https://doi.org/10.36375/prepare_u.iiche.a414

Intelligent Techniques for Wastewater Treatment: A Technical Review

Swati Sharma[a], Mita K. Dalal[b]

[a]*Department of Chemical Engineering, Sarvajanik College of Engineering & Technology, Surat 395001, India*
[b]*Department of Information Technology, Sarvajanik College of Engineering & Technology, Surat 395001, India*

Abstract

Industrial wastewater treatment is a crucial but challenging task. The perpetual chemical and bio-chemical reactions impart a great deal of complexity to the composition of industrial wastewaters. While conventional modeling approaches can handle linear processes, complex systems exhibiting non-stationary behavior can prove challenging. Machine learning techniques based on variants of Artificial Neural Networks, Bayesian approaches and Genetic Algorithms have proven promising for outlier detection, model generation and prediction in the field of wastewater treatment. In this context, intelligent techniques enable both feature extraction and application of suitable algorithms to datasets to obtain precise results. Inference mechanisms that support decision-making combined with visualization render machine learning algorithms as the most dependable techniques for analyzing various factors affecting wastewater treatment systems. Machine learning approaches are useful for data processing, real-time modeling and actionable inference for compliance with government norms for wastewater treatment. Moreover, machine learning algorithms have also been applied in wastewater treatment to optimize efficiency parameters.

This paper reviews the application of machine learning algorithms for data processing, modeling, parameter optimization, prediction, and decision-making for efficient management of wastewater treatment processes. The challenges and limitations of these approaches are also discussed.
Keywords: wastewater treatment; machine learning; algorithm; modeling; optimization

1. Introduction

Industrial wastewaters are teeming with a plethora of pollutants. Wastewater treatment process (WWTP) is a challenging task due to the complex dynamics of the perennial reactions taking place in the natural environment. This makes real-time prediction analysis more difficult than ever. Intelligent Machine Learning techniques such as Bayesian Learning [7, 21], Artificial Neural Networks (ANN) [4, 10, 14, 17, 19, 22, 24, 29], Support Vector Machines (SVM)[6], Decision Trees [20], Genetic Algorithms (GAs) [15] and Fuzzy Learning based methods [15-18] have proven effective in the generation of models that are applicable to a diverse range of applications in the field of water-quality monitoring, wastewater treatment as well as plant design for the same. For example, Bayesian inference methods have been applied

https://doi.org/10.36375/prepare_u.iiche.a414

to generate multi-objective water-quality models which can determine the sources of contamination in water, detect presence of pathogenic micro-organisms and suggest optimal placement of sensors for quality monitoring [1]. Likewise, ANNs can be trained to predict the concentrations of continuous valued attributes like suspended solids (SS) concentrations and biochemical oxygen demand (BOD) in wastewater plant effluent [15, 22]. ANNs can also be used to model nitrogen and phosphorous removal from wetlands constructed for wastewater treatment [2, 19] Further, ANNs are found to be suitable for modeling and prediction of chemical precipitation of heavy metals in mining industry wastewaters [26]. The use of ANNs in adsorption modeling helps to address the shortcomings in traditional adsorption models and thereby enable better predictions in various systems [2, 4]. Section II of the paper summarizes diverse intelligent methods for wastewater treatment found in literature.Section III of the paper discusses the major challenges faced by machine learning based methods when applied to the task of wastewater treatment. Finally, Section IV of the paper provides observations and concluding remarks regarding application of machine learning technology and tools to the challenging task of wastewater treatment.

2. Intelligent Techniques in Wastewater Treatment

Conventional mathematical modeling approaches are capable of demonstrating the water quality parameters which tend to change with time. This approach can very well handle linear processes but are subject to various limitations while handling unstationary behavioural patterns arising due to biological growth or algal growth in industrial wastewaters.

It is observed from Table 1 that ML based inductive learning approaches are helpful in monitoring the waste water treatment processes, minimize problems and also come up with efficient solutions to the problems being encountered in waste water treatment and management.

ML based algorithms can extract relevant features and can be used to train models which are capable of achieving better results in terms of accuracy and sensitivity [10]. AI based techniques can moreover pre-process and sample raw datasets, perform data smoothing and noise removal, identify outliers and train models and thus have emerged as versatile tools in managing day to day operations in WWTPs and rendering effluent of a better quality. As per the literature surveyed, it is evident that different AI based approaches offer a varied set of advantages. ANN serves to provide prediction and control models for parameters as BOD, COD and other organic pollutants and can thus be utilized in most wastewater applications [10, 28]. While GAs are known for their high versatility, they can also be used for the qualitative analysis of wastewater [15, 28]. PSO algorithms are highly flexible and can be used in optimization of wastewater treatment systems [31].

https://doi.org/10.36375/prepare_u.iiche.a414

Table 1: Intelligent approaches in wastewater treatment

Sr No.	Intelligent Modeling Approach	Parameters predicted	References
1.	BLS (Broad learning system) with MOPIO-OBLS :optimized MOPIO-OBLS and unoptimized OBLS	BOD_5	[8]
2.	Bayesian Networks for the analysis of MSBR	COD, Total Nitrogen and Total Phosphorous	[21]
3.	Multi-layer perceptron	BOD, COD, TSS	[3]
4.	Feedforward Neural Network, adaptive neuro-fuzzy inference system and SVM	BOD	[26]
5.	Adaptive neuro-fuzzy inference system and SVM	Prediction of removal of Kjeldahl Nitrogen	[23]
6.	ANN and SVM	Prediction of TSS and COD	[13]
7.	ANN and SVM	Prediction of TDS and COD	[11]
8.	ANN	COD and trace metals	[24]
9.	Recurrent Neural Network, Deep Neural Network	NO_2	[5]
10.	Time Stacked Broad Learning System	mechanism faults considered are sludge bulking, toxicity shock and inhabitation	[9]
11.	Multi-objective particle swarm optimization algorithm, Fuzzy neural network controller	dissolved oxygen and nitrate	[15]
12.	ANN & Response Surface Methodology	COD, TSS, TDS, TS	[27]

3. Major challenges for Intelligent Techniques

The complex dynamics of industrial wastewaters are best understood by AI tools and formulated into specific mathematical models. However, abrupt changes in process parameters may lead to incorrect results and inconclusive outputs, which in turn may pose a deterrent in decision making, minimize the accuracy of the model trained with selected data using AI tools and thereby affect the prediction accuracies required for operational performance. Far more reliable outputs can be achieved by appropriate selection of historical, real-time or raw data and adequate training of the models ordained for WWT tasks. Lack of robust security mechanisms may lead to crucial situations which warrant comprehensive management meticulous handling and operation of WWTPs.

The remarkable solutions offered by AI tools could be marred by cyber attacks, malware [28]. So in a nutshell, protection from cyber attacks, optimizing operational costs and energy consumptions and training data to capture complex situations would render AI tools more reliable and profitable. Specifically, the challenges to intelligent techniques comprise, ‘sampling of data for training of the model’, ‘parameter tuning for ML based models’, ‘relevant feature extraction' and 'interpretation and visualization of results', which are described next.

3.1 Sampling of data for training the ML model: The efficiency and generalization of any ML based model depends upon efficient sampling of data. In wastewater plants the consistency of the samples is usually not uniform across the collection grid. Hence, it is necessary to use optimal placement of sensors for collecting training samples from different acquisition points [7, 30]. Moreover, water quality could keep changing due to complex internal reactions and environmental effects. So, reliance should not be built upon a model trained using historical samples alone, but should be time-variant and dynamically adjusted using adaptive techniques [12, 22].

3.2 Parameter tuning for ML model: Machine Learning models often require tuning of configuration parameters [32, 33]. For instance, efficiency of Neural Networks based models for WWTP will also depend upon selection of activation function and tuning of hyper-parameters such as number of hidden layers, learning rate and number of epochs [32, 33]. Popular ML tools like WEKA facilitate iterative hyper-parameter tuning for model training which in turn helps to achieve acceptable accuracy and avoid over-fitting in the derived models [36].

3.3 Feature Extraction: In order to train an accurate model for WWTP, it is important to prioritize and extract the most relevant features from waste water. Deep learning methods have proven effective in this regard [24].

3.4 Interpretation and Visualization of Results: A trained ML model may be accurate in its predictions, however it may still remain difficult to interpret for humans. Some techniques like Decision Trees accord easy visual interpretation and can also be translated into rule sets, however this is difficult for ANN based models. Hence, domain experts may still be required to interpret the learned results from an ML model, thus limiting the scope for automation. Soft computing tools like MATLAB [34], TensorFlow [35] and WEKA [36] can assist in visualization of results to some extent.

4. Conclusion

The literature reviewed reiterates the fact that the use of intelligent techniques has emerged as a boon in the field of wastewater treatment. ML based intelligent techniques have proven versatile and more efficient in modeling various aspects of wastewater treatment compared to conventional methods. The increased ability of various modeling approaches to remove hazardous contaminants and predict wastewater quality is really commendable. It is expected that future research will further strive to work upon the existing limitations for more robust intelligent approaches for wastewater treatment and management.

Declaration of Interests: The authors declare no competing interests.

https://doi.org/10.36375/prepare_u.iiche.a414

References

1. Ailamaki, A., Faloutsos, C., Fischbeck, P.S, Small, M.J., VanBriesen, J. (2003). An environmental sensor network to determine drinking water quality and security. *SIGMOD RECORD, 32.*

2. Akratos, C. S., Papaspyros I. N. E., Tsihrintzis, V. A. (2009). Artificial neural network use in ortho-phosphate and total phosphorus removal prediction in horizontal subsurface flow constructed wetlands. *Biosystems Engineering, 102*, 190-201. doi:10.1016/j.biosystemseng.2008.10.010

3. Arismendy, L., Cardenas, C., Gomez D., Maturana, A., Mejia, R., Quintero, M. C. G. (2020). Intelligent system for the predictive analysis of an industrial wastewater treatment process. *Sustainability, 12.* https://doi.org/10.3390/su12166348

4. Bahramian, M., Dereli, R. K., Zhao, W., Giberti, M., Casey, E. (2023). Data to intelligence: The role of data-driven models in wastewater treatment. *Expert Systems with Applications*, *217*, 11945. https://doi.org/10.1016/j.eswa.2022.119453

5. Bakht, A., Nawaz, A., Lee, M., Lee, H. (2022). Ingredient analysis of biological wastewater using hybrid multi-stream deep learning framework. *Computers & Chemical Engineering, 168, 108038.* https://doi.org/10.1016/j.compchemeng.2022.108038

6. Bellamoli, F., Di Lorio, M., Vian, M., Melgani, F. (2023). Machine learning methods for anomaly classification in wastewater treatment plants. *Journal of Environmental Management, 344*, 118594. https://doi.org/10.1016/j.jenvman.2023.118594

7. Candelieri, A., Perego, R., Archetti, F. (2018). Bayesian optimization of pump operations in water distribution systems. *Journal of Global Optimization*, *71*, 213. https://doi.org/10.1007/s10898-018-0641-2

8. Chang, P., Bao, X., Meng, F. C., Lu, R. W. (2023a). Multi-objective Pigeon-inspired Optimized feature enhancement soft-sensing model of Wastewater Treatment Process. *Expert Systems with Applications, 215*:119193 doi:10.1016/j.eswa.2022.119193

9. Chang, P., Xu, Y., Meng, F. C (2023b). Efficient fault monitoring in wastewater treatment processes with time stacked broad learning network. *Expert Systems with Applications, 233*, 120958. https://doi.org/10.1016/j.eswa.2023.120958

10. Cheng, T., Harrou F., Kadri, F., Sun, Y., Leiknes, T. (2020). Forecasting of Wastewater Treatment Plant Key Features Using Deep Learning-Based Models: A Case Study. *IEEE Access*, 8, 184475. doi: 10.1109/ACCESS.2020.3030820

11. Curteanu, S., Godini, K., Piuleac, C. G., Azarian, G., Rahmani, A. R., Butnariu, C. (2014). Electro-oxidation method applied for activated sludge treatment: experiment and simulation based on supervised machine learning methods. *Industrial Engineering Chemistry Research, 53*, 4902. doi: 10.1021/ie500248q

12. Fang, X., Zhai, Z., Xiong, R., Zhang, Li., Gao, B. (2022). LSTM-based Modelling for Coagulant Dosage Prediction in Wastewater Treatment Plant. 3rd International Conference on Artificial Intelligence in Electronics Engineering (AIEE 2022). Bangkok, Thailand, ACM, New York, NY, USA.

13. Guo, H., Jeong, K., Lim, J., Jo, J., Kim, Y. M., Park, J-p., Kim, J. H., Cho, K. H. (2015). Prediction of effluent concentration in a wastewater treatment plant using machine learning models. *Journal of Environment Science, 32,* 90. doi: 10.1016/j.jes.2015.01.007.

14. Hamed, M. M., Khalafallah, M. G., Hassanien, E. A. (2004). Prediction of wastewater treatment plant performance using artificial neural networks. *Environment Modelling & Software 19*, 919. https://doi:10.1016/j.envsoft.2003.10.005

15. Han, H-G., Zhang, L., Liu, H-X., Qiao, J-F. (2018). Multiobjective design of fuzzy neural network controller for wastewater treatment process. *Applied Soft Computing, 67*,467. https://doi.org/10.1016/j.asoc.2018.03.020

16. He, Y., Tang, C., Zhang, D., Liao, N. (2023). Assessing the effects of the influencing factors on industrial green competitiveness fusing fuzzy C-means, rough set and fuzzy artificial neural network methods. *Ecological Indicators, 147*, 109921. https://doi.org/10.1016/j.ecolind.2023.109921

17. Jana, D. K., Bhunia, P., Adhikary, S. D., Bej, B. (2022). Optimization of Effluents Using Artificial Neural Network and Support Vector Regression in Detergent Industrial Wastewater Treatment. *Cleaner Chemical Engineering, 3,* 100039. https://doi.org/10.1016/j.clce.2022.100039

18. Kambli, A., Modi, S. (2019). Fuzzy Neuro Approach to Water Management Systems ICMLSC '19: Proceedings of the 3rd International Conference on Machine Learning and Soft Computing. 215. https://doi.org/10.1145/3310986.3311026

19. Kiiza, C., Pan, S-q., Bockelmann-Evans B., Babatunde, A. (2020). Predicting pollutant removal in constructed wetlands using Artificial Neural Networks. *Water Science Engineering, 13*,14. https://doi.org/10.1016/j.wse.2020.03.005

20. Krovvidy, S., Wee, W. G. (1990). A knowledge based planning approach for waste water treatment system. 3rd International conference on Industrial and engineering applications of artificial intelligence and expert systems, Volume 2

21. Li, D., Yang, H. Z., Liang, X. F. (2013). Prediction analysis of a wastewater treatment system using a Bayesian network. *Environmental Modelling & Software,40,*140. http://dx.doi.org/10.1016/j.envsoft.2012.08.011

22. Liu, Y., Li, K., Huang, D. (2021). Prediction of Biochemical Oxygen Demand Based on VIP-PSO-Elman Model in Wastewater Treatment. ACM International Conference on Intelligent Computing and its Emerging Applications (ACM ICEA ’21), Jinan, China. 3506502 https://doi.org/10.1145/3491396.3506502

23. Manu, D. S., Thalla, A. K. (2017). Artificial intelligence models for predicting the performance of biological wastewater treatment plant in the removal of Kjeldahl nitrogen from wastewater. *Applied water science,7*,3783. https://doi.org/10.1007/s13201-017-0526-4

24. Matheri, A. N., Ntuli, F., Ngila, J. C., Seodigeng, T., Zvinowanda, C. (2021). Performance prediction of trace metals and COD in wastewater treatment using artificial neural network. *Computers & Chemical Engineering*, *149*, 107308. https://doi.org/10.1016/j.compchemeng.2021.107308

25. Mehrpour, P., Mirbagheri, S. A., Kavianimalayeri, M., Sayyahzadeh, A. H., Ehteshami, M. (2023). Experimental pH adjustment for different concentrations of industrial wastewater and modeling by Artificial Neural Network. *Environmental Technology & Innovation, 31*, 103212. https://doi.org/10.1016/j.eti.2023.103212

26. Nourani, V., Elkiran, G., Abba, S. I. (2018). Wastewater treatment plant performance analysis using artificial intelligence - an ensemble approach. *Water Science Technology*, *78*, 2064. doi:10.2166/wst.2018.477

27. Rai, P. K., Kant, V., Sharma, R. K., Gupta, A. (2023). Process optimization for textile industry-based wastewater treatment via ultrasonic-assisted electrochemical processing. *Engineering Applications of Artificial Intelligence*, *122*, 106162. https://doi.org/10.1016/j.engappai.2023.106162

28. Ray, S. S., Verma, R. K., Singh, A., Ganesapillai, M., Kwon, Y-N. (2023). A holistic review on how artificial intelligence has redefined water treatment and seawater desalination processes. *Desalination, 546,*

116221.
https://doi.org/10.1016/j.desal.2022.116221

29. R. Vijayabhanu, V. Radha (2012). Statistical Normalization Techniques for the Prediction of COD Level for an Anaerobic Wastewater Treatment Plant. Proceedings of the 2nd International Conference on Computational Science, Engineering and Information Technology (CCSEIT-12), Coimbatore, Tamilnadu, India.

30. Venkatasubramanian, N., Davis, C. A., Eguchi, R. T. (2020). Designing Community Based Intelligent Systems for Water Infrastructure Resilience. 3rd ACM SIGSPATIAL Workshop on Advances in Resilient and Intelligent Cities (ARIC'20), Seattle, WA, USA.
https://doi.org/10.1145/3423455.3430318

31. Yadav, A., Roy, S. M. (2023). An artificial neural network-particle swarm optimization (ANN-PSO) approach to predict the aeration efficiency of venturi aeration system. *Smart Agricultural Technology, 4, 100230*
https://doi.org/10.1016/j.atech.2023.100230

32. Mitchell, T. M. (1997). Machine Learning. McGraw-Hill, New York. (ISBN: 0070428077)

33. Jiawei, Han. and Micheline, Kamber. (2006). Data Mining: Concepts and Techniques, 2nd edition. Morgan Kaufmann Publishers.

34. MATLAB: https://in.mathworks.com/products/matlab.html

35. TensorFlow: https://www.tensorflow.org

36. WEKA: https://www.cs.waikato.ac.nz/ml/weka