

Principal component analysis for monitoring membrane bioreactors: trend detection, outlier detection and optimization

Wouter Naessens¹, Thomas Maere¹, Lieven De Temmerman^{1,2}, Ingmar Nopens¹

¹BIOMATH, Department of Mathematical Modelling, Statistics and Bioinformatics, Ghent University, Coupure Links 653, B-9000 Ghent, Belgium (ingmar.nopens@ugent.be)

²Wetsus Centre of Excellence for Sustainable Water Technology, P.O. Box 1113, 8900 CC Leeuwarden, The Netherlands

Keywords: Principal component analysis, monitoring, fouling, warning system

Session 3: MBR Design, operation and maintenance or Session 4: Case studies

Introduction

Membrane fouling, both in literature and in full-scale plant operation, appears to be the most cumbersome process for membrane bioreactors (MBR). Since the process is not fully understood, typical operation consists of fixed conservative schemes involving membrane aeration, backwashing and chemical cleaning. Not only do these fouling mitigation actions shorten the membrane lifetime, such a fixed scheme can never be optimal since it ignores the dynamics in influent, biokinetics and membrane condition. Moreover, this results in a waste of energy, chemicals and membrane uptime, thus leaving room for optimization (Maere et al., 2013). In this case study, a data-mining technique known as principal component analysis (PCA) will be illustrated on a lab-scale as well as a full-scale MBR, showing its ability for monitoring the membrane state and its potential for use in control structures.

Material and methods

The lab-scale MBR, located in the Biomath research group laboratory (Ghent, Belgium), was run on a synthetic effluent and capable of removing COD, nitrogen and phosphorous compounds, using an anaerobic compartment (8L) prior to an aerobic/anoxic compartment (17L). The filtration membrane was in a sidestream configuration, using a tubular membrane module (Pentair X-Flow, The Netherlands) with a surface area of 0.17 m². Most design and operation related parameters were fixed, and can be found in Jiang (2007). A typical filtration cycle lasted for 475s, consisting of 450s of filtration, 17s of backwash and 8s of relaxation.

The full-scale MBR 'De drie Ambachten' (Terneuzen, The Netherlands) is treating effluent of the wastewater treatment plant of Terneuzen, in order to produce high quality process water for industrial reuse. The filtration modules were organized in 14 sidestream multitubular skids (Pentair X-Flow, The Netherlands) of which skid 6 was selected for analysis, based on its representative behaviour. A typical filtration cycle lasted 455s.

PCA is a technique that exists for over a 100 years, but only recently has proved its potential for monitoring wastewater treatment plants (Rosén and Olsson, 1998). Especially its use to build early warning systems is a sought-for quality. It is a multivariate method, based on the rotation of the coordinate system, from its original position around the multidimensional data cloud, to an orientation in which the orthogonal axes point in the direction of the largest variance in the dataset (the direction of elongation of the data cloud). This simply implies creating new variables (referred to as principle components - PCs) as linear combinations of the original measured variables. The exact composition of the PCs forms the data-based model, explaining the new coordinate system.

Result and discussion

For the lab-scale MBR, transmembrane pressure (TMP) data at a frequency of 1/s for a period of 6 months (18 November 2009 – 30 April 2010) were analysed (Figure 1a). When fouling got too severe, the membrane module was replaced with a new but identical one instead of chemically cleaning it, to avoid the influence of membrane history on the results. This was done three times during the investigated period, leading to four subperiods. From each of the filtration cycles, five characteristic parameters were estimated which were subsequently subjected to PCA: the peak filtration pressure $+\Delta P$, the backwash pressure $-\Delta P$, an exponential curve at the start of filtration with parameters a and b , and the slope of filtration S (figure 1b).

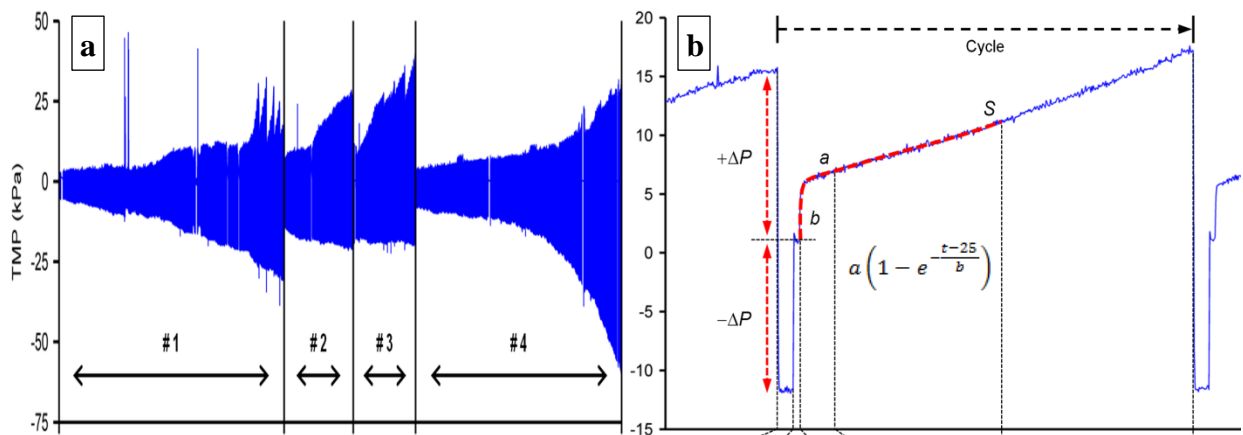


Figure 1 - (a) TMP dataset of 6 months of the lab-scale MBR - (b) Typical TMP cycle showing the parameter estimation.

From the PCA model (figure 2a), it can be seen by vertically projecting the vectors, that PC1 consists of an equal amount of all 5 parameters, but for $-\Delta P$ with a negative sign. It can be concluded that PC1 thus represents fouling severity, as values will rise as $+\Delta P$, a , b and S rise and $-\Delta P$ drop. Similarly, PC2 is composed mainly of $-\Delta P$ versus S , thus implying fouling reversibility (Maere et al., 2013). Finally, from the transformed data (figure 2b), where each point represents a filtration cycle, it can be seen that the four subperiods behave differently. For the first membrane (blue), cycles slowly evolve towards more (PC1) and dominating irreversible (PC2) fouling (i.e. pore blocking), while suddenly shifting towards reversible fouling (i.e. cake

layer). The next two membranes (green and purple) immediately shift towards reversible fouling according to PC2, but in the last of these two (purple), a shift is noticeable at the end (upper right). The fourth membrane (red) again shows a dominant irreversible fouling, as was the case for the first membrane. The explanation might be a change in the filterability of the sludge, causing this different behaviour. More importantly, it can be seen that fouling trends can easily be detected by PCA, and further quantified by the use of cluster centers (yellow diamonds), in this case one for a clean membrane (leftmost), one for dominating reversible fouling (upper right) and one for dominating irreversible fouling (lower right). In the future, this PCA-model might be used online to evaluate new cycles on their fouling state, thereby opening up a window for real-time control strategies (Maere et al., 2013).

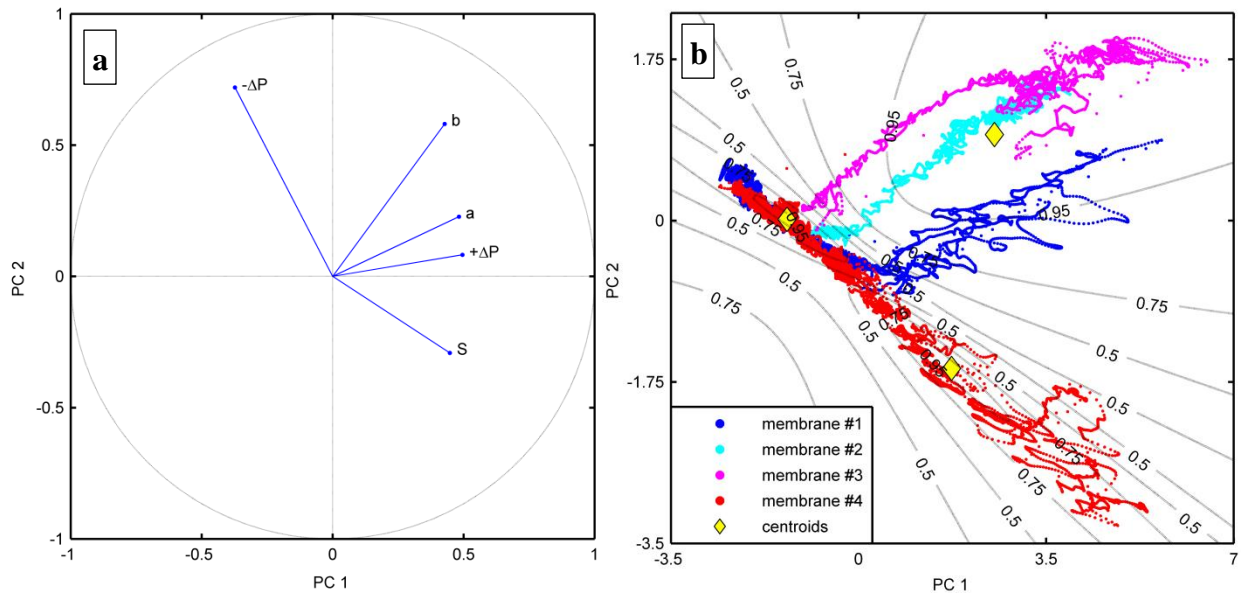


Figure 2 - (a) PCA model composition - (b) Transformed data (each data point represents a filtration cycle)

For the full-scale MBR, similar results were obtained. Temperature-corrected TMP data with a frequency of 1/s were collected for 8 months (1 August 2011 – 31 March 2012), during which 18 chemical cleanings took place (figure 3a). Since an exponential part at the start of filtration was absent, parameters a and b are removed from the parameter estimation (figure 3b). On the other hand, as temperature (T) and flux (J) were not a constant setting, these data were included in the analysis, be it on a daily and hourly basis respectively. From the constructed model (figure 4a) it can be seen that PC1 values will now decrease as general fouling increases (rising $+\Delta P$ and S , decreasing $-\Delta P$). It can also be seen that T and $-\Delta P$ are somewhat correlated (similar position in the model), something that is confirmed by a correlation coefficient R^2 of 0.83. On the other hand, PC2 being highly influenced by flux is more difficult to interpret as this is an operator setting. From the transformed results (figure 4b), it can be seen that, going from blue to red, the filtration cycles evolve towards more fouling (PC1) in general, although they recover somewhat at the end of the period (red). Linked to a higher frequency, excursions according to PC2 with a variable magnitude can be seen from lower right to upper left, which are related to the flux,.

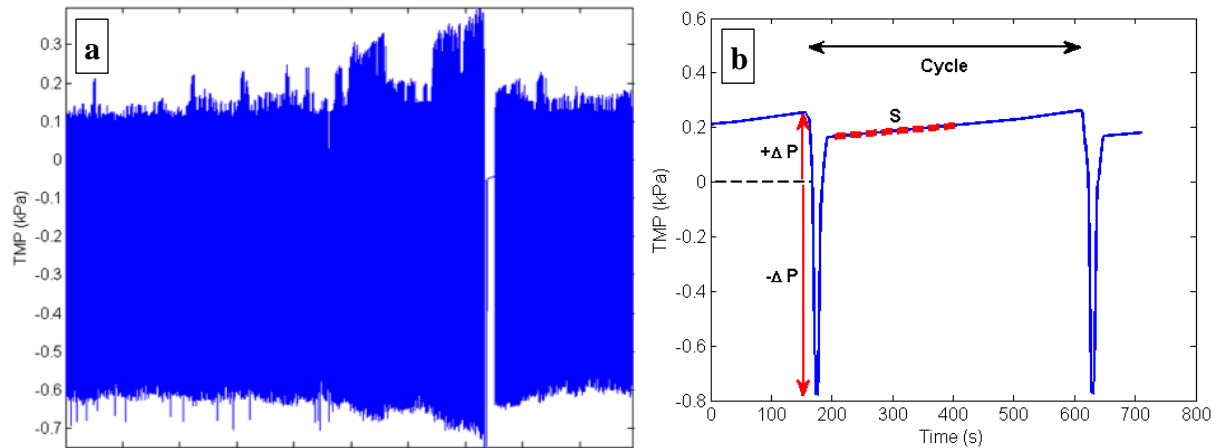


Figure 3 - (a) TMP dataset of 8 months of the full-scale MBR - (b) Typical TMP cycle showing the parameter estimation.

From these results, a clear evolution of fouling state of the membranes can again be monitored, albeit with more frequent excursions due to the more complex dynamics of the system as well as the frequent chemical cleanings. It can also be demonstrated that not all cleanings were necessary, i.e. effective. Control strategies might indicate this in future work on the topic. A current study also indicates great potential for outlier detection.

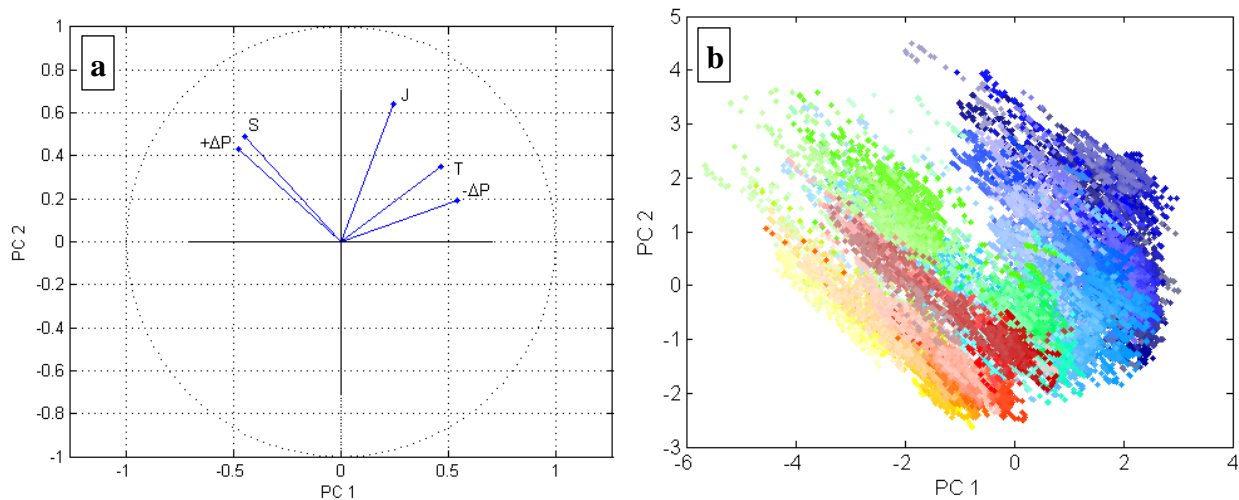


Figure 4 - (a) PCA model composition - (b) Transformed data (each data point represents a filtration cycle). Time is indicated by a color change from blue to red.

References

- Maere T., Villez K., Marsili-Libelli S., Naessens W. and Nopens I. (2012) Membrane bioreactor fouling behaviour assessment through principal component analysis and fuzzy clustering. *Water Research*, 46, 6132–6142.
- Jiang T. (2007) Characterization and modelling of soluble microbial products in membrane bioreactors. PhD thesis, Ghent University, Belgium, 241p.
- Rosén C. and Olsson G. (1998) Disturbance detection in wastewater treatment plants. *Water Science and Technology*, 37, 197-205.