control for Wastewater Treatment Process. *IEEE Access*, *6*, 1498–1512. https://doi.org/10.1109/ACCESS.2017.2779175

Han, H., Liu, Z., Hou, Y., & Qiao, J. (2019). Data-Driven Multiobjective Predictive

Control for Wastewater Treatment Process. *IEEE Transactions on Industrial Informatics*, 1–1. https://doi.org/10.1109/tii.2019.2940663

Han, H., Wu, X., & Qiao, J. (2019). A self-organizing sliding-mode controller for wastewater treatment processes. *IEEE Transactions on Control Systems Technology*, *27*(4), 1480–1491. https://doi.org/10.1109/TCST.2018.2836358

Harja, G., Vlad, G., & Nascu, I. (2016). MPC advanced control of dissolved oxygen in an activated sludge wastewater treatment plant. *2016 20th IEEE International Conference on Automation, Quality and Testing, Robotics, AQTR 2016 - Proceedings*, *274*. https://doi.org/10.1109/AQTR.2016.7501329

Harrou, F., Dairi, A., Sun, Y., & Senouci, M. (2018). Wastewater treatment plant monitoring via a deep learning approach. *Proceedings of the IEEE International Conference on Industrial Technology*, *2018-Febru*(1), 1544–1548. https://doi.org/10.1109/ICIT.2018.8352410

Hassen, E. B., & Asmare, A. M. (2018). Predictive performance modeling of Habesha Brewery's wastewater treatment plant using artificial neural networks. *Journal of Environmental Treatment Techniques*, *6*(2), 15–25.

Henze, M., Grady Jr, C. P. L., Gujer, W., Marais, G., & Matsuo, T. (1987). *Activated sludge model No. 1* (Issue 1).

Hongyang, X., Pedret, C., Santin, I., & Vilanova, R. (2018). Decentralized model predictive control for N and P removal in wastewater treatment plants. *2018 22nd International Conference on System Theory, Control and Computing, ICSTCC 2018 - Proceedings*, 224–230. https://doi.org/10.1109/ICSTCC.2018.8540675

Huang, G. Bin. (2003). Learning capability and storage capacity of two-hidden-layer feedforward networks. *IEEE Transactions on Neural Networks*, *14*(2), 274–281. https://doi.org/10.1109/TNN.2003.809401

Ingildsen, P., Jeppsson, U., & Olsson, G. (2002). Dissolved oxygen controller based on on-line measurements of ammonium combining feed-forward and feedback. *Water Science and Technology : A Journal of the International Association on Water Pollution Research*, *45*(4–5), 453–460. http://www.ncbi.nlm.nih.gov/pubmed/11936667

Jaramillo, M. A., Peguero, J. C., Salazar, E. M. De, & Valle, M. G. del. (2005). Neural Network Control in a Wastewater Treatment Plant. *Recent Advances in Multidisciplinary Applied Physics, Aphys 2003*, 241–245.

https://doi.org/10.1016/B978-008044648-6.50039-2

Jinchuan, K., & Xinzhe, L. (2008). Empirical analysis of optimal hidden neurons in neural network modeling for stock prediction. *Proceedings - 2008 Pacific-Asia Workshop on Computational Intelligence and Industrial Application, PACIIA 2008*, *2*, 828–832. https://doi.org/10.1109/PACIIA.2008.363

Kumar, S. S., & Latha, K. (2017, October 10). A hybrid intelligent controller to reduce the energy of a wastewater treatment plant. *Proceedings - TIMA 2017: 9th International Conference on Trends in Industrial Measurement and Automation*. https://doi.org/10.1109/TIMA.2017.8064803

Liu, Y. B., Zong, X. J., Jian, Q. Z., Li, S., & Cheng, X. G. (2019). A nonlinear observer for activated sludge wastewater treatment process: Invariant observer. *Asian Journal of Control*, *January*, 1–9. https://doi.org/10.1002/asjc.2078

Medinilla, V. R., Sprague, T., Marseilles, J., Burke, J., Deshmukh, S., Delagah, S., & Sharbatmaleki, M. (2020). Impact of Ammonia-Based Aeration Control (ABAC) on Energy Consumption. *Applied Sciences*, *10*(15), 5227. https://doi.org/10.3390/app10155227

Miller, M. W., Regmi, P., & Jimenez, J. (2019). Sensors versus analyzers: The case for ammonia-based aeration control. *WEFTEC 2019 - 92nd Annual Water Environment Federation's Technical Exhibition and Conference*, *67*(2013), 116–120.

Møller, M. F. (1993). A scaled conjugate gradient algorithm for fast supervised learning. *Neural Networks*, *6*(4), 525–533. https://doi.org/10.1016/S0893-6080(05)80056-5

Mulas, M., Corona, F., Sirviö, J., Hyvönen, S., & Vahala, R. (2016). Full-scale implementation of an advanced control system on a biological wastewater treatment plant. *IFAC-PapersOnLine*, *49*(7), 1163–1168. https://doi.org/10.1016/j.ifacol.2016.07.360

Newhart, K. B., Holloway, R. W., Hering, A. S., & Cath, T. Y. (2019). Data-driven performance analyses of wastewater treatment plants: A review. *Water Research*, *157*, 498–513. https://doi.org/10.1016/j.watres.2019.03.030

Nguyen, L. Van, Bach, N. Van, Do, H. T., & Nguyen, M. T. (2020). Combined ILC and PI regulator for wastewater treatment plants. *Telkomnika (Telecommunication Computing Electronics and Control)*, *18*(2), 1054–1061.

https://doi.org/10.12928/TELKOMNIKA.V18I2.14895

Park, S., & Kwak, N. (2017). Analysis on the dropout effect in convolutional neural networks. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 10112 LNCS*, 189–204. https://doi.org/10.1007/978-3-319-54184-6_12

Phan, M. C., & Hagan, M. T. (2013). Error surface of recurrent neural networks. *IEEE Transactions on Neural Networks and Learning Systems*, *24*(11), 1709–1721. https://doi.org/10.1109/TNNLS.2013.2258470

Pisa, I., Morell, A., Vilanova, R., & Lopez Vicario, J. (2020). Noisy Signals in Wastewater Treatment Plants data-driven control: Spectral Analysis approach for the design of ANN-IMC controllers. *Proceedings - 2020 IEEE Conference on Industrial Cyberphysical Systems, ICPS 2020*, 320–325. https://doi.org/10.1109/ICPS48405.2020.9274704

Pisa, I., Santín, I., Vicario, J. L., Morell, A., & Vilanova, R. (2019). ANN-based soft sensor to predict effluent violations in wastewater treatment plants. *Sensors (Switzerland)*, *19*(6), 1–26. https://doi.org/10.3390/s19061280

Qiao, J. F., Han, G., & Han, H. G. (2014). Neural network on-line modeling and controlling method for multi-variable control of wastewater treatment processes. *Asian Journal of Control*, *16*(4), 1213–1223. https://doi.org/10.1002/asjc.758

Qiao, J. F., Han, G. T., Han, H. G., Yang, C. L., & Li, W. (2019). Decoupling control for wastewater treatment process based on recurrent fuzzy neural network. *Asian Journal of Control*, *21*(3), 1270–1280. https://doi.org/10.1002/asjc.1844

Qiao, J., Han, G., Han, H., Yang, C., & Li, W. (2017). A hybrid intelligent optimal control system design for wastewater treatment process. *Information Technology and Control*, *46*(3), 382–394. https://doi.org/10.5755/j01.itc.46.3.16061

Rahmat, M. F., Samsudin, S. I., Wahab, N. A., Razali, M. C., & Gaya, M. S. (2014). Decentralized adaptive PI with adaptive interaction algorithm of wastewater treatment plant. *Jurnal Teknologi (Sciences and Engineering)*, *67*(5), 15–21. https://doi.org/10.11113/jt.v67.2837

Rawat, W., & Wang, Z. (2017). Deep Convolutional Neural Networks for Image Classification: A Comprehensive Review. *Neural Computation*, *29*(9), 2352–

2449. https://doi.org/10.1162/neco_a_00990

Revollar, S., Vega, P., Francisco, M., Meneses, M., & Vilanova, R. (2020). Activated Sludge Process control strategy based on the dynamic analysis of environmental costs. *2020 24th International Conference on System Theory, Control and Computing, ICSTCC 2020 - Proceedings*, 576–581. https://doi.org/10.1109/ICSTCC50638.2020.9259637

Revollar, Silvana, Vega, P., Vilanova, R., & Francisco, M. (2017). Optimal Control of Wastewater Treatment Plants Using Economic-Oriented Model Predictive Dynamic Strategies. *Applied Sciences*, *7*(8), 813. https://doi.org/10.3390/app7080813

Rieger, L., Jones, R. M., Dold, P. L., & Bott, C. B. (2014). Ammonia-Based Feedforward and Feedback Aeration Control in Activated Sludge Processes. *Water Environment Research*, *86*(1), 63–73. https://doi.org/10.2175/106143013X13596524516987

Roxana, R., & Ioan, N. (2016). *Advanced Control of a Wastewater Treatment Plant*. 0–3.

Samsudin, S. I., Rahmat, M. F., & Abdul Wahab, N. (2014). Nonlinear PI control with adaptive interaction algorithm for multivariable wastewater treatment process. *Mathematical Problems in Engineering*, *2014*. https://doi.org/10.1155/2014/475053

Samuelsson, P., & Carlsson, B. (2002). Control of the aeration volume in an activated sludge process for nitrogen removal. *Water Science and Technology*, *45*(4–5), 45–52. https://doi.org/10.2166/wst.2002.0548

Santin, I., Pedret, C., Meneses, M., & Vilanova, R. (2015a). Artificial Neural Network for nitrogen and ammonia effluent limit violations risk detection in Wastewater Treatment Plants. *2015 19th International Conference on System Theory, Control and Computing, ICSTCC 2015 - Joint Conference SINTES 19, SACCS 15, SIMSIS 19*, 589–594. https://doi.org/10.1109/ICSTCC.2015.7321357

Santin, I., Pedret, C., Meneses, M., & Vilanova, R. (2015b). Process based control architecture for avoiding effluent pollutants quality limits violations in wastewater treatment plants. *2015 19th International Conference on System Theory, Control and Computing (ICSTCC)*, 396–402. https://doi.org/10.1109/ICSTCC.2015.7321326

Santín, I., Pedret, C., & Vilanova, R. (2015). Fuzzy Control and Model Predictive Control Configurations for Effluent Violations Removal in Wastewater Treatment Plants. *Industrial and Engineering Chemistry Research*, *54*(10), 2763–2775. https://doi.org/10.1021/ie504079q

Santín, I., Pedret, C., Vilanova, R., & Meneses, M. (2016). Advanced decision control system for effluent violations removal in wastewater treatment plants. *Control Engineering Practice*, *49*(January), 60–75. https://doi.org/10.1016/j.conengprac.2016.01.005

Sariev, E., & Germano, G. (2020). Bayesian regularized artificial neural networks for the estimation of the probability of default. *Quantitative Finance*, *20*(2), 311–328. https://doi.org/10.1080/14697688.2019.1633014

Sheik, A. G., Tejaswini, E., Seepana, M. M., Ambati, S. R., Meneses, M., & Vilanova, R. (2021). Design of feedback control strategies in a plant-wide wastewater treatment plant for simultaneous evaluation of economics, energy usage, and removal of nutrients. *Energies*, *14*(19). https://doi.org/10.3390/en14196386

Shibata, K., & Ikeda, Y. (2009). Effect of number of hidden neurons on learning in large-scale layered neural networks. *ICCAS-SICE 2009 - ICROS-SICE International Joint Conference 2009, Proceedings*, 5008–5013.

Smirnov, E. A., Timoshenko, D. M., & Andrianov, S. N. (2014). Comparison of Regularization Methods for ImageNet Classification with Deep Convolutional Neural Networks. *AASRI Procedia*, *6*(December), 89–94. https://doi.org/10.1016/j.aasri.2014.05.013

Spellman, F. R. (2010). Activated sludge process. In *Spellman's Standard Handbook for Wastewater Operators* (Second, pp. 291–339). CRC Press. https://doi.org/10.1201/EBK1439818862-9

Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R. (2014). Dropout: A Simple Way to Prevent Neural Networks from Overfitting. *Journal of Machine Learning Research*, *15*(56), 1929–1958. http://jmlr.org/papers/v15/srivastava14a.html

UNESCO. (2020). The United Nations World Water Development Report 2020: Water and Climate Change. In *UNESCO*. https://unesdoc.unesco.org/notice?id=p::usmarcdef_0000372985&locale=en

United Nations World Water Assessment Programme. (2016). *The United Nations*

World Water Development Report 2016 Report United Nations Educational, Scientific and Cultural Organization. https://doi.org/ISBN 978-92-3-100146-8

Uprety, K., Kennedy, A., Balzer, W., Baumler, R., Duke, R., & Bott, C. (2015). Implementation of Ammonia-Based Aeration Control (ABAC) at full-scale Wastewater Treatment Plants. *Proceedings of the Water Environment Federation*, *2015*(3), 1–10. https://doi.org/10.2175/193864715819557902

Várhelyi, M., Brehar, M., & Cristea, V. M. (2018). Control strategies for wastewater treatment plants aimed to improve nutrient removal and to reduce aeration costs. *2018 IEEE International Conference on Automation, Quality and Testing, Robotics, AQTR 2018 - THETA 21st Edition, Proceedings*, *3*, 1–6. https://doi.org/10.1109/AQTR.2018.8402750

Vinayak, J. R., & Narayanan, S. (2018). Nonlinear PI with state feedback control for activated sludge process. *IEEE International Conference on Information, Communication, Instrumentation and Control, ICICIC 2017*, *2018-Janua*, 1–7. https://doi.org/10.1109/ICOMICON.2017.8279055

Vrečko, D., Hvala, N., Stare, A., Burica, O., Stražar, M., Levstek, M., Cerar, P., & Podbevšek, S. (2006). Improvement of ammonia removal in activated sludge process with feedforward-feedback aeration controllers. *Water Science and Technology*, *53*(4–5), 125–132. https://doi.org/10.2166/wst.2006.098

Wahab, N. a., Katebi, R., Balderud, J., & Rahmat, M. F. (2011). Data-driven adaptive model-based predictive control with application in wastewater systems. *IET Control Theory & Applications*, *5*(6), 803–812. https://doi.org/10.1049/iet-cta.2010.0068

Xu, J., Yang, C., & Qiao, J. (2017). A novel dissolve oxygen control method based on fuzzy neural network. *Chinese Control Conference, CCC*, 4363–4368. https://doi.org/10.23919/ChiCC.2017.8028044

Yang, T., Qiu, W., Ma, Y., Chadli, M., & Zhang, L. (2014). Fuzzy model-based predictive control of dissolved oxygen in activated sludge processes. *Neurocomputing*, *136*, 88–95. https://doi.org/10.1016/j.neucom.2014.01.025

Yu, H., & B.M. Wilamowski. (2011). Levenberg–Marquardt Training. In *Industrial Electronics Handbook Intelligent Systems* (pp. 12–15). CRC Press. https://doi.org/10.1201/9781315218427

Zhang, W., & Qiao, J. fei. (2020). Multi-Variable Direct Self-Organizing Fuzzy

Neural Network Control for Wastewater Treatment Process. *Asian Journal of Control*, *22*(2), 716–728. https://doi.org/10.1002/asjc.1919

Zhang, W., Zhang, J. L., & Bai, R. F. (2019). Direct Adaptive Neural Network Control for Dissolved Oxygen Concentration∗. *Proceedings of the World Congress on Intelligent Control and Automation (WCICA)*, *2018-July*, 1494–1499. https://doi.org/10.1109/WCICA.2018.8630484

Zhang, Y., & Wei, W. (2019). Finite-Time Extended State Observer-based PI Control for Dissolved Oxygen. *International Conference on Control, Automation and Systems*, *2019-Octob*(Iccas), 40–43. https://doi.org/10.23919/ICCAS47443.2019.8971715

LIST OF PUBLICATIONS

1. M. H. Husin, M. F. Rahmat, and N. A. Wahab, 2020, Decentralized proportional-integral control with carbon addition for wastewater treatment plant, Bulletin of Electrical Engineering and Informatics, vol. 9, no. 6, pp. 2278–2285. (Scopus Q3)

2. M. H. Husin, M. F. Rahmat, N. A. Wahab, and M. F. M. Sabri, 2021, Neural Network Ammonia-Based Aeration Control for Activated Sludge Process Wastewater Treatment Plant, Md Zain Z. et al. (eds) Proceedings of the 11th National Technical Seminar on Unmanned System Technology 2019, Lecture Notes in Electrical Engineering, vol. 666, pp. 471–487. (Scopus)

3. M. H. Husin, M. F. Rahmat, N. A. Wahab, M. F. M. Sabri and S. Suhaili, 2020, Proportional-Integral Ammonium-based Aeration Control for Activated Sludge Proces, 13th International UNIMAS Engineering Conference (EnCon), pp. 1-5. (IEEE Xplore)

4. Maimun Huja Husin, Mohd Fua'ad Rahmat, Norhaliza Abdul Wahab and Mohamad Faizrizwan Mohd Sabri, " Neural Network ABAC with Dropout Layer for Activated Sludge System", ICEID 2021, ELEKTRIKA - Journal of Electrical Engineering (in press).