Optimal control of the microfiltration of sugar product using a controller combining fuzzy and genetic approaches

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A SUGENO type fuzzy controller is proposed for the automatic control of the crossflow microfiltration process for raw cane sugar. This process is becoming a field of increasing importance in the food industry. In most cases, and especially for sugar products, widespread applications of crossflow microfiltration is limited by the low permeate fluxes usually obtained. This limitation is linked to the difficulty to reduce the degree of membrane fouling (settling of particles on the membrane), a phenomenon which is dependent on several variables and difficult to control. In the present work, human expertise of the process is used to set up the fuzzy controller. The fuzzy controller is validated through simulations using a neural network model of this process and by real time experimentation on a pilot plant. The results of simulations and pilot tests show that it becomes possible to impose dynamics to the process which permits to maintain the state variable close to a given reference and to limit membrane fouling considerably. An off-line optimization of the fuzzy controller is performed using genetic algorithms. The cost results obtained during a real experiment, after genetic optimization of the fuzzy controller are much better than those obtained previously. Furthermore, the tuning of the controller through optimization is realized under constraints which lead, after optimization, to a heuristic structure completely understandable by microfiltration experts.

Keywords: Fuzzy control; Knowledge acquisition and learning; Engineering; Process control

0. Introduction

In food industries, processes are often complex because of nonlinearity, unsteady state, interactions between process variables and the lack of knowledge concerning their control. The widespread numerical approaches (decisional or control theories) are still in those cases of restricted efficiency. As a consequence, many open loops are encountered in which the role of the human operator becomes more and more important. Product properties which contribute to quality, and process productivity depend mainly on the accuracy of the operator's reaction. In this context, fuzzy control can be considered as a relevant approach [5, 16]. Indeed when physical knowledge of the process is not available,

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the fuzzy concept enables us to handle the heuristic rules provided by the expert of the process [6]. Use of fuzzy coding permits a representation of the graduality and vagueness of expert knowledge. Consequently, it gives a good fuzzy control robustness with respect to sensor noise. In fact fuzzy approach leads to an operator behavior model rather than a process model.

Among food industries, the crossflow microfiltration process is a good example. Crossflow microfiltration is becoming a field of increasing importance [1–3]. This technique of separation is particularly used to clarify different types of liquids [15] thanks to the sifting properties of a porous membrane submitted to a pressure gradient. The most commonly used performance criterion in this process is the permeate flux which is directly linked to the efficiency of the filtration. On an industrial scale, the development of the crossflow microfiltration process is partly limited by membrane fouling [1]. Filtration properties and membrane selectivity are influenced by membrane fouling development during filtration time [2]. Permeate fluxes are mostly linked to the degree of membrane fouling. Its intensity depends on membrane characteristics, nature of the product and operating conditions. The dynamic development of fouling and operating condition effects are nonlinear. Indeed a given stepwise change in the control variables at different filtration times does not affect the permeate flux in the same way [13]. As a result conventional control methods are difficult to use and process control is often non optimal, the efficiency is uncertain and essentially based on operator's experience.

In this context it is interesting to use fuzzy logic to control the crossflow microfiltration process. For the moment, there are few applications of fuzzy logic in food industries. Some of them can be found in drying [17], fermentation [8] and extrusion [10].

The objective of this paper is to use a fuzzy controller to control the crossflow microfiltration process of raw cane sugar so as to maintain the permeate flux (F_p) at a given reference value (consequently so as to control membrane fouling) and to optimize this control. Two major variables could be considered for this process control: transmembrane pressure and crossflow velocity [4]. This paper consists of two sections: in the first, methods and tools used to validate and optimize the fuzzy controller are presented. In the second, simulation and experimental results are discussed.

Before we proceed further, we present a list of symbols used in this paper,

Filtration characteristic variables

delta(F_p)	$F_{p[sp]} - F_p(t)$ gap between permeate flux set point and current measured permeate flux (l/(h m^2))
delta(P_{min})	$P_{tm}(t) - P_{tm\,min}$ gap between the current measured transmembrane pressure and the minimal transmembrane pressure (bar)
F_p	permeate flux (l/(h m^2))
$F_{p\,moy}$	average permeate flux in a simulation (l/(h m^2))
$F_{p[sp]}$	permeate flux set point (l/(h m^2))
η	average dynamic viscosity of the syrup (m Pa)
P_p	permeate pressure (bar)
P_r	retentate pressure (bar)
P_{tm}	transmembrane pressure (bar)
$P_{tm\,max}$	maximal value of transmembrane pressure (bar)
$P_{tm\,min}$	minimal transmembrane pressure (bar)
$P_{tm\,moy}$	average transmembrane pressure in a simulation (bar)
$P_{tm\,[sp]}$	transmembrane pressure set value (bar)
R_t	total hydraulic resistance (10^{10} m^{-1})
U	crossflow velocity (m/s)
$U_{[sp]}$	crossflow velocity set value (m/s)
U_{max}	maximal value of crossflow velocity (m/s)
U_{moy}	average crossflow velocity in a simulation (m/s)

Fuzzy controller characteristic variables

a_1, a_2, m	fuzzy parameters of the partition of delta(F_p)
b_1, b_2	fuzzy parameters of the partition of delta(P_{min})
$p_j[U]$	constant value of the output variable U associated to each rule R_j (bar)

$p_j[P_{tm}]$ constant value of the output variable P_{tm} associated to each rule R_j (m/s)
R_j rule j of the knowledge base

Optimization variables

β coefficient of compromise between accuracy and stability of the control
FF fitness function
L size of the population
P_m probability of mutation
P_c probability of crossover

1. Materials and methods

1.1. The microfiltration process

In a crossflow microfiltration process, liquids are passed through a microfiltration module, at a tangential velocity, U. The part of the liquid which goes through the membrane is called the permeate. The other part of the liquid is called the retentate. During the filtration, particles settle on the membrane and increase membrane fouling. As a consequence, the permeate flux (F_p) decreases and the resistance of the membrane increases. The total hydraulic resistance (R_t) is defined by Darcy's law ($F_p = P_{tm}/\eta \times R_t$). At 80°C, the average dynamic viscosity of the syrup is about 4.86 mPa. In our study the performance criterion considered is either permeate flux (F_p) or total hydraulic resistance (R_t).

The filtration module is composed of a porous membrane, submitted to a transmembrane pressure (P_{tm}). This transmembrane pressure is defined as the difference between retentate and permeate pressure ($P_{tm} = P_r - P_p$). To avoid malfunction during filtration, it is important to maintain a minimal transmembrane pressure ($P_{tm\,min}$). This minimal pressure is linked to the crossflow velocity by

$$P_{tm\,min} = \frac{1}{4}\lambda\rho U^2 \frac{L'}{D}$$

(λ = friction coefficient linked to the Reynolds number; ρ = liquid density (kg/m^3); U = velocity (m/s); L' = equivalent length of piping (m); D = diameter of the pipe).

The ENSIA crossflow microfiltration unit is a batch unit with partial recycling of retentate. On-line data acquisition as well as different regulations around set point value are done by a programmable microprocessor. This system (control level) is connected to a micro-computer which ensures interface with operator and data handling (supervision level). The automatic system controls the crossflow velocity (U) around a set value ($U_{[sp]}$) by means of a centrifugal pump (P_{cent}), the transmembrane pressure (P_{tm}) around a set value ($P_{tm[sp]}$) by means of a volumetric pump (P_{vol}) and the average temperature in the filtration module around a set value by means of electrical resistances and a heat exchanger (Fig. 1.) [3, 12]. The filtration experiments presented in this paper are carried out with total recycling of the permeate (without concentration) and at a constant temperature of 80 °C. The maximal values of transmembrane pressure and crossflow velocity acceptable for the pilot are fixed, respectively, to $P_{tm\,max} = 3$ bar and $U_{max} = 7$ m/s.

The solutions used are obtained by direct remelting of raw cane sugar. The dry matter content is about 56% DM. Before filtration, the syrup is prefiltered on a 360 μm diameter screen.

The chosen membrane of 1.4 μm average pore diameter, was supplied by 'Société des Céramiques Techniques' (SCT, France) under the registered trade-mark MEMBRALOX. This tubular and asymmetrical module is composed of 19 channels each with a 4 mm hydraulic diameter corresponding to a total 0.2 m^2 effective filtration area.

1.2. The microfiltration controller

(A) *Methods used to control the process*

Feedback control principle. Our aim is to maintain a constant permeate flux by acting on the relevant control variables of the process: transmembrane pressure (P_{tm}) and crossflow velocity (U). We use a closed loop control. It consists of action on the set point values of transmembrane pressure and crossflow velocity according to the gap (delta(F_p)) between the permeate flux set point ($F_{p[sp]}$) and the current measured permeate flux ($F_p(t)$) so as to maintain a constant permeate flux. An other input variable has to be taken into

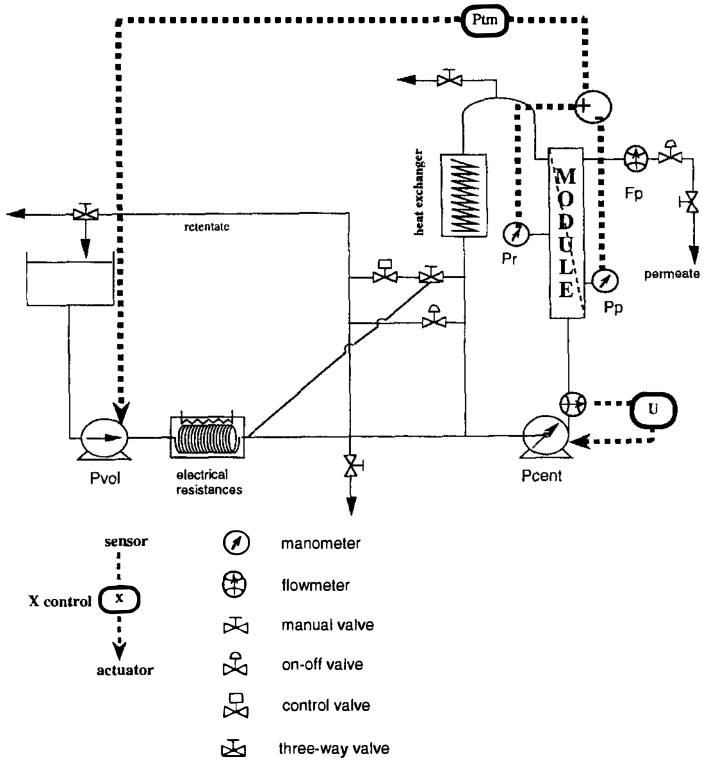

Fig. 1. Schematic representation of the microfiltration unit.

account to ensure the filtration on the whole membrane area: a minimal positive gap between the transmembrane pressure (P_{tm}) and the minimal transmembrane pressure ($P_{tm\,min}$) (delta(P_{min}) = $P_{tm} - P_{tm\,min}$) (Fig. 2).

Principle of the validations. The procedure adopted to validate the fuzzy controller regulation of the permeate flux (at a constant value) consists of two consecutive stages. In the first step, validation is provided by simulations using a neural network based process model. In the second step, experimental tests on the ENSIA filtration unit are performed. All the validations (simulated or experimental) are carried out for a given membrane/product combination as explained in the previous section.

Simulations are done on the one hand to evaluate the real control capacity of the developed fuzzy algorithm and on the other hand to tune approximately the controller in manual fashion. The simulation algorithm is implemented on PC using the Matlab software toolbox. Two imbricated loops compose the algorithm: (1) the neuronal simulation of the process and (2) the simulation of the fuzzy controller (Fig. 3). The fuzzy controller acts on the input of the model (P_{tm} and U) every six loops of the neuronal model after having evaluated delta(F_p) and delta(P_{min}). This corresponds to a control action on the process every two minutes.

For the experimental validation, the fuzzy controller is implemented in the computer used for the supervisory level. Thus, the fuzzy controller is activated every two minutes and the new set points are calculated according to the previous set points and the current process state.

(B) *The fuzzy controller*

Variables of the fuzzy controller. The input/output variables of the controller are represented in Fig. 2.

Input variables:

delta(F_p) = $F_{p[sp]} - F_p(t)$; the gap between the permeate flux set point and the current measured permeate flux

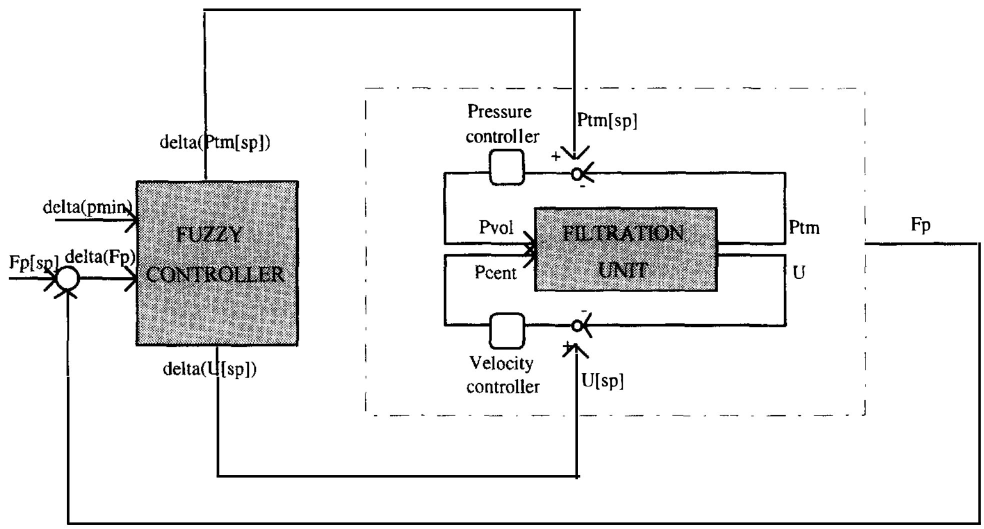

Fig. 2. Representation of the control loop of the microfiltration process using a fuzzy controller.

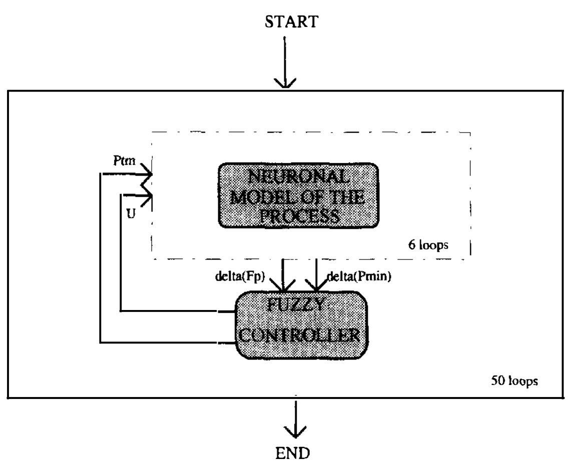

Fig. 3. Simulation algorithm of the control of microfiltration process by fuzzy logic.

delta(P_{min}) = $P_{tm} - P_{tm\,min}$; the gap between the current transmembrane pressure and the minimal transmembrane pressure.

Output variables:

delta($P_{tm[sp]}$) = $P_{tm}(t+1)_{[sp]} - P_{tm}(t)_{[sp]}$; where $P_{tm}(t+1)_{[sp]}$ is the new calculated pressure set point and $P_{tm}(t)_{[sp]}$ is the previous pressure set point.

delta($U_{[sp]}$) = $U(t+1)_{[sp]} - U(t)_{[sp]}$; where $U(t+1)_{[sp]}$ is the new calculated velocity set point and $U(t)_{[sp]}$ is the previous velocity set point.

Internal structure of the fuzzy controller. The *control strategy* consists of two consecutive steps revealed by human expertise (ENSIA-INRA researchers). This expertise was collected over one month.

Step 1 (while $U < U_{max}$): simultaneous action on crossflow velocity (U) and transmembrane pressure (P_{tm}) until the maximal velocity (U_{max}) is reached. The shearing stress at the membrane wall must be kept as high as possible to limit membrane fouling. For this reason, the strategy in this step consists of increasing crossflow velocity before transmembrane pressure and maintaining the transmembrane pressure as low as possible. The gap between the current permeate pressure and the minimal transmembrane pressure is maintained above 0.05 bar in order to initiate filtration over the total area of the membrane.

Step 2 (for $U \geqslant U_{max}$): action only on transmembrane pressure with crossflow velocity fixed at U_{max} until the maximal transmembrane pressure ($P_{tm\,max}$) is reached.

The *fuzzy control unit* developed is conventional [11]. Thus the inputs of the fuzzy controller are measurable parameters (delta(P_{min}) and delta(F_p)) and the outputs are actions on the process (delta($P_{tm[sp]}$) and delta($U_{[sp]}$)). The numerical inputs are transformed at the first stage into equivalent fuzzy inputs by the way of linguistic terms so as to be treated by fuzzy logic (fuzzification). Then the fuzzy controller calculates the fuzzy output from the fuzzy input with the help of a set of linguistic rules (knowledge base) and fuzzy reasoning. Finally, a numerical output is calculated from the fuzzy output (defuzzification). Different kinds of fuzzy reasoning (and consequently different fuzzy controllers) could be applied to calculate through the linguistic rules the actions on the process from the numerical input parameters of the controller. The fuzzy controller implemented in the supervisor of the microfiltration unit is a TAKAGI-SUGENO constant output type fuzzy controller [14]. Thus the numerical control (c) is directly calculated with the activation grades (α_j) and the constant output parameters (p_j) of each rule j ($c = \sum_i \alpha_j p_j / \sum_j \alpha_j$). The Tnorme operator is the minimum one.

The fuzzy membership functions of the input variables delta(F_p) and delta(P_{min}) are represented on Fig. 4. (respectively (a) and (b)). Delta(F_p) is defined on the scale of ([−100; 100]) and the linguistic notions associated to its input are: 'NEG' for a permeate flux over the permeate flux set point, "ZERO" for a permeate flux near the permeate flux set point and 'POS' for a permeate flux under the permeate flux set point. Delta(P_{min}) is defined on the scale ([0; 2]) and the linguistic notions associated to its input are: "BAD" for a pressure gap under 0.05 bar and "GOOD" for a nonlimiting transmembrane pressure considering the control policy (above 0.1 bar). The safety margin of this constraint is 0.05 bar.

The knowledge base is composed of two blocs according to the two stages of the control strategy previously described. The first rule basis (RB1) is associated to step 1 of the strategy and the second rule basis (RB2) to step 2 of the strategy. One of this rule bases (RB1) is presented below.

RB1:

R1_If *delta*(F_p) POS and *delta*(P_{min}) BAD
then increase $P_{tm[sp]}$ and do not increase $U_{[sp]}$,
R2_If *delta*(F_p) POS and *delta*(P_{min}) GOOD
then increase $U_{[sp]}$ and do not increase $P_{tm[sp]}$,

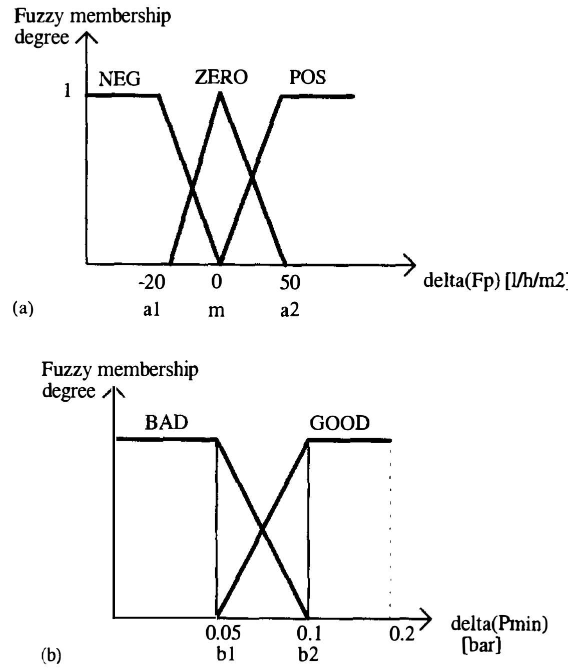

Fig. 4. Fuzzification of the input variables of the fuzzy controller (delta(F_p) and delta(P_{min})).

R3_If *delta*(F_p) NEG and *delta*(P_{min}) BAD
then decrease $U_{[sp]}$ and do not decrease $P_{tm[sp]}$,
R4_If *delta*(F_p) NEG and *delta*(P_{min}) GOOD
then decrease $P_{tm[sp]}$ and do not decrease $U_{[sp]}$,
R5_If *delta*(F_p) ZERO
then keep $P_{tm[sp]}$ and keep $U_{[sp]}$.

The conclusion of each rule (R_j) is associated to a constant value for each output: $p_j[P_{tm}]$ and $p_j[U]$. All those constant parameters in a first step are determined with the help of the expert and by manual tuning during simulations. For example, $p_1[P_{tm}]$ is fixed at 0.05 bar because the transmembrane pressure must be increased in a moderate way.

(C) *The process simulation*

The model used in simulation is a neural network model with one hidden layer with two neurons. The input layer contains the transmembrane pressure, the crossflow velocity at time t and the total hydraulic resistances measured at time t and $(t-1)$. The output layer contains the predicted total hydraulic resistance at time $(t+1)$ (Fig. 5).

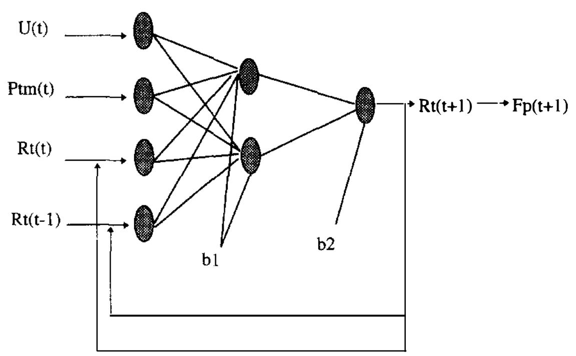

Fig. 5. Neural network model of the microfiltration process ((·) = R_t simulated and (+) = R_t real).

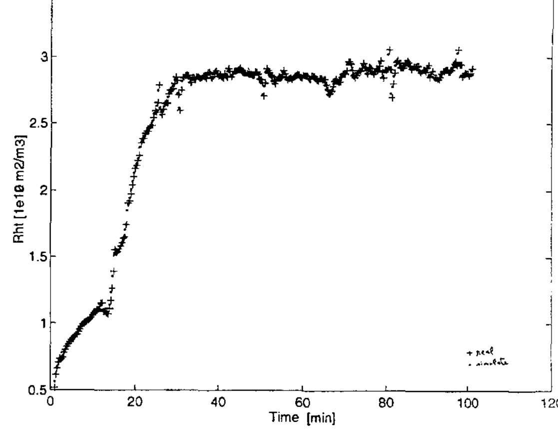

Fig. 6. Comparison on a test base between an experimental curve and a curve calculated by the neuronal model.

The data base used to model the process comes from previous experiments [4] on the microfiltration pilot plant. Filtration runs on a Membralox membrane (of 1.4 μm average pore diameter) with total recycling (without concentration) and at a constant temperature of 80 °C. The filtered product is raw cane sugar syrup with a dry matter content of about 60 g/100 g. During start-up, transmembrane pressure and crossflow velocity are progressively increased.

The neural network can be exploited directly to predict the total hydraulic resistance over the range of transmembrane pressures and crossflow velocities studied and not over the whole available parametric region. The limits on the pressure and the velocity are: a restriction of the velocity between 2.25 m/s and 5 m/s and a restriction of the pressure between 0.3 bar and 2.3 bar.

One comparison between the experimental and calculated curves obtained with one experiment of the test base is presented (Fig. 6). The experimental and calculated curves are almost superposed (the calculated values are very close to the experimental points and the mean error on data test points is under 10%). Nevertheless some experiments seem to show that the neuronal model does not take into account totally the fouling of the membrane especially in the second part of its development.

1.3. Optimization of the fuzzy controller

Our goal is to optimize the parameters of the fuzzy controller and not its structure. To realize this optimization, we use a heuristic approach called: "genetic algorithms" (GA). Proposed by Holland in 1975 [9], GA are optimum search algorithms based on the mechanism of natural selection in a population [7]. A population is a set of artificial creatures (individuals or chromosomes). These creatures are strings of length 1 coding a potential solution to the problem to be solved. In our case an individual is composed by the parameters to optimize (i.e. each parameter can be seen as a gene in a chromosome). The size L of the population is constant. The population is nothing but a set of points in a search space. The population is randomly generated and then evolves: in every generation, a new set of individuals is created using the best fit or pieces of the best fit individuals of the previous one. The fitness of each individual is simply the value of the function to be optimized (the fitness function FF) for the point corresponding to the individual. The iterative process of population creation is achieved by three basic genetic operators [9]: selection, reproduction or crossover (promotes exploration of new regions of the search space) and mutation (protects the population against an irrecoverable loss of information). Each iteration is called a generation. Genetic operators are randomized ones (*crossover* is applied with a *probability* P_c and mutation with a probability P_m).

The parametric optimization of the fuzzy controller is performed off-line with a genetic algorithm

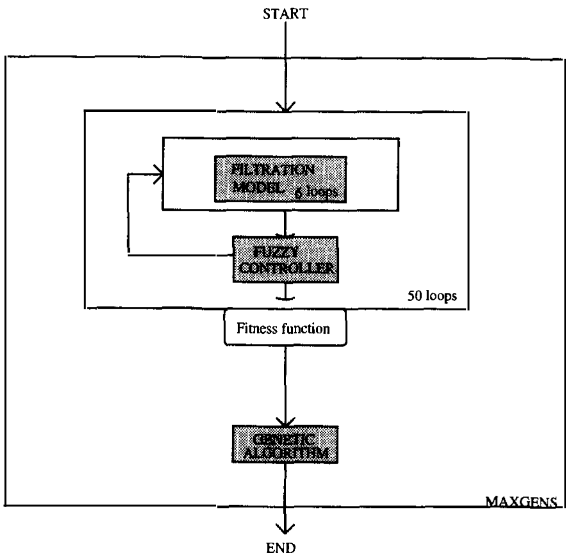

Fig. 7. Schematic algorithm of optimization of the fuzzy controller.

working on the model of the process described in the previous section. The schematic algorithm is presented Fig. 7. Simulations run on an IBM RS6000. A simulation for a given population of 100 individuals and for 500 generations takes 10 min.

Considering the imperfection of the process model (especially on the second part of the development of the permeate flux; see Section 2.1), the optimization is only done on the parameters of the rule basis 1 which corresponds to the first part of the development of the permeate flux. The goals fixed for this study are limited to the optimization of the length of time to reach F_p set point and the accuracy of the control.

Fifteen parameters are used to defined the fuzzy membership functions of delta(F_p) and delta(P_{min}) and the parameters $P_j[P_{tm}]$ and $P_j[U]$ of each rule j of RB1. A study on the sensibility of those parameters (the sensibility is represented here by the effect of a variation of 10% of each parameter on the output of the fuzzy controller) reveals that the sensibility is very different from one parameter to another. Globally the parameters used to define the fuzzy membership function of delta(F_p) and delta(P_{min}) are less sensitive than those used to define the conclusion of each rule j ($P_j[P_{tm}]$ and $P_j[U]$). Thus for example the sensibility of the parameter b_2 is about 70 and the sensibility of the parameter $p_1[P_{tm}]$ is about 400. Among the parameters used to define the fuzzy membership function of delta(F_p) and delta(P_{min}) the most sensitive parameter is b_2. This result is coherent with the expert analysis which underlines the crucial role played by the pressure on the membrane fouling.

In order to respect the linguistic logic established in collaboration with the experts and to keep an interpretable linguistic structure after optimization, 8 parameters out of 15 are fixed. For example $p_1[U]$ is fixed at zero because in the case of rule 1 the expert never accepts an increase or decrease of the crossflow velocity. Two types of constraints are imposed on the other 7 parameters optimized:

- First the fuzzy partition of the input variables space must be the same before and after optimization. This leads to two constraints:

  $a_1 \leqslant m \leqslant a_2$ and $b_1 \leqslant b_2$.

- Second, variation of $P_{tm[sp]}$ and $U_{[sp]}$ must be reasonable and logical to avoid cake formation (as it was underlined by the experts). It leads to constraints on the output variable parameters ($p_j[P_{tm}]$ and $p_j[U]$). For example $p_1[P_{tm}]$ can only be adjusted between 0 and 0.2.

Before the optimization, the population is randomly initialized. The genetic algorithm used has to find an individual (i.e. a set of parameters) which maximizes the fitness function (FF). This function is the following:

FF = 1000/C

with:

$$C = \sum_{300}\left[\left(\frac{F_p - F_{p[sp]}}{F_{p\,moy}}\right) + \beta(UM'UM)\right],$$

$$UM = \begin{bmatrix} \dfrac{P_{tm}(k) - P_{tm}(k-1)}{P_{tm\,moy}} \\ \dfrac{U(k) - U(k-1)}{U_{moy}} \end{bmatrix}$$

$$F_{p\,moy} = \frac{\sum_{300} F_p}{300}\,;\ P_{tm\,moy} = \frac{\sum_{300} P_{tm}}{300}\,;$$

$$U_{moy} = \frac{\sum_{300} U}{300}\,.$$

FF is composed of two parts: the first takes into account the gap between the observed variable (F_p)

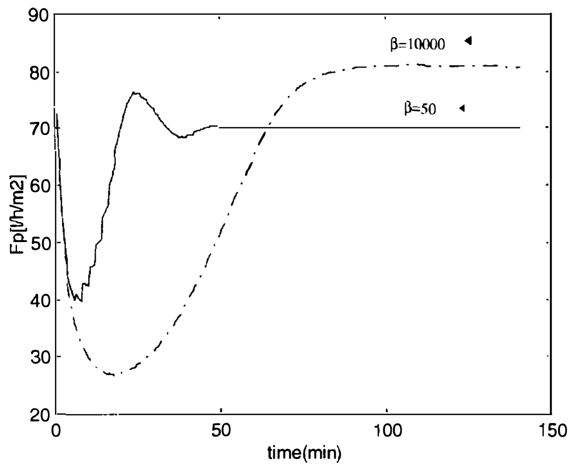

Fig. 8. Influence of β on the control dynamics during a simulation of the fuzzy regulation at a flux set point of 70 l/(h m^2). Parameters obtained by optimization with two different values of β: 50 and 10 000.

and its set point. The algorithm acts on the fuzzy controller parameters so as to reduce this gap. The second one allows to reduce the effect of an optimization only based on the first criterion so as to have a good solution compromise between accuracy of the regulation (brought by the first criterion) and good stability of the regulation. β is the key of this compromise. After a study on the influence of β on the optimization results (Fig. 8 shows an example of the influence of β on the dynamics of the control during a simulation of the fuzzy regulation at a flux set point of 70 l/(h m^2)), for parameters obtained by an optimization with two different values of β : 50 and 10 000), an importance of 30% is given to this last criterion compared to the first criterion (β is set to 50). Thus this is a good compromise between stability (for $\beta < 50$ the stability of the controller is bad) and accuracy (for $\beta > 100$ the accuracy of the control is bad).

2. Results and discussion

2.1. Validation of the fuzzy controller through simulations

Before simulations, the dynamic reaction of the model is tested in open-loop with different kinds of steps and ramps. The model reaction seems to be coherent with the real dynamic behavior of the process. Then, different simulation tests in closed-loop are performed with the fuzzy controller.

For a given permeate flux set point (70 l/(h m^2)), different parameters values are tested before having a quite satisfactory control of the microfiltration process. The better parameters are used for all the other simulations. An example of these parameters for the first rule basis (RB1) is given Table 1.

To validate the fuzzy controller thus obtained, different permeate flux set point values are tested. An example of the change of the controlled variables [P_{tm} and U; delta(P_{min}) and delta(F_p)] versus time as well as the variation of permeate flux versus time are represented Fig. 9 for a permeate flux set

Table 1
Output variable parameters of the fuzzy controller for the first rule basis

BF1/RULE$_j$	$p_j[P_{tm}]$	$p_j[U]$
1	0.05	0
2	0	0.2
3	− 0.05	0
4	0	− 0.1
5	0	0

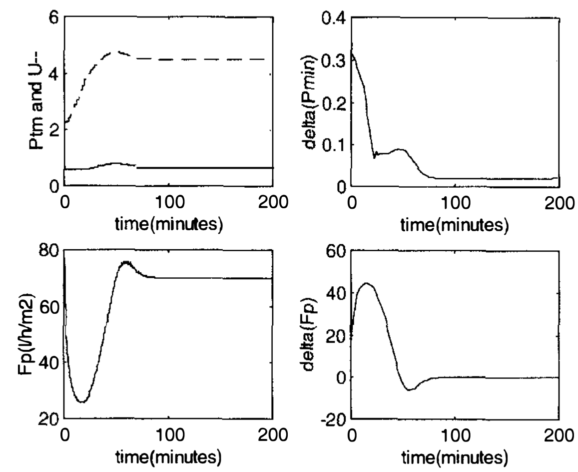

Fig. 9. Variation of P_{tm}, U, delta(P_{min}), delta(F_p) and F_p versus time during a simulation. Closed loop fuzzy control. Set point: 70 l/(h m^2).

point of 70 l/(h m^2). Similar results are obtained for a scale set point values of [40 l/(h m^2), 110 l/(h m^2)].

As shown in Fig. 9, the permeate flux reaches its set-point value in 80 min. The control accuracy and the stability are both good. Moreover, the results are coherent with the fuzzy controller implemented strategy. Thus the curve of delta(P_{min}) shows that the transmembrane pressure is kept as low as possible (near the minimum transmembrane pressure). Whatever the permeate flux set point value, the permeate flux development always follows the same trend and stabilizes at its set-point value. At the same time, transmembrane pressure and crossflow velocity stabilize at an equilibrium value. This situation does not seem to follow the real trend. Indeed membrane fouling increases continuously [4] and pressure and velocity should be manipulated and should change to stabilize the permeate flux. Consequently, it seems that the neuronal model does not take into account the total fouling of the membrane.

To complete this study and before implementing the fuzzy controller on an pilot scale, we tested the fuzzy controller robustness to disturbances or noised values. Thus, for example, the fuzzy controller robustness to noised permeate flux values has been tested. A random gaussian white noise centered at 0 is added to F_p. Results are analyzed for three signal/noise ratios ($R = 30$ db, $R = 23.5$ db, $R = 15.6$ db). Whatever the level of noise measure is, the permeate flux is coming back to its set point.

These results show the ability of the fuzzy controller to control the permeate flux at a constant set-point. This control seems validate in simulation in normal condition as well as in disturbated one. Nevertheless, the neuronal model seems imperfect because it does not seem to take into account the total fouling observed in the experimental variation of the permeate flux. Consequently, experimental validation of the fuzzy controller on the pilot plant is necessary.

2.2. *Validation of the fuzzy controller by experimental results*

Different experimental validations (at two different set points: 70 and 100 l/(h m^2)) are carried out

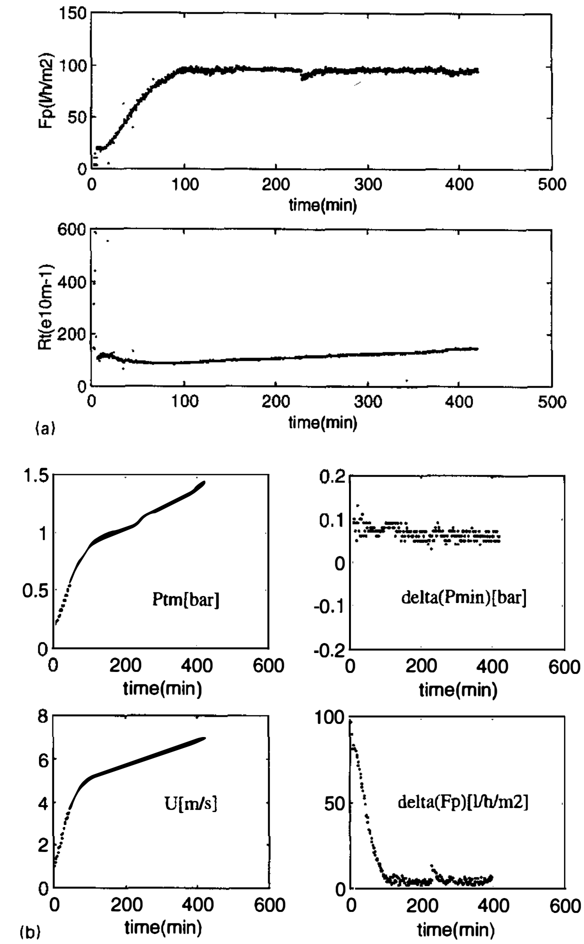

Fig. 10. Variation of permeate flux, total hydraulic resistance (a) versus time and controlled variables (b) versus time. Closed loop fuzzy control. Experiment at a permeate flux set point: 100 l/(h m^2).

on the ENSIA crossflow microfiltration unit. Examples are presented and discussed below.

(A) *Experiment at a set point of* 100 l/(h m^2). The total filtration time is about 7 h. During this trial, the main perceptible disturbance is a temperature increase of 1.5°C above the set point (80°C) in 200 min. Otherwise the variation interval of temperature around the set point is of 0.5°C. The variation of the permeate flux and of the total hydraulic resistance (R_t) versus time are represented on Fig. 10(a). The permeate flux increases regularly until about the set value (100 l/(h m^2)) in 90 min.

Concurrently, the total hydraulic resistance increases at a low rate ($0.20 \times 10^{10}\ m^{-1}\ min^{-1}$).

The change of the controlled variables [P_{tm} and U; delta(P_{min}) and delta(F_p)] versus time are represented on Fig. 10(b). The fuzzy controller acts gradually on the crossflow velocity set point according to the value of delta(F_p). Thus as long as delta(F_p) > 50 (during about 50 min) the crossflow velocity is strongly increased (with a maximum increase of 0.2 m/s in 2 min). After 50 min of filtration, the crossflow velocity is proportionally increased according to the value of delta(F_p) (thus the increase of crossflow velocity is low (slope of 0.005 m/s per minute) when delta(F_p) is near zero). At the same time, the head losses increase in the filtration module and consequently P_{min} increases. As a consequence, the fuzzy controller acts also on the P_{tm} set point so as to maintain a constant value of delta(P_{min}) within the safety margin of 0.05 bar ([0.05;0.1] bar).

(B) *Controller robustness at a set point of* 70 l/(h m^2). Different disturbances on control variables are realized during an experimental constant permeate flux control validation at 70 l/(h m^2) with a closed loop fuzzy control. The filtration duration is about 300 min. The main disturbances are presented in detail in Table 2. The change of the fuzzy controller input variables delta(F_p) and delta(P_{min}) versus time are represented on Fig. 11. An arrow indicates every disturbance (associated to an event numeral in Table 2).

Remark. In addition to the disturbances previously displayed, the temperature oscillates around the set point of 80. Thus, the viscosity of the product is not quite constant during filtration and the permeate flux is noisy.

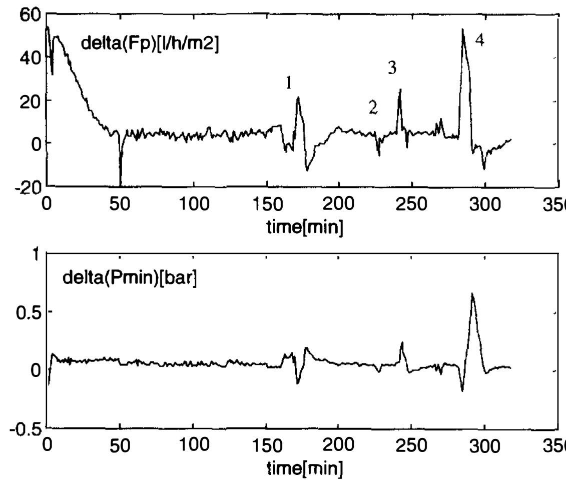

Fig. 11. Curves of delta(F_p) and delta(P_{min}) versus time for an experiment at 70 l/(hm^2) to test the robustness of the fuzzy controller.

The curves show the robustness of the fuzzy controller to different disturbances events. Thus, following velocity, pressure or temperature disturbances, the permeate flux comes back to its set point value in about 15 min.

(C) Discussion. To conclude on those experimental results, two essential remarks are in order:

a: Permeate flux is maintained near the set point of 100 l/(h m^2) with a good stability (set point value is reached in about 100 min). The experimental

Table 2
Fuzzy controller reaction to different disturbances applied to the process

Filtration duration (min)	Pressure variation (%)	Velocity variation (%)	Impact on the permeate flux (%)	Time to return to the set point 70 l ($h^{-1}\ m^{-2}$) (min)	Event numerotation
170	− 18		− 19.6	10	1
226	+ 23	+ 10.0	+ 37.7	5	2
240	− 41	− 22.9	− 36.6	3	3
283	− 96	− 57.5	− 79.2	25	4

permeate flux regulation accuracy is about 3% under the set point value. This can be explained by problems to round the variables during the recording of data or by nonoptimal tuning of the fuzzy controller parameters.

b: The control strategy is well respected. Indeed, the curve of delta(P_{min}) shows that pressure gap is kept as low as possible with a safety margin of 0.05 bar. This control seems to limit membrane fouling in spite of a relatively high fixed set value. The slope obtained from the curve of R_t versus time (calculated by simple linear regression during the linear final phase of filtration) is lower ($0.20 \times 10^{10}\,m^{-1}\,min^{-1}$) for this experiment than for an experiment without a control policy ($0.45 \times 10^{10}\,m^{-1}\,min^{-1}$). Thus, for a given total hydraulic resistance of $140 \times 10^{10}\,m^{-1}$, the total collected volume of permeate flux is $0.54\,m^3/m^2$ in 385 min and $0.01\,m^3/m^2$ in 4 min for constant permeate flux control and constant operating conditions experiment.

2.3. *Optimization of the fuzzy controller by the genetic algorithm*

(A) *Tuning of the parameters of the genetic algorithm.* The definitive off-line optimization results used in experiments on the pilot are obtained after tuning the essential parameters of the genetic algorithm: size L of the population; probability P_c of crossover; probability P_m of mutation. This tuning is realized off-line by using the model process and the algorithm described previously. For this purpose, different sets of genetic parameters are tested for a given number of generation (MAXGEN = 500) and for a given permeate flux set point ($F_{p[sp]} = 70$ l/(h m^2)). Thus, for example, the influence of the size of the population on the fitness function of the best individual of each generation is presented Fig. 12 for a probability of crossover fixed at 0.8 and a probability of mutation fixed at 0.001 ($L = 50$; 100; 300; 500). Results for populations of small size seem heterogeneous from one simulation to another. This is probably due to a disproportionality between the complexity of the optimization problem and the small size of the population that leads the algorithm in local

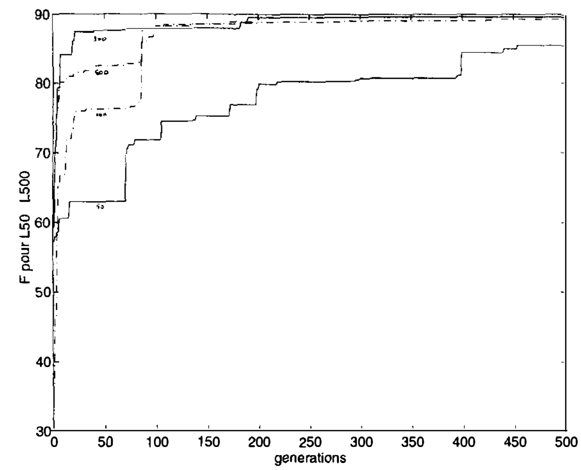

Fig. 12. Influence of the population size (L) on the fitness function.

optima. A population of a size equal or bigger than 100 appeared to be well adapted to our optimization problem.

Finally, the best set of genetic parameters (the set that gives the best fitness value during a simulation of regulation: $L = 100$; $P_m = 0.8$; $P_c = 0.01$) is implemented in the genetic algorithm used to optimize off-line the fuzzy controller. The best individual on a means of five simulations is implemented in the fuzzy controller implemented in the computer of the ENSIA pilot.

(B) *Experimental results of the optimization.* The fuzzy controller, optimized off-line by genetic algorithms, is tested during several experiments on the ENSIA crossflow microfiltration unit. An experiment at a set point of 100 l/(h m^2) is taken as an example. This experiment is carried out under the same conditions as the experiment previously presented (without optimization). The comparative variation of the permeate flux obtained with or without an optimized fuzzy controller versus time is shown Fig. 13. Thus the permeate flux set point is reached faster (25 min) for the optimized controller than for the non optimized one (100 min). The fitness value is multiplied by about 3 in the first 150 min of the experiment. Moreover, the accuracy of the regulation is better with this optimized controller.

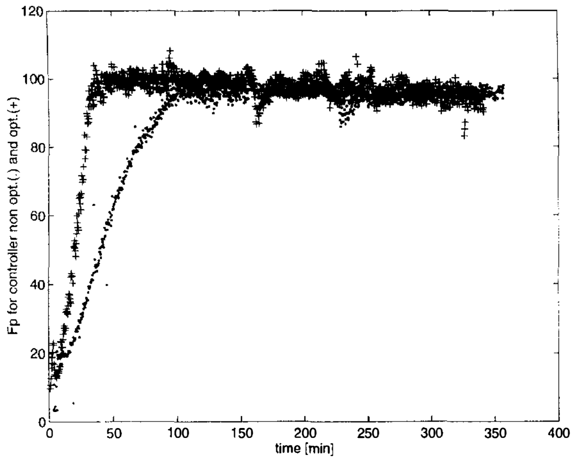

Fig. 13. Comparative curves obtained with or without an optimized fuzzy controller. Experiments are carried out in the same conditions and at a permeate flux set point of 100 l/(hm^2).

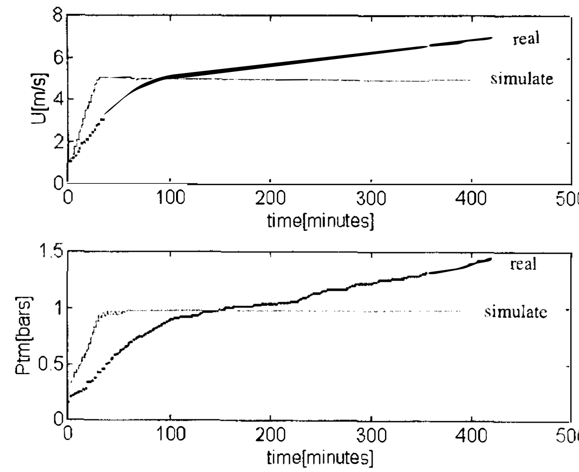

Fig. 14. Comparison of P_{tm} and U versus time for an experimental control and a simulated control carried out in the same conditions. $F_{p[sp]} = 100$ l/(h m^2).

2.4. Discussion and conclusion

A fuzzy algorithm is proposed to control the crossflow microfiltration process of a solution of raw cane sugar so as to maintain the permeate flux at a given reference value. Results show that the development of such a control is rapid and that it is interesting to use it to limit significant fouling of the membrane. Moreover, the fuzzy controller is robust whatever be the disturbances or noises applied to the process (even if those disturbances are applied on state variables not explicitly taken into account in the fuzzy controller "if then" rules). It is also robust to manual tuning done without having a perfect process model. Indeed, the real process behavior is different from the simulated one. Thus, in the first place, the peak of permeate flux obtained in simulation is not present in reality (see for example Section 2.1). This peak could come from an incomplete data base used to model the process (the process variables increased more rapidly than in the case of a fuzzy gradual control). Furthermore, pressure and velocity did not stabilize at an equilibrium value as we can see in simulation (Fig. 14). This confirms that the neuronal model used in simulation is not perfect and does not take into account the total membrane fouling. Thus, a fuzzy controller tuned on an imperfect process model adapts correctly its control to the real process without any new adjustments because the design of the controller is based upon a process knowledge linguistically synthesized by the expert.

The manual tuning of such a controller is difficult because of the numerous parameters involved in the control (for this controller 15 parameters). To complete this study an off-line optimization of the fuzzy controller is performed using the neural network model of the process and a genetic algorithm. This automatic tuning is done only on a reduced set of the whole set of parameters (8 on 15). Indeed a study on the influence and sensibility of each parameter of the knowledge base lead us to a reduction of the space of optimization. After optimization, the accuracy of the control is improved and the time to reach the permeate flux set point is reduced. Furthermore, with such an optimization under constraint, the heuristic structure of the optimized fuzzy controller remains completely logic and understandable to microfiltration experts. Nevertheless, this optimization is limited by the imperfection of the model and the difficulty to define a fitness function totally adapted to our fixed goals. Further studies will be focused on those points and other food processes will possibly be involved.

This study illustrates the interest to use an approach combining fuzzy logic, neural network and genetic algorithms to control an unsteady state, nonlinear and multivariable process. This type of approach can be applied even if the model of the process is imperfect because it is compensated by the heuristic knowledge implemented in the fuzzy algorithm.

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