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Development of artificial neural networks to predict membrane fouling in an anoxic-aerobic membrane bioreactor treating domestic wastewater

Félix Schmitt[a,b], Rajesh Banu[c], Ick-Tae Yeom[d], Khac-Uan Do[a,*]

[a] School of Environmental Science and Technology, Hanoi University of Science and Technology, Hanoi, Vietnam
[b] Energy and Environmental Department, National Institute of Applied Sciences of Lyon, 69621 Villeurbanne Cedex, France
[c] Department of Civil Engineering, Regional Centre of Anna University, Tirunelveli, India
[d] Graduate School of Water Resources, Sungkyunkwan University, South Korea

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ABSTRACT

An artificial neural network (ANN) was first developed to predict the transmembrane pressure in an anoxic-aerobic membrane bioreactor (AO-MBR) treating domestic wastewater. A few studies about prediction of membrane fouling in MBRs using ANNs have been published so far, even though our recent work indicates that ANNs show a great potential for this application. In this study, 10 parameters linked to wastewater treatment and measured in the different parts of the AO-MBR system were used as the input variables of the ANN. The goal was to select the most relevant input parameters to predict the evolution of the transmembrane pressure based on the performances of the ANN. An ANN model was selected for its satisfying performances ($R^2 = 0.850$). In conclusion, ANNs could be a valid method to predict membrane fouling in AO-MBR systems treating domestic wastewater.

1. Introduction

Membrane bioreactor (MBR) technology is an increasing and attractive option for the treatment and reuse of industrial and municipal wastewater [1–5]. However, membrane fouling still remains the most challenging issue in MBR operation and attracts considerable attention in MBR studies [5–12]. Several techniques are currently employed to mitigate membrane fouling in MBRs, such as applying a pre-treatment to the influent, increasing the aeration or chemically modifying the mixed liquor [7,13,14]. Therefore, prediction of membrane fouling will play an important role in adjusting the operational conditions to prolong the membrane filtration time effectively. Currently, prediction of membrane fouling in MBRs using a model which would be able to simulate the membrane fouling phenomenon has been widely developed. Numerous simulations of the transmembrane pressure (TMP) or permeate flux evolution using mathematical models [15–18] and computational fluid dynamics simulations [19,20] gave satisfying and promising results. However, the development of these models was limited by the complexity of membrane fouling phenomenon and many simplifications on the operational conditions and the wastewater characteristics have to be made in order to obtain usable dynamic equations.

Facing the difficulty to develop such models, artificial neural networks (ANNs) represented a good compromise to evaluate membrane fouling in MBRs. ANNs are a statistical tool inspired by biological neural systems. Basically, calculating units called neurons, gathered in several layers, compose the network which takes some variables as inputs and compute their outputs. The structure of the network is adapted through a training phase by comparing its outputs to experimental values which correspond to the target outputs. When applied to MBRs, ANNs can allow to describe the complex membrane fouling phenomenon by reducing it to a black-box and considering only input parameters linked to the MBR and the wastewater characteristics which could affect it.

The results of the following literature is summarized in Table 1 and further information about the ANNs developed is also given.

Abbreviations: Alk, alkalinity; ANN, artificial neural network; AO-MBR, anoxic-aerobic membrane bioreactor; COD, chemical oxygen demand; DO, dissolved oxygen; HRT, hydraulic retention time; MBR, membrane bioreactor; MLSS, mixed liquor suspended solids; MLVSS, mixed liquor volatile suspended solids; MSE, mean squared error; RMSE, root mean squared error; SRT, sludge retention time; TMP, transmembrane pressure; TN, total nitrogen; TP, total phosphorus.

* Corresponding author.
E-mail address: uan.dokhac@hust.edu.vn (K.-U. Do).

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Table 1
A summarization of the inputs, structure, output, and limitations for the ANNs used in MBRs.

Reference	Outputs	Inputs	Structure	Performance	Comments/Limitations
Piron et al. [21]	R_t	TMP Crossflow velocity SS	Recurrent	$Error = 11\%$	• Dynamic simulation of membrane fouling but constant operational parameters, which does not represent real conditions in MBRs
Hamachi et al. [22]	E_p J	TMP Crossflow velocity SS	Recurrent	$Error = 10\%$	
Çinar et al. [23]	COD Ammonia Nitrate Phosphate *In the effluent*	COD Ammonia Nitrate Phosphate *In the influent* SRT HRT J TMP	Cascade forward ANN	Perfect match but no value of R^2 or RMSE	• Small database (only 30 data over 100 days of operation) • Membrane fouling characteristics taken as inputs
Pendashteh et al. [24]	COD TOC oil in sludge MLSS *In the effluent*	OLR TDS reaction time operational time	Basic ANN	$R^2 > 0.99$	• Optimization of the ANN structure with a genetic algorithm (GA) • Operational time taken as input • Membrane fouling characteristics not considered either as inputs or outputs
Giwa et al. [25]	COD NH_4^+-N PO_4^{3-}-P *In the effluent*	DO MLVSS pH Electric conductivity	Basic ANN	$R^2 > 0.97$	• Membrane fouling characteristics not considered either as inputs or outputs • Small database (only 16 data over 60 days of operation)
Geissler et al. [26]	J	TMP, $dTMP/dt$, TMP during backwash, Filtration cycle length, Backwash cycle length, SRT, TSS, Temperature, Oxygen decay rate	Elman network 55 neurons	$Error = 2.7\%$	• Database size >1000, which can lead to overfitting • Influent and mixed liquor characteristics not considered
Mirbagheri et al. [27]	TMP Perm	TSS COD_{in} SRT MLSS Time	Basic ANN	TMP: $Error = 1\%$ Perm: $Error = 1\%$	• Optimization with a GA • 31 data only • Operational time taken as input
			Radial basis ANN	TMP: $Error = 2\%$ Perm: $Error = 3\%$	