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Neural networks: a tool to improve UF plant productivity

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Abstract

The aim of this work is to develop a predictive control algorithm to improve the productivity of an ultrafiltration pilot plant producing drinking water from surface raw water. The objective is to avoid irreversible fouling, that means to get a constant quality of the membrane after backwash and at the same time to optimise the productivity of the process. This control strategy is based on a model able to predict long-term performances of the ultrafiltration pilot plant. This model consists in two interconnected recurrent neural networks coupled with the Darcy's law. The parameters taken into account are water quality parameters, operating conditions during filtration time and during the backwash procedure. The model allows predicting satisfactorily the filtration performances of the experimental pilot plant obtained for different water quality and changing operating conditions, during several hundred filtration cycles.

Keywords: Drinking water production; Ultrafiltration; Fouling; Long-term modelling; Predictive control

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1. Introduction

Due to intense regulatory activity and recent microbial outbreaks, low-pressure membrane technologies (microfiltration and ultrafiltration) are recognised by the water industry as very attractive processes for producing drinking water. Moreover UF technology has been demonstrated to be a very efficient process to meet the requirements for *Giardia* turbidity, and virus removal.

With UF systems, the quality of the produced water (in terms of particles, bacteria and viruses) is constant and independent on operating conditions and on the raw water quality. On the contrary the plant productivity depends on these parameters which influence membrane fouling. It seems now necessary to be able to operate industrial plants taking into account the influence of raw water quality and its time-variations on membrane fouling, with the aim to further enhance the plant productivity.

Let us consider filtration/backwash cycles. In the case of a constant permeate flow rate, transmembrane pressure increases during the filtration period and decreases after backwash, as presented in Fig. 1. Therefore a production curve is composed of cycles, each characterised by the transmembrane pressure at the end of the filtration cycle (Tmp-e) and at the beginning of the next cycle, i.e. after backwash (Tmp-b). Variations of Tmp-b and Tmp-e with the cycle number are parameters that can be used to characterise and to describe UF efficiency. Fouling by particle deposition on the membrane surface appears at the scale of a filtration cycle. It is a short-term phenomenon and the difference between Tmp-b and Tmp-e is representative for this so called reversible fouling. Moreover variations of Tmp-b with cycle number are significant of irreversible fouling (non-removable by backwashes), which is mainly due to adsorption of natural organic matters (NOMs) on the membrane surface and into the membrane pores. This is a long-term phenomenon.

2. Long-term modelling

The aim is to develop a long-term predictive model to describe the productivity of a UF membrane pilot plant when operated with surface water. It means to be able to compute transmembrane pressure at cycle ends and at cycle starts on a long term, just knowing the time variation of some water quality parameters and

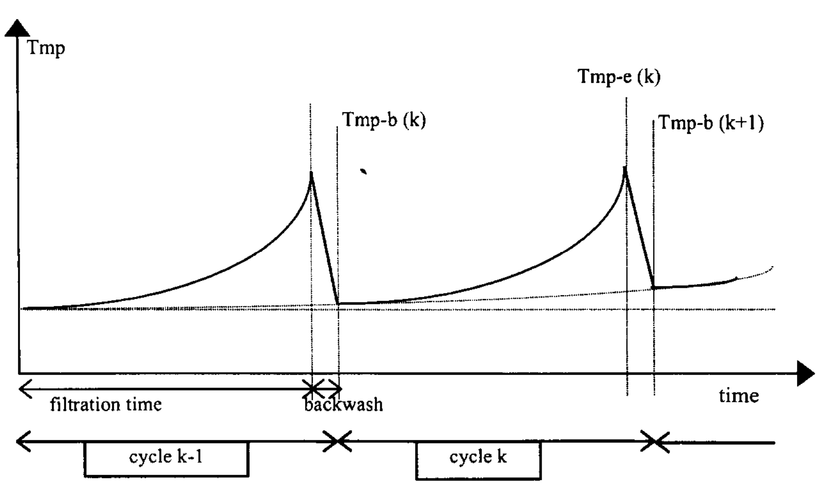

Fig. 1. Example of transmembrane pressure time-variation.

of operating parameters that can vary from one cycle to the other. Parameters that are easy and cheap to measure will be preferably used, so as the model could be applied to industrial plants for simulation.

2.1. Structure of the hybrid model

Parameters involved in fouling in the case of surface water treatment are numerous (water quality and operating parameters) and interdependent. Despite the great number of studies focusing on fouling, phenomenological models developed for ideal solutions are not able to describe membrane fouling by natural water. The only available relationship is the Darcy's law which describes the total hydraulic resistance R at a given time as a function of mean transmembrane pressure Tmp, permeate flow rate Q_p and water viscosity m which varies with temperature:

$$R = \text{Tmp} / (\mu . Q_p / S) \quad (1)$$

The total resistance R includes the membrane resistance, the resistance due to reversible fouling and the resistance due to irreversible fouling.

The model developed here lies on the coupling of an empirical model with the only knowledge model available, which means with Darcy's law. The principle of this modelling is introduced on Fig. 2. For a given cycle, k, the values of Tmp-b(k), $Q_p(k)$ and $T(k)$ allow computing the resistance at the beginning of cycle k, R-b(k). A model is then necessary to compute the value of R-e(k) the resistance at the end of the cycle k and R-b(k+1), the resistance at the beginning of next cycle knowing the water quality parameters and the operating parameters during cycle k. From the computed value of R-e(k) and of R-b(k+1), the Darcy's law can be used again to compute Tmp-e(k) and Tmp-b(k+1).

2.2. Choice of a model to describe cycle-variations of resistance

As far as a large number of data can be obtained from pilot plants, statistical models appear as promising tools for developing simulation models. Among such tools, the model chosen in this work lies on a combination of artificial neural networks (ANNs). In the field of process engineering, neural networks have been successfully used in

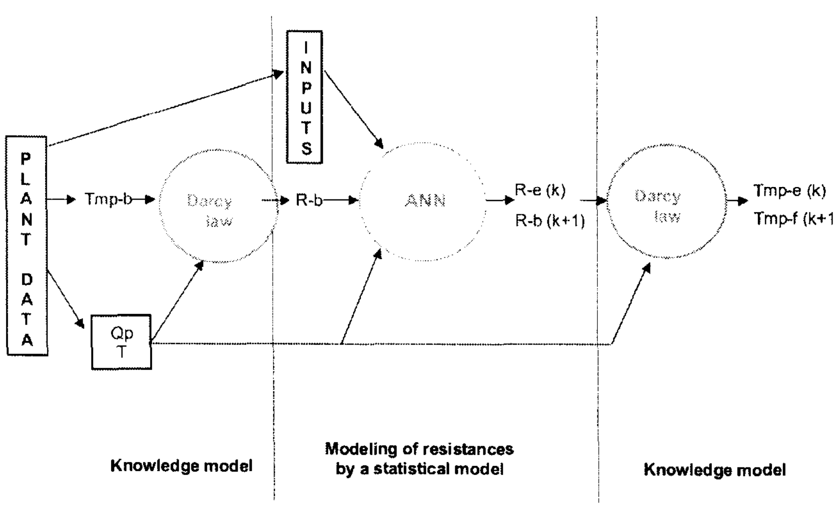

Fig. 2. Structure of the hybrid model.

process modelling and control [1–4], and some trials have been promising in the field of crossflow microfiltration of cane sugar [5] and of baker's yeast [6], reverse osmosis of ethanol and acetic acid [7] and ultrafiltration of surface water [8] and of proteins [9]. In a previous study, neural networks have been successfully used to predict short-term performances of UF for drinking water production [8].

3. The pilot plant and data collection

The pilot plant schematised in Fig. 3 used one 7.2 m^2 Aquasource UF module containing cellulose acetate hollow fibres. The fibres inner diameter was 0.93 mm. Raw water (Seine river water) was pre-filtered to 200 μm, then injected in the circulation loop by the feed pump P1. The pilot plant was operated at a constant permeate flow rate (Q_p). The feed velocity at the module inlet was fixed by the circulation flow rate (Q_c). Experiments were performed both in dead-end and in crossflow filtration. Sequential backwashes were automatically operated with a constant volume of chlorinated UF water.

The following operating parameters, concerning both filtration and backwash operating conditions, were varied during long term periods at different seasons: permeate flow rate (Q_p), circulation flow rate (Q_c), filtration time (t_F), chlorine concentration in the backwash water ($[Cl]_{back}$), backwash pressure (P_{back}), backwash duration (t_{back}).

During the test period, various parameters were recorded, the range of which is introduced in Table 1.

- Water quality parameters: turbidity (TUR), pH, dissolved oxygen (O_2), temperature (T) and oxido-reduction potential (E_h) of the raw water; UV_{254} absorbency, Total Organic Carbon (TOC) of the permeate
- Performance parameters: transmembrane pressures at the beginning and at the end of each filtration cycle.

The whole data base was composed of curves, each containing between 60 and 140 filtration/backwash cycles. It totalled about 4000 filtration/backwash cycles. Different kinds of curves were obtained depending on the raw water quality. Three behaviours were observed:

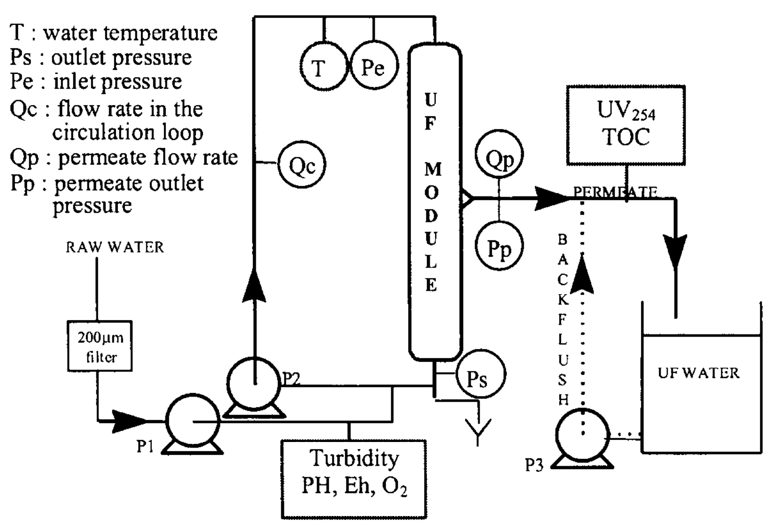

Fig. 3. The pilot plant.

Table 1
Range of operating and water quality parameters during on site-testing

Operating conditions						Water quality parameters								
F_p $L.h^{-1}.m^{-1}$	t_F min	V_c $m.s^{-1}$	P_{back} bar	Cl_{back} $mg.L^{-1}$	t_{back} s	Tur NTU	TOC $mg.L^{-1}$	UV_{254} m^{-1}	O_2 $mg.L^{-1}$	pH	Eh mV	T °C	Tmp bar	R-c m^{-1}
40	5	—	1.5	2	60	0	0.4	1.7	3.6	7.2	130	6	0.1	$1.3\ 10^{12}$
100	60	1.1	2.5	15	150	170	5.9	13.9	9.1	8.4	940	24	1.8	$8.5\ 10^{12}$

- No fouling occurs whatever the operating conditions,
- Reversible fouling without irreversible fouling: backwashes are efficient to remove fouling, as the resistance at cycle starts remains quite constant,
- Both reversible and irreversible fouling: R-b increases with the cycle number, which means that irreversible fouling occurs, backwashes are not efficient enough to remove fouling.

4. Development of the ANN to describe the resistance variation

4.1. Architecture of the model

The aim for the ANN is to compute resistances at cycle ends and at cycle starts on a long term, just knowing the time variation of water quality parameters and of operating parameters that can vary from one cycle to the other. The only resistance data given to the model is the one measured at time 0. The model thus requires a recurrent neural network. The most interesting architecture consists of two interconnected neural networks. The first one (ANN1) is specialised in the prediction of R-e while the second (ANN2) computes R-b (i.e. after backwash). In the first network (ANN1), the inlets should be the resistance at the current cycle beginning, and water quality parameters that are necessary to quantify fouling. In ANN2, the inlets should be the resistance at the end of the filtration period (which was computed by ANN1), the water quality parameters previously used to quantify fouling, and the operating conditions during the backwash procedure so as to predict the backwash efficiency. These considerations lead to the architecture presented in Fig. 4.

4.2. Neural network design and training

Each neural network used in this modelling is composed of three layers: an input layer, one hidden layer and an output layer. The activation function used was the sigmoid function. Only some of the curves from the database were used for training. From these curves, two data sets were considered. The first one, called the learning data set, was used to update the weights. The second one, called the test database, was used to determine the optimal weights, which give the minimum error on this test base, in order to avoid over-training. The two neural networks ANN1 and ANN2 were independently trained using the following learning procedure, then connected and used recurrently.

Different neural networks were developed for ANN1 and ANN2: the number of inlet parameters and the network structure were varied. Several ANNs lead to satisfying predictions. Coupled with the Darcy's law, these ANNs allow predicting variations of Tmp with cycle number with a very good accuracy, taking into account variations of water quality and operating parameters. Let us point out that, for a specific curve, the only transmembrane pressure given to the model is the one at time 0. The model only needs Tmp at the first filtration cycle to predict the variation of Tmp

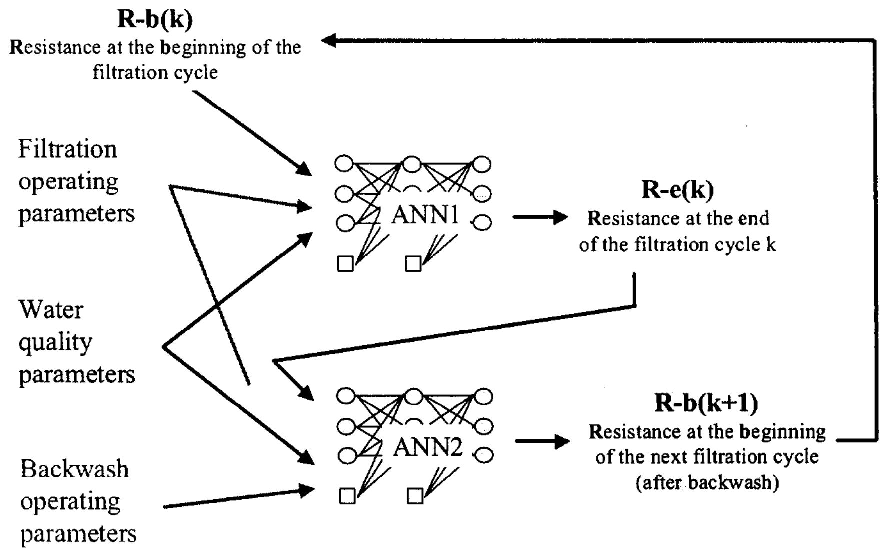

Fig. 4. Architecture of the ANN for modelling of resistances.

during several hundred cycles. The operating parameters found to be influent are permeate flow rate, filtration time, backwash pressure and chlorine concentration.

Validation of this model in case of experiments with or without irreversible fouling, was presented in a previous paper [10]. Globally, it should be pointed out that the most important result is that the model allows predicting the shape of the different experimental curves (variations of Tmp with time and with cycle number) and the effects of water quality parameters and operating conditions.

5. Control strategy

Once validated, the global model was used in a predictive optimal control procedure to simulate the behaviour of the process in terms of trans-membrane pressure at the end of the cycle and at the beginning of the next cycle.

The objective of the control is to avoid irreversible fouling, that means to get a constant quality of the membrane after backwash and at the same time to optimise the productivity of the process which is characterised by the ratio: amount of produced water on filtration time.

Generally speaking, the control variables which can be modified at every filtration cycle concerned the operating conditions (filtration time, permeate flux) and backwash conditions. In this work, backwash conditions are fixed and therefore the control variables concern the filtration operating conditions: filtration time (t_F) and permeate flux (J_p). According to normal operating conditions, the variation ranges of these variables are 40–90 $l.h^{-1}.m^{-2}$ for J_p and 25 to 55 min for t_F. To perform the determination of the manipulated variables (t_F and J_p), a grid space was used with steps of respectively ΔJ_p=2.5 $l.h^{-1}.m^{-2}$ and Δt_F=5 min.

As far as limitation of irreversible fouling is considered as a priority, it is translated by a constraint on the permeability (L_p) of the membrane (defined by $L_p = 1/(\mu_p R)$) which must not become lower than a given value at the end of the prediction horizon. In practice, the permeability of a new membrane is around 200 $L.h^{-1}.m^{-2}.bar^{-1}$. It has been established that, after some working period, it is possible to avoid irreversible fouling when the permeability is maintained greater than 160 L.h^{-1}.m^{-2}.bar^{-1} after backwash. Therefore this value has been taken for constraint L_p-c in the optimal control procedure.

At each cycle, variation of the permeability is computed on a prediction horizon of 10 cycles ($L_p(t+10)$) assuming constant water quality parameters. Among the couples of operating conditions (t_F, J_p) which satisfy $L_p(t+10) >= L_p$-c, the one which is chosen to be applied to the process during the next filtration cycle is the one which leads to the best water productivity. This productivity is defined by the ratio of the amount of produced water (filtered water minus water used for backwash) on the cycle duration. To avoid strong variations of the permeate flux from one cycle to the other, a maximal variation of 5 L.h^{-1}.m^{-2} is introduced.

Experiments have been carried out for several months on Seine river water with a constant circulation velocity in the fibres (0.9 m.s^{-1}). Backwash pressure was fixed to 2.5 bar, chlorine concentration to 5 mg.L^{-1} and backwashes were operated with a constant volume (55 L). Variation of the manipulated variables (t_F and J_p) for a period of 20 d are presented in Fig. 5.

The predicted values of Lp at the end of the 10 cycles prediction horizon (L_p10-e: at the end of the cycle and L_p10-b at the beginning of the next cycle, that means after backwash) are plotted in Fig. 6. It is clear that L_p10-b never decreases under the constraint L_p-c even if L_p10-e reaches this value. Let us notice that interruptions in the curves correspond to breaks due to technical incidents (sensor problems, etc.).

To show the interest of such a control strategy, two performance indexes have been estimated: the net permeate flux (J_p net) of produced water (filtered water minus water used for backwash) and water losses (water used for backwash on filtered water) during the complete filtration-backwash cycle. We can observe that the value of J_p net is rather high (around 80 L.h^{-1}.m$^{-2)}$ while water losses (WL) are very small around 10–15%. It is interesting to compare these values to those which would have been obtained if usual operating conditions (60 L.h^{-1}.m^{-2} and 30 min) had been applied: 40 L.h^{-1}.m^{-2} and 25%.

6. Conclusions

In this work a model was developed to predict long-term performances of an ultrafiltration pilot

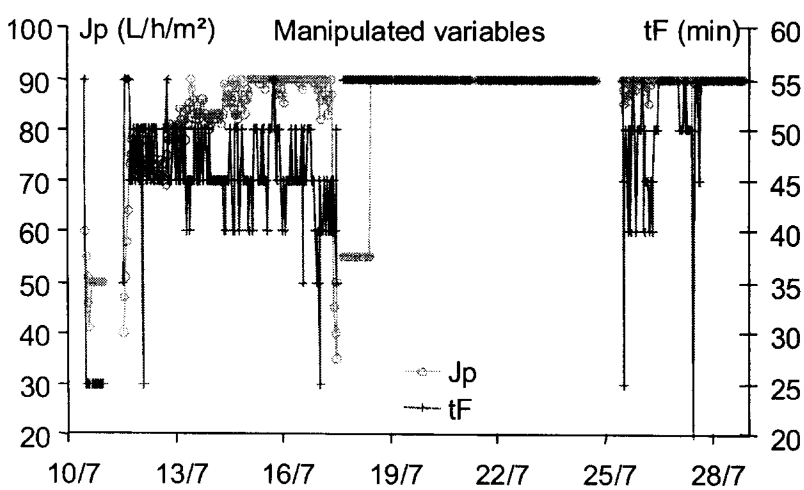

Fig. 5. Variation of the manipulated variables (t_F and J_p).

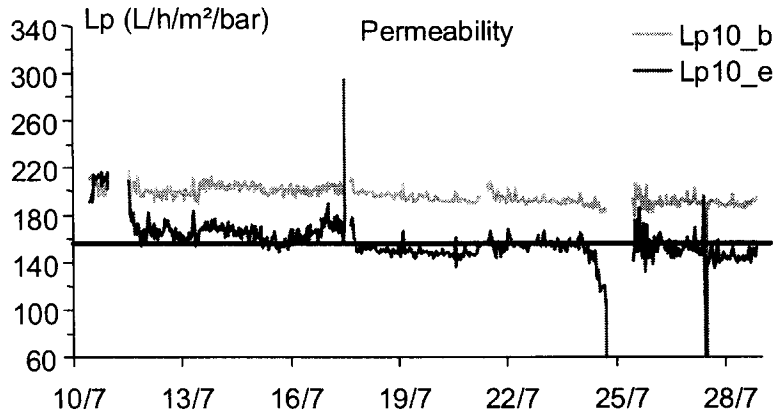

Fig. 6. Comparison of the predicted values of L_p with the constraint.

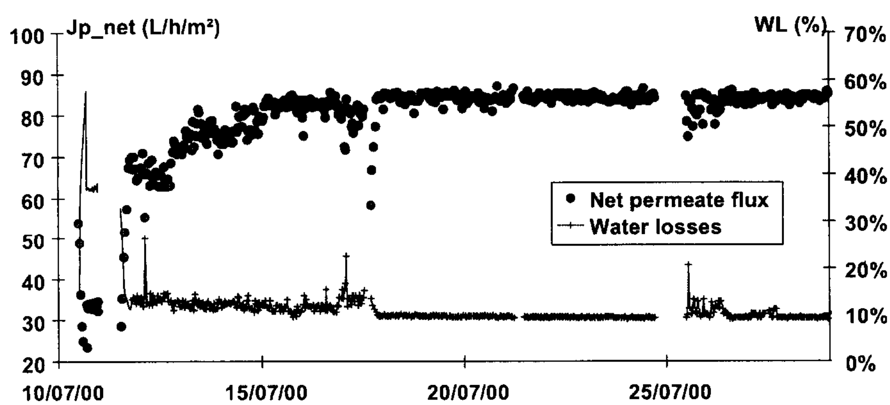

Fig. 7. Variation of net permeate flux and water losses for an experiment with control.

plant producing drinking water from surface raw water. The model consists in two interconnected recurrent neural networks coupled with the Darcy's law: the first one is specialised in the prediction of membrane permeability at the cycle end, the second one computes the membrane permeability after backwashing. The model only needs membrane property at the first filtration cycle to predict the variation of transmembrane pressure during several hundred cycles. The model inputs are water quality parameters and operating conditions during filtration time and during backwash. The model allows predicting satisfactorily the filtration performances of the experimental pilot plant obtained for different water quality and changing operating conditions, even in the case of hard fouling conditions.

This model was integrated in a predictive optimal control strategy to improve the operation of the filtration unit. The objective was to avoid irreversible fouling and to increase the plant productivity. The efficiency of the control strategy was experimentally demonstrated on the pilot plant and the performances were advantageously compared to those obtained with usual industrial operating conditions.

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