Statistical interpretation and modelling of daily permeability evolution in full-scale membrane bioreactors using fuzzy inference methods

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Summary

A fuzzy inference method was used to model the fouling evolution of a full-scale Membrane Bioreactor (MBR) treating rejection water from the sludge treatment of a water resource recovery facility (WRRF), using a dataset of 1.5 years. The six generated fuzzy rules replicate the fouling evolution with a promising correlation coefficient of 0.7.

Keywords

Fouling control, membrane bioreactor, fuzzy inference system

Introduction

Fouling control is of prime importance for full-scale membrane bioreactors operation to limit energy consumption and to maintain production capacity. Model developments are needed to describe and interpret the mechanisms inducing fouling but also to predict and optimize the operation of such treatment unit at large scales. While deterministic models allow a better understanding of fouling using detailed parameters, statistical approaches, such as regression model trees (Dalmau *et al.*, 2015) or multivariate linear correlations (Philippe *et al.*, 2013) could represent an efficient alternative for this application. The purpose of this study was to model daily permeability evolution of a full-scale MBR unit using fuzzy inference methods (Zahed, 1965), suitable for complex system modelling and unusual to date for MBR fouling control.

Material and Methods

Studied WRRF and data collection: Data are issued from the Seine Aval water resource recovery facility (nominal flow = 1,700,000 m^3/d), located in the Parisian area (France). Membrane bioreactors treat rejection water from digested sludge dewatering after their thermal treatment (about 10,000 m^3/d). The biological treatment unit comprises 4 biological tanks (anoxic zone 2600 m^3 and oxic zone 7500 m^3 each) and 6 separated membrane tanks (480 m^3 and 15000 m^2 of membrane each – Type of membrane: KMS Puron). Chemicals (Polymers, $FeCl_3$ and anti-foaming agents) are added during the pretreatment stage (flotation / 1mm rotating sieves). The study was performed using a dataset of 1.5 years of monitoring data. Pollutant concentrations (MLSS, BOD_5, total and soluble COD, NTK, NGL, $N\text{-}NH_4^+$, $N\text{-}NO_2^-$, $N\text{-}NO_3^-$, P_T, $P\text{-}PO_4^{2-}$) in the pretreated influent and in the permeate, MLSS in the recirculating sludge, flow rates and volume of added chemicals were measured daily. For each filtration cell, transmembrane pressure (TMP), temperature, permeate and air flow rates were recorded every five seconds. The permeability of the membranes was calculated using permeate flux and transmembrane pressure measurements. Days of chemical cleanings for each membrane tank are precisely known. Dataset validation was done using hydraulic balance and statistical analyses (Filali *et al.* 2015).

Fuzzy inference method: After parameter selection using a statistical analysis, the inference system was developed using the Fispro Open-Source Software[1]. Partitions and rules were manually adjusted. A more complete description of the fuzzy logic and the FisPro tool can be found in Guillaume & Charnomordic (2011).

Results and Conclusions

Figure 1 presents the resulting fuzzy decision tree. This decision tree is composed of six rules involving 4 parameters from the 8 parameters initially incorporated in the analysis. The global correlation coefficient between inferred and observed data is 0.7, a rather high value considering the complexity of the system. The cumulated filtrated volume since last chemical cleaning and the daily filtrated volume appear to be the most relevant parameters.

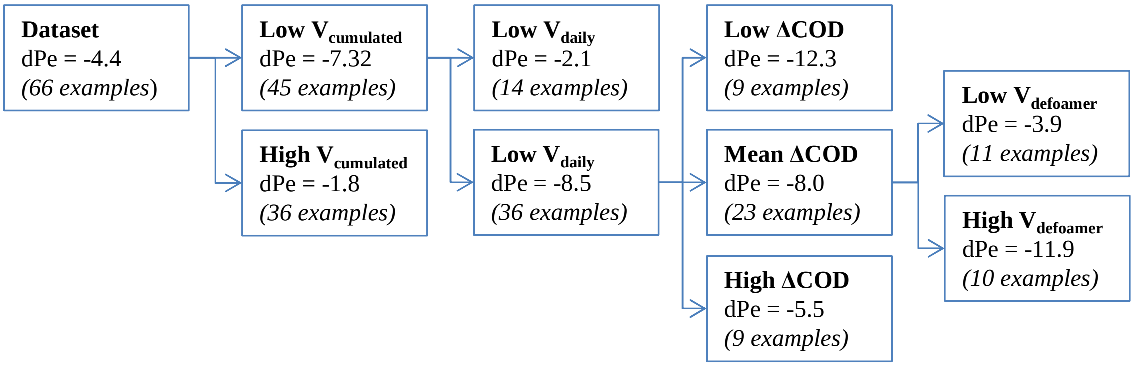

Figure 1: Resulting fuzzy decision tree [dPe = daily permeability evolution at 20°C (L/m^2/h/bar); $V_{cumulated}$ = cumulated filtrated volume since last chemical cleaning (m^3); V_{daily} = daily filtrated volume (m^3/d) ; ΔCOD = difference between the supernatant COD in membrane tank and the permeate COD (g/L); $V_{aiti\text{-}fooaming}$ = the daily added anti-foaming solution volume (m^3/j)]

Another dataset (1 year) and specific event periods (chemical cleaning, atypical relaxation periods), previously discarded during the initial model development, will be integrated in the dataset to potentially increase the performance of the model and will be presented.

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[1] Fuzzy Inference System Professional (https://www7.inra.fr/mia/M/fispro/fispro2013_en.html)