Full Paper

MODELLING HYDRAULIC BACKWASH IN ULTRAFILTRATION PROCESS: A STATISTICAL APPROACH

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ABSTRACT

Modelling of hydraulic backwash (*HB*) during ultrafiltration process is presented in this paper with the aim to studying the influence of operating parameters on *HB* using statistical approach under pilot scale conditions. The *HB* model describes change in transmembrane pressure (ΔTMP) as a function of backwash frequency, backwash flux and backwash time. The development and validation of the model was based on the experimental data from a series of experiments designed using full 2^3 factorial design method and implemented in SMART XIGA pilot plant with an 8-inch polyether sulfone (PES) membrane module. The results showed that *HB* is largely influenced by backwash time and backwash frequency but with insignificant influence from the backwash flux. However for further implementation in practice, due to changes in the feed water quality, a regular update of the models is necessary and can be easily obtained using the methodology presented in this paper.

Keywords: *ultrafiltration, backwash, filtration, modelling, response surface methodology*

1. INTRODUCTION

Over 70% of our Earth's surface is covered by water. Although water is seemingly abundant, the real issue is the amount of fresh water available. About 97.5% of all water on Earth is salt water, leaving only 2.5% as fresh water. Nearly 70% of that fresh water is frozen in the icecaps of Antarctica and Greenland; most of the remainder is present as soil moisture, or lies in deep underground aquifers as groundwater not accessible to human use. However, less than 1% of the world's fresh water (~0.007% of all water on earth) is accessible for direct human uses. This is the water found in lakes, rivers, reservoirs and those underground sources that are shallow enough to be tapped at an affordable cost. Only this amount is regularly renewed by rain and snowfall, and is therefore available on a sustainable basis (Wikipedia, 2009). To make the fresh water available for human usage, it has to be treated to a specific acceptable level at which no harm is done to human life. One of the cost effective processes of doing this is ultrafiltration (UF).

In the last decade, ultrafiltration applied to drinking water production has demonstrated its reliability and its cost effectiveness (Moll *et al*., 2007). However, membrane fouling and scaling, major problems in UF affect the performance of the process and eventually damage the membranes. In clarification and filtration operations, deposits from fouling create an additional resistance to mass transfer (Serra *et al*., 1998). Fouling decrease would increase permeate flux and so proportionally reduce plant size and /or operating costs. In UF, fouling decrease depends on the method of removal such as backwashing, backflushing etc. Also, accurate backwash modelling and optimization could be helpful to achieving greater backwash effectiveness and thus reducing fouling. In UF, backwashing can either be hydraulic backwashing (*HB*) or chemically enhanced backwashing (*CEB*) (Cheryan, 1998).

During *HB*, permeate flows back through the membrane, lifts off the cake and flushes it out of the module in dead-end mode. Each operating cycle is thus made up of a filtration phase followed by a backwash phase that allows the membrane to recover its initial properties. However, the efficiency of *HB* depends on the backwash flux, backwash frequency and the backwash time (Cheryan, 1998). The ideal situation regarding hydraulic backwash flux and frequency is to use a high backwash flux as frequently as possible. However, such practice results in a low net flux, as permeate is consumed in backwashing. Hence, the need to optimise the *HB*. However, optimizing this process depends on availability of accurate models that will adequately explain the interactions among the influencing factors. Consequently, the objective of this paper is to provide a methodology to find appropriate backwash models using the so-called Response Surface Methodology (*RSM*) (Box and Hunter, 1965) for further insight and optimization of the process because the effectiveness of cleaning procedures (e.g. *HB*) plays an important role in the performance of membranes (Heijman *et al*., 2007).

Response surface methodology (*RSM*) was initiated with the work of Box and Hunter (Box and Hunter, 1961a,b). This method employs statistically designed experiments to obtain appropriate data that can be analyzed statistically to produce concrete and valid conclusions. The essence of this is to obtain descriptions of the responses to the factors considered. These experiments usually developed for modelling phenomena lead to most favourable responses. Specifically, response surface design is classified as a simultaneous method being used in the stage of optimization (Kuehl, 2000; Lazic, 2004). Its application allows selecting the optimum combination of levels to obtain the best response for specific conditions (Montgomery, 1991). Based on the responses and the considered independent variables, polynomial models are developed.

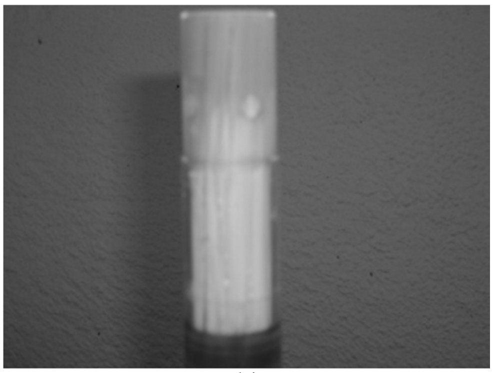
The developed polynomial models are used as practical approach to the real response function (Anunziata and Cussa, 2008).

2 EXPERIMENTAL

2.1. Materials and methods

A two-level full 2^3 factorial design was used. The experiments were performed using *SMART-XIGA* pilot plant containing a 8-inch polyether sulfone (*PES*) capillary hollow fibre UF membrane module (Area 0.0754 m^2 ; number of fibre 120; effective length 25 cm) and operated dead-end mode to clean a sample of wastewater containing some impurities such as microorganisms, volatile organic compounds (VOC) etc. The fouled membrane was cleaned during *HB* by using some of the permeated. Nine experimental runs were performed and the change in transmembrane pressure, TMP (ΔTMP) in bar was estimated from Eq. (1). The experimental range and coded factors used in the experimentation are presented in Table 1. Fig. 1 shows the clean membrane and the experimental set-up. Schematic of a cube representing 2^3 factorial design implemented in this study is depicted in fig. 2.

$$\Delta TMP = TMP_f - TMP_o \tag{1}$$



(a)

(b)

Fig. 1. (a) Clean capillary UF membrane module and (b) Experimental set-up

Table 1: Experimental range and coded levels of the three independent variables for HB

Variables	actual	coded	actual	coded	actual	coded
Backwash frequency	2	-1	3	0	4	+1
Backwash time(min)	0.5	-1	1	0	1.5	+1
Backwash flux ($l\ m^{-2}h^{-1}$)	150	-1	200	0	250	+1

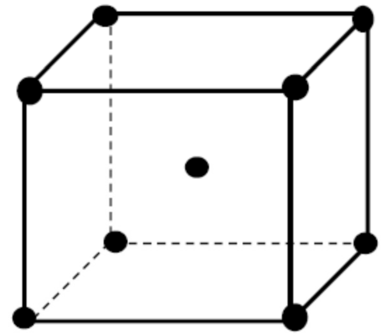


Fig. 2. Schematic of the cubic representation of the 2^3 factorial design (The black dot at the edges of the cube represents each experimental run with a nominal point at the centre).

2.2. Model formulation, development and validation

The model formulation was based on the second order regression polynomial with interactions included. The proposed mathematical relationship is given in Eq. (2).

$$\Delta TMP = \Delta TMP_0 + \alpha_1 t_b + \alpha_2 B_f + \alpha_3 J_b + \alpha_4 {t_b}^2 + \alpha_5 {B_f}^2 + \alpha_6 {J_b}^2 + \alpha_7 t_b J_b + \alpha_8 t_b B_f + \alpha_9 J_b B_f \tag{2}$$

where TMP_f is the final transmembrane pressure at the end of filtration, i.e. at T_f = 20 min., and TMP_o the transmembrane pressure of the membrane at the commencement of the filtration. J_b, t_b, and B_f, are backwash flux, backwash time and Backwash frequency, respectively. α_1, ... α_9 denote the regression coefficients related to linear, quadratic and interaction terms, ΔTMP is the predicted response.

Five models were considered based on the combination of B_f, t_b and J_b as shown in Table 2. Least square (LS) estimation method was used to estimate the regression coefficients. Selection of the most suitable regression model was based on the mean square error (MSE) and mean residuals. However, MSE was considered to be more significant in the selection. The model with the lowest MSE was considered as the most suitable candidate. Based on MSE, models 3 & 4 could be considered to be suitable but model 4 has lower mean residuals compared to model 3. Hence, model 4 was considered as the most suitable regression model.

Table 2: Different combinations of B_f, t_b, J_b in relation to ΔTMP

Model	ΔTMP_o	t_b	B_f	J_b	${t_b}^2$	${B_f}^2$	${J_b}^2$	$B_f t_b$	$J_b t_b$	$J_b B_f$	Mean residuals	MSE
1	+	+	+	+	-	-	-	-	-	-	-6.11E-17	4.34E-05
2	+	+	+	+	+	+	+	-	-	-	0.7432	0.08
3	+	+	+	+	+	-	-	+	+	-	4.12E-15	2.48E-05
4	+	+	+	+	-	+	-	+	-	+	2.32E-15	2.48E-05
5	+	+	+	+	-	-	+	-	+	+	1.55E-15	4.34E-05

+ Combined; - Not combined

For model validation, a cross-validation method was used. In cross-validation method, a testing set of data which is a complimentary subset of the data used for model development is normally used.

3. RESULTS AND DISCUSSION

Eq. (3) is the resulted model (a reduced form of Eq. (2)) with standard deviations of the estimated coefficients. Fig. 3 gives the response surface and the contour plots based on Eq. (3). Table 3 depicts the results of cross-validation of the models.

$$\Delta TMP = -0.020 - 0.512t_b + 0.074B_f - 0.015B_f^{\ 2} - 0.104B_f t_b \qquad (3)$$

$$(\pm 0.032)\ (\pm 0.472)\ (\pm 0.023)\ \ (\pm 0.004)\ \ \ (\pm 0.149)$$

Table 3 shows that the predicted ΔTMP_p agrees with the estimated ΔTMP from the experimental data to some extent with a mean square error (*MSE*) of 0.18 and thus confirming the validity of the model. Hence, there is a clear indication that the model is valid in the region of the nominal working points employed in this study.

Table 3: Results of model validation for HB using the 2^3 factorial design

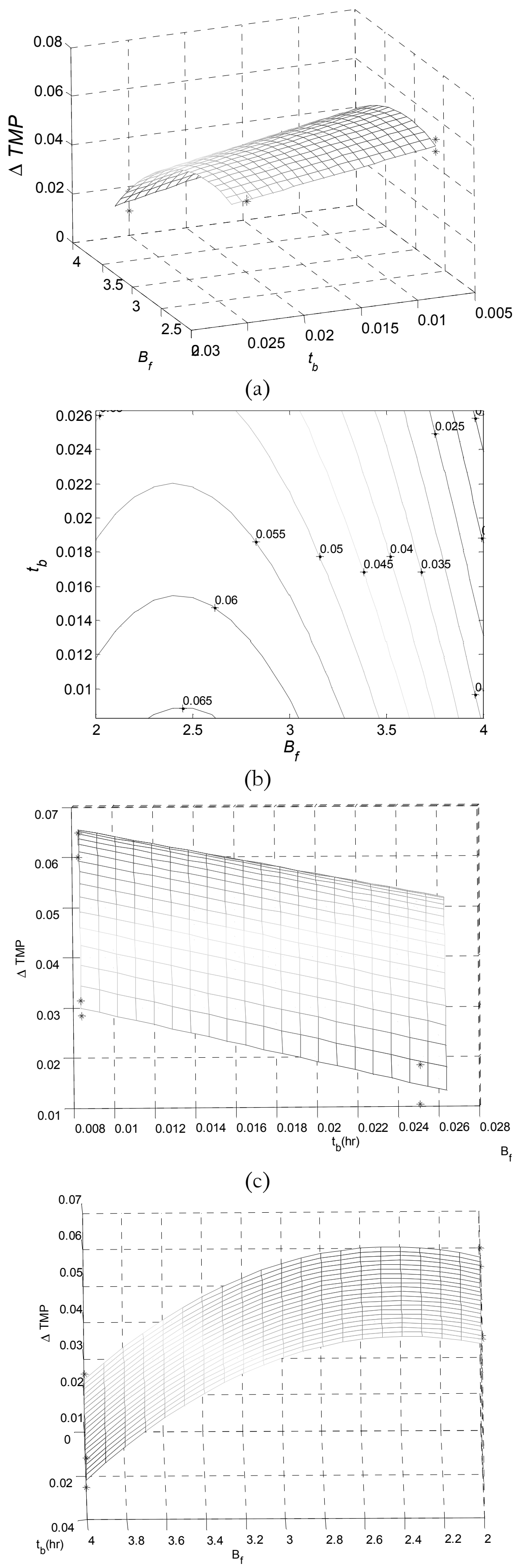
No. of Expt.	J_b ($l\,m^{-2}h^{-1}$)	t_b (min)	B_f	ΔTMP (bar)	ΔTMP_p (bar)
1	0	0	0	0.036	0.054
2	+1	+1	+1	0.022	0.014
3	+1	+1	-1	0.044	0.051
4	+1	-1	+1	0.050	0.030
5	-1	+1	+1	0.013	0.014
6	-1	+1	-1	0.015	0.051
7	-1	-1	+1	0.032	0.030
8	+1	-1	-1	0.074	0.063
9	-1	-1	-1	0.080	0.063

** see Table 1 for coded levels. Filtration flux was 100 $l\,m^{-2}h^{-1}$ for all the experiments*

Depending on the process conditions, an individual experimental run can take several hours to more than one day. Hence, effective experimental designs must be chosen and thus, usually small data sets are obtained. In our application on the influencing factors related to *HB*, nine experimental runs (Table 3) have been performed, while the number of regression coefficients was five (Eq. 3). Consequently, the error characteristics, and especially the auto-correlation of the residuals, were difficult to evaluate and thus the standard deviations presented in (Eq. 3) are only rough indications. As an alternative to the stochastic approach, and most appropriate to small data sets, in the past, a so-called set-membership or bounded-error approach has been proposed.

In this approach, it is assumed that the measurement error is bounded, so that effectively at each sample instant, only intervals are considered instead of single points. For a full treatment of this approach, Walter (2002), Norton (2002), and Keesman (2002) should be consulted. In particular, for the linear estimation case exact solutions can be found. These exact solutions can be tightly bound by boxes, which can be found by solving a couple of linear programming (LP) problems. Assuming an error bound on *ΔTMP* of 0.005; the following bounded (interval) estimates of the coefficients in (Eq. 3) were found and presented in the second row of Table 4.

If the error bound chosen is too small, no feasible solution will be found. Hence, there exists a minimum error bound for which the interval estimates reduce to a single point. This point estimate is called the min-max estimate. For our application, the min-max estimate of the coefficients is presented in the third column of Table 4. Note that these min-max estimates are not too far from the least-squares estimates. The essence of this bounded-error approach is that now reliable uncertainty regions around the estimates are found.



(a) (b) (c) (d)

Fig. 3. Response surfaces and contour plots (plus data points) for HB (a) response surface showing relationship between ΔTMP and t_b and B_f (b) the contour plot relating ΔTMP to t_b. and B_f (c) response surface showing the relationship between ΔTMP and t_b. (d) the contour plot relating ΔTMP to t_b.

Table 4: Bounded-error estimation results for HB

ΔTMP_0	α_1	α_2	α_3	α_4
[-0.081 0.042]	[-1.62 0.60]	[0.028 0.119]	[-0.023 -0.007]	[-0.45 0.24]
-0.022	-0.518	0.076	-0.015	-0.114

From the contour plot of Fig. 3, it can be seen that the model predicts a small decrease of ΔTMP when B_f is smaller than 2.5. This is a rather unlikely phenomenon. If there is sufficient evidence that the maximum should be at B_f = 2, then this information can be easily incorporated into the empirical modelling approach. Setting $\left.\frac{\partial \Delta TMP}{\partial B_f}\right|_{B_f=2} = 0$, where the derivative can be easily found from (Eq. 3), leads to the following constraint between α_2 and α_3: $\alpha_2 + 2\alpha_3 B_f = 0$, so that $\alpha_2 = -4\alpha_3$. Hence, after substitution of this relationship, the model structure of (Eq. 3) becomes

$$\Delta TMP = \Delta TMP_0 + \alpha_1 t_b + \alpha_3(-4B_f + B_f^2) + \alpha_4 t_b B_f \qquad (4)$$

in which the coefficients have to be re-estimated.

Fig. 3 shows that as the t_b increases, the ΔTMP linearly decreases. It can be explained that the longer the time for backwashing, the lower the change in the TMP. This shows a good removal of the fouled layer. Meanwhile, it is expected that for $t_b \to 0$, ΔTMP will become very high (i.e. indicating no removal of foulant), indicating a hyperbolic relationship. Note, however, that the experimental data (Table 3) only support a linear relationship. Therefore, most likely the relationship between ΔTMP and t_b is inverse proportionality. However, this can only be verified through additional experimental runs to get more data points beyond the region considered in this study.

Also, Fig. 3 shows that as the backwash frequency B_f increases from 2 to 4, ΔTMP decreases quadratically with increasing B_f. It can be explained that at low frequencies, there is more formation of cake layer than can be removed with backwash. But as the frequency increases, the cake layer is washed off the membrane. This restores the original property of the membrane. Therefore, the model shows that the higher the frequency of hydraulic backwash, the lower the ΔTMP (i.e. the higher the degree of recovery of the initial membrane flux).

4. CONCLUSIONS

In this study, a model for hydraulic backwash has been developed and cross-validated using an empirical modelling approach, in particular the *RSM*. The modelling was based on experimental data from the *SMART-XIGA (Norit)* pilot plant, using 2^3 factorial designs to limit the number of experimental runs, with the aim of studying the full behaviour and possibilities for optimization of a UF plant. Cross-validation led to the conclusion that the model is reliable under the given experimental conditions. The model showed that *HB* is largely influenced by backwash time and backwash frequency with backwash flux having no effect. However, for further implementation in practice, due to changes in the feed water quality, a regular update of the models is necessary and can be obtained using the methodology presented in this paper.

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