

Optimal Control of Beer Filtration Process

Smaranda P. Cristea*, Rogelio Mazaeda.*
César de Prada*

*System and Automation Department, University of Valladolid, Spain.
(e-mails: smaranda@autom.uva.es, rogelio@cta.uva.es, prada@autom.uva.es)

Abstract: The use of membrane microfiltration in the production of beer is becoming an attractive alternative. Due to fouling there is the need of performing frequent backflushes and the more expensive membrane-damaging chemical cleanings. An optimal operation of the installation would minimize the costs by reducing the number of chemical cleanings and the consumption of energy while complying with the task of processing, on time, the assigned amount of beer. This paper discusses the opportunities for a more efficient, optimal operation of such a plant by using a model based real time optimization scheme that uses the framework of predictive control but with an economic motivated target.

Keywords: process control, food processing, optimal control, predictive control, process models

INTRODUCTION

The industrial production of most beers requires a filtering step as part of the so called downstream processing. The purpose is to remove the unwanted particles from the incoming suspension, so as to guarantee quality of the marketable product. The traditional use of kieselguhr filters has started to be seriously challenged by the use of the environmentally friendlier membrane microfiltration units. The market share of the latter is now around 10% and increasing; but there are still issues concerning the operation of beer microfiltration that should be addressed to realize the full potential of the technology.

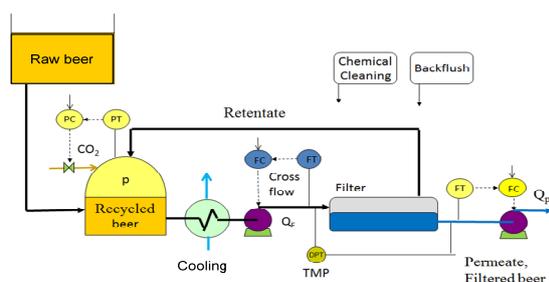


Figure 1. Beer micro-filtration plant.

A typical installation of beer microfiltration is shown in figure 1. The arriving raw product contains many particles of different characteristics and size range. The filtering section must remove those above some specified size and for that purpose the product is made to circulate in cross flow through a bundle of filtering fibres with some controlled velocity. The plant setup is such as to guarantee the existence of a pressure difference across the membrane that drives the flow of beer through filter. The non-filtered suspension that emerges at the other end of the filter bundle, the so called retante, is recycled

back to an upstream intermediate buffer tank which remains pressurized to avoid foam creation.

But the accumulation in the membrane of the removed particles makes that the process just briefly described cannot go on forever. Some of these particles, of size bigger than the membrane pores, creates a growing cake deposited on the inner walls of the fibres; while the others, of lesser size, gets trapped inside the pores reducing their volume. The combined net effect of this fouling process is the progressive reduction of the filtering capabilities of the installation and the increase of the hydraulic resistance opposing the cross flow of the beer. Up to a point, this situation can be coped with by progressively increasing both, the trans-membrane (*TMP*) and the cross-flow driving pressure by using the available pumps. But eventually, some technological and operational limits are reached (see figure 2), indicating the need of cleaning of the filtering medium.

There are two types of cleanings: initially it is enough to perform a backflush (BF) with acid/caustic solution to remove the superficial cake layer and part of the fouling obstructing the pores: the so called reversible fouling. But this is not enough: the compounded impact of the accumulated irreversible fouling, represented by those particles which are adsorbed into the membrane pore walls, reduce the duration and the filtering ability of these BF cycles in a way that demands the performing of a more expensive and lengthier chemical cleaning in place (CIP) that restores the original characteristics of the medium at the cost of reducing its lifetime.

The current operational strategy simply reduces to keep the cross and permeate flows at constant values by increasing the pressure delivered by the pumps. It is reasonable to expect that a clever, better approach would be possible by a suitable election of both flows profiles. This contribution describes the design of a model based strategy that optimizes an economically justified cost function that intends to improve

the existing situation. Section 2 deals with the description of the model, which has been developed by other authors (Vollbregt et al., 2010) but included here to better understand the rationale behind the proposed control solution, discussed in section 3, which is the main contribution of this work. Finally some simulation results are provided for the sake of conclusion in section 4.

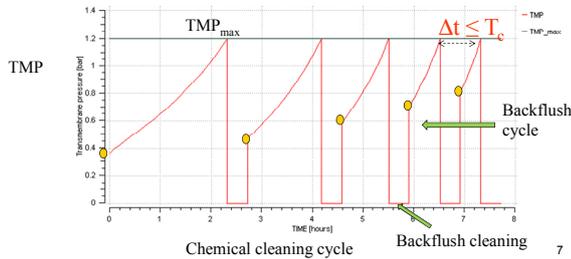


Figure 2. One CIP cycle.

2. BEER MICROFILTRATION PLANT MODEL

The Pilsner type of beer here taken as reference is a very complex suspension (van der Sman et al., 2012). Among the particles that the solution carries, there are yeast cells, different aggregates of protein and polyphenols and other macromolecules. Size distribution studies has shown a bimodal character with one peak centered at 5 μm and with a width from 2 to 10 μm and the other in the range from 0.2 to 2 μm . The first segment, of larger particles, is formed by yeast cells and the bigger aggregates; while in the second category the rest of the aggregates are included. The first range essentially corresponds to the so called permanent haze. On the other hand, the smaller sized range is consistent with the presence of chill haze, so denominated because its existence is triggered when the temperature of beer is reduced to values around 0°C. The need of creating this low temperature to get rid of chill haze particles is the reason for the presence of the cooling heat exchanger of fig. 1. Both the yeast cell and the aggregates should be filtered out because their presence provokes turbidity and the reduction of the users' perceived quality. Macromolecules, on the contrary, have a much smaller size and should be preserved since they provide taste and help in the stabilization of foam.

Figure 3 shows an axial cut of one of the cylindrical fibers composing the filter bundle. The polymer membrane walls have an asymmetric structure: there is a selective layer that can be thought of as an array of tiny parallel cylinders of diameter that grows on a support layer, which is a more loosely arranged structure of interconnected pores of larger average diameter. The yeast cells and larger aggregates, with diameters larger than support layer pores, forms the cake layer, while the smaller aggregates can penetrate and reach the selective layer to either completely block the pores or to form a gel deposit, of height h_{gel} , reducing the volume available for filtering. Most of macromolecules can pass freely through the membrane and both the cake and gel layers.

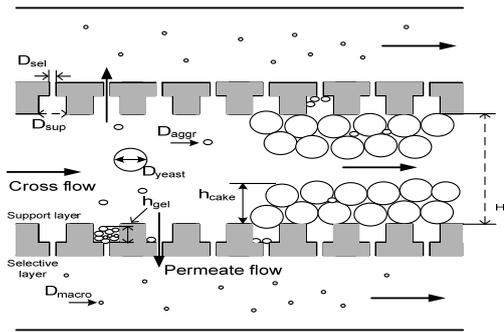


Figure 3. Membrane and fouling characteristics.

The first principles beer cross flow microfiltration model to be briefly described in what follows has been developed in detail in van der Sman and Vollebregt (2013), further insights can be gathered in Romero and Davies, (1990) and in Vollbregt et al. (2010). A formal scale analysis, also put forward in the aforementioned references, established that a distributed 1D model can be safely stated in the axial direction postulating the existence of two separated homogeneous phases: the bulk of the cross flowing beer to be filtered with a volume fraction of yeast ϕ_{bulk} and a stagnant cake layer of the yeast that gets deposited in the inner surface of the fibre (fig. 3) with a random packaging of ϕ_{cake} . These two radially homogenous phases are separated by a boundary or flowing cake layer of height δ with variable particle volume fraction between the two limits ϕ_{bulk} and ϕ_{cake} . The reason for the presence of the excess particle region is the existence of permeate flow of velocity u_{wall} and it flows downstream due to the shear stress provided by the velocity of the bulk of the suspension in the same direction but with a higher velocity U . The experience and the theory concerning cross flow filtration show that, for range of working regimes, the axial cake profile takes a shape similar to the one shown in fig. 4, where there is a region of the membrane, at the entrance of the channel and to the left of some critical distance x_{cr} , which is not covered by the cake.

The distributed parameter model will be directly stated by means of the finite volume approximation. So the following description is valid for any i element, of width Δx , along the axial direction.

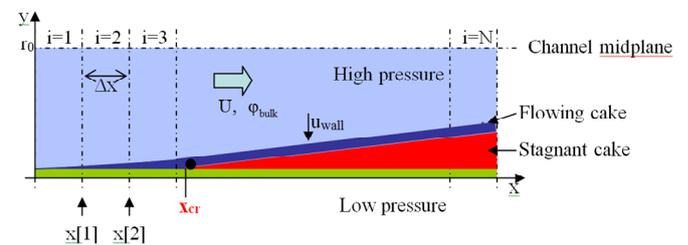


Figure 4. Fibre axial cut.

The excess particle flux q (m^2/s) (1) to the left of x_{cr} is simply the one coming from the previous discretization plus the particles transported from the bulk by the filtrate. But to the right of x_{cr} , the q is calculated according to the expression

(1).b as a function of shear rate γ^* , the radius of the particles r_{yeast} and the permeate velocity. The parameter Q_{cr} is to be adjusted for each case.

$$q[i] = \begin{cases} q[i-1] + \varphi_{bulk} u_{wall}[i] \Delta x & \text{if } x[i] < x_{cr} \quad (a) \\ Q_{cr} \frac{\gamma[i]^3 r_{yeast}^4}{u_{wall}^2} & \text{if } x[i] \geq x_{cr} \quad (b) \end{cases} \quad (1)$$

The shear rate, on its turn, depends on the cross flow velocity U and the radius of the channel $r[i]$ according to:

$$\gamma[i] = 4 \frac{U[i]}{r[i]} \quad (2)$$

The critical distance is related with the shear rate and the permeate flow velocity as in (3).

$$x_{crit}[i] = \frac{Q_{cr}}{\varphi_{bulk}} r_{yeast} \left(\frac{\gamma[i] r_{yeast}}{u_{wall}[i]} \right)^3 \quad (3)$$

The single global parameter x_{cr} is chosen from the $X_{crit}[i]$ above as the first one from the left that checks the following condition:

$$x[j-1] \leq x_{crit}[j] \leq x[j] \quad (4)$$

The radius of the channel, free for cross flow, is calculated with the differential equation (5) which describes the formation of the stagnant cake layer downstream x_{cr} . The radius decrease rate is such as to guarantee that the increase in excess particle flux in the current discretization, as dictated by (5).b, compensates exactly the amount of particles dragged by the filtrate from the bulk of the suspension.

It is to be noted that u_{wall} velocity in (5).b is, on its turn, dependent on the height of the stagnant cake since it has now to overcome the resistance offered by the progressively fouled membrane. Then, the permeate flow rate Q_p is determined with a Darcy type of relation (6) between the driving pressure difference and the series combination of the resistances represented by the membrane (R_{mb}), the cake (R_{cake}) and by a gel type layer (R_{gel}) of the aggregates that reduce the size of the membrane pores.

$$\frac{dr[i](t)}{dt} = \begin{cases} 0 & x[i] < x_{cr} \quad (a) \\ -\frac{\varphi_{bulk}}{\varphi_{cake}} u_{wall}[i] + \frac{q[i] - q[i-1]}{\varphi_{cake} \Delta x} & x[i] \geq x_{cr} \quad (b) \end{cases} \quad (5)$$

$$Q_p[i] = \frac{u_{wall}}{2\pi r[y] \Delta x} = \frac{p_{up}[i] - p_{filt}[i]}{R_{cake}[i] + R_{mb}[i] + R_{gel}[i]} \quad (6)$$

$$R_{cake}[i] = 45\eta_{eff} \frac{(1 - e_{cake}[i])^2}{r_{yeast}^2 (e_{cake}[i])^3} \frac{(r_0 - r[i])}{2\pi r_0 \Delta x} \quad (7)$$

The resistance of the cake (7) depends on its height ($r_0 - r[i]$), the size of the particles (r_{yeast}), the effective dynamic viscosity of the suspension (η_{eff}) and the porosity of the cake $e_{cake}[i]$. In this expression, the evolution of fouling is due to the increase of the cake layer but also to the diminution of the

porosity (8), a term that begins at the value that corresponds to the initial packaging as in $e_{cake}[i] = 1 - \varphi_{cake}$, to start decreasing as aggregates are captured in the pores of the cake. The φ_{cake} is taken as the random close packing for the yeast cells taking into account some degree of compressibility as a function of the developed pressure.

$$e_{cake}[i] = (1 - \varphi_{cake}) \left(1 - \frac{V_{screen}[i]}{V_{cake}[i]} \right) \quad (8)$$

Where V_{cake} and V_{screen} are, respectively, the volume of the cake and of the pores inside the cake. Then V_{screen} evolves as (9) balancing the growth due to the increase in the size of the cake with the reduction caused by the aggregates that are captured with a rate $k[i]$.

$$\frac{dV_{screen}[i]}{dt} = -k[i] \varphi_{aggr} Q_p[i] - \frac{V_{screen}[i] \cdot 2\pi r[i] \Delta x}{V_{cake}[i]} \frac{dr[i]}{dt} \quad (9)$$

The parameter $k[i]$ on its turn is considered to depend on the height of the cake $h_{cake}[i]$ and on the parameter λ as in (10).

$$k[i] = 1 - e^{-\lambda \cdot (r_0 - r[i])} = 1 - e^{-\lambda \cdot h_{cake}[i]} \quad (10)$$

Furthermore, the current resistance of the membrane depends on its original resistance (R_k), affected over time by a factor representing the relative amount of completely blocked pores $N_{pores}[i]$ in relation with the initial available amount N_0 (see 11). The aggregates which are not retained in the cake or completely obstructing pores in the selective layer are considered to create an additional layer of height h_{gel} . The corresponding resistance is calculated by the expression (12) which is essentially similar to the one previously seen in (7) but now with r_{aggr} representing the size of aggregates, φ_{gel} a fixed parameter that stands for this layer close random packaging. In this case, $h_{gel}[i]$ represents the height of the gel layer which is determined from the current volume of membrane pores occupied by particles (13).

$$R_{mb}[i] = \frac{R_k}{2\pi r_0 \Delta x} \frac{1}{1 - \frac{N_{pore}[i]}{N_0}} \quad (11)$$

$$R_{gel}[i] = \frac{45\eta_{eff} h_{gel}[i] \varphi_{gel}^2}{r_{aggr}^2 (2\pi r_0 \Delta x) (1 - \varphi_{gel})^3} \quad (12)$$

$$h_{gel}[i] = \frac{V_{pore}[i]}{\varphi_{gel} (2\pi r_0 \Delta x)} \quad (13)$$

The dynamics of the amount of completely blocked pores is found as (14) depending on the permeate flow rate. The parameter β represents the fraction of the aggregates that go pass the cake to completely obstruct some pore in the selective layer. Notice that the remaining aggregates, represented by the $1 - \beta$ factor, contribute to the creation of the gel layer with a dynamics for the reduction of the volume of the pores given by (15).

$$\frac{dN_{pore}[i](t)}{dt} = (1 - k[i]) \frac{\varphi_{aggr}}{V_{aggr}} \beta Q_{out}[i] \quad (14)$$

$$\frac{dV_{pore}[i](t)}{dt} = (1 - k[i])(1 - \beta) \varphi_{aggr} Q_{out}[i] \quad (15)$$

The existing cross flow at each volume has to account for the incoming stream from the previous one minus the filtered flow expelled through the membrane.

$$Q_C[i] = Q_C[i - 1] - Q_P[i - 1] \quad (16)$$

There is also the need of modelling the effect of a backflush cleaning on the state variables related to fouling. The cake is considered to be completely wiped out by this process but it also eliminates, to some extent captured by an efficiency parameter C_{BF} , the aggregates trapped in the gel layer and blocking the pores, as represented by the variables $V_{pore}[i]$ and $N_{pore}[i]$ respectively.

$$N_{pore}[i]_{t=t_{begin,j}} = C_{BF} N_{pore}[i]_{t=t_{end,j-1}} \quad (17)$$

$$V_{pore}[i]_{t=t_{begin,j}} = C_{BF} V_{pore}[i]_{t=t_{end,j-1}} \quad (18)$$

The important TMP variable is considered to be equal to the difference between the average value for the pressure inside the fibre and the pressure at the output of the permeate side.

$$TMP = \frac{p_{in} + p_{out}}{2} - p_{filt}[N] \quad (19)$$

There are many other details that can be followed in the original references. They are concerned with the description of the resistance to the cross flow, mass balances around the auxiliary plant equipment like buffer tanks and the fact that it leads to the increase of the volume concentration of yeast, among others.

The full model dynamics of the membrane filter is captured with enough accuracy by employing 30 discretizations.

3. OPTIMAL CONTROL STRATEGY

The beer filtration stage has certain special characteristics derived from its position in the overall industrial chain. The installation is market driven in the sense that it must process a specified batch of raw beer in a certain period of time.

So the problem at hand is that of minimizing an index (20-21) which is related to the cost of operating the plant, subject to the operational constraints (22-23) by choosing the profile of the cross flow and permeate flow rates. The optimal solution so found will consist of a number N_{CIP} of chemical cleanings, each with $N_{F,j}$ backflushes.

$$C = \min_{Q_C, Q_P, N_{CIP}, N_{F,j}} \left[\sum_{j=1}^{N_{CIP}} \left(\sum_{i=1}^{N_{F,j}} C_{F,ij} \right) + N_{F,j} C_{BF} + C_{CIP} \right] \quad (20)$$

$$C_{F,ij} = \min_{Q_C, Q_P} C_E \int_0^{t_{F,ij}} \left(\frac{n Q_C (P_F - P_{BT})}{\eta_F} + \frac{n Q_P TMP}{\eta_P} \right) dt \quad (21)$$

The cost function (21) weighs the cost of operating the plant $C_{F,ij}$ during one BF cycle of length $t_{F,ij}$ (20) and then counting each BF i at each chemical cleaning cycle j . The term $C_{F,ij}$ is the cost of operating the two pumps, which is calculated as the energy consumed, with prize C_E , for establishing the given flow rates (Q_C and Q_P) with the corresponding pressure heads ($P_F - P_{BT}$ and TMP) taking into consideration their respective efficiencies. The flowrates are multiplied by n , the number of fibres in the bundle. Two important contributions to the economic index (20) are the cost of each BF and, fundamentally, the cost of the chemical cleanings, a term that has a dominant role since it includes not only the price of the chemicals but more importantly the depreciation of the expensive membrane as well.

$$\sum_{j=1}^{N_{CIP}} \left(\sum_{i=1}^{N_{F,j}} V_{F,ij} \right) = V_{beer0} \quad (22)$$

$$\sum_{j=1}^{N_{CIP}} \left(\sum_{i=1}^{N_{F,j}} t_{F,ij} + N_{F,j} t_{BF} + t_{CIP} \right) \leq t_{max} \quad (23)$$

The first restriction (22) simply establishes the requirement that the total initial volume of raw beer is entirely filtered out at the end of the process. The fulfilment of (23), on its turn, would guarantee that the complete procedure is finished before the deadline t_{max} . Although no explicitly written, there are bounds on the decision variables Q_P and Q_C , and, of course, the need to comply with the dynamic equations of the process model.

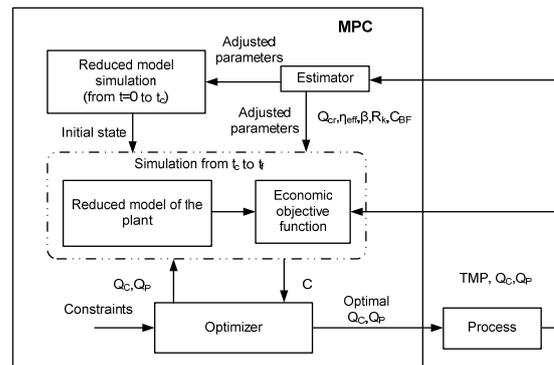


Figure 5. Optimal control strategy.

Traditionally, the solution to this type of economically motivated dynamic optimization problems has been approached hierarchically. The economic index optimization is solved at the upper layer with lesser frequency and using a static simplified model. This higher level optimizer gives the setpoints to the control layer below which is in charge of enforcing them. The lower layer is typically implemented by a predictive controller (MPC) which uses yet another model, this time dynamic. This strategy provides a sound division of

concerns at the expense of having to maintain two different models, and the need to deal with the sub-optimality that derives from this fact. A scheme of this type has been proposed in Blankert (2007) for the beer filtering case. In this paper another strategy has been taken with the so called optimizing controller approach whereby the two previous layers are coalesced into just one MPC controller with a single dynamic model and an economic cost function (see fig 5) (Engell, 2007; Rodríguez et al., 2007).

Table 1. Adjustable parameters

	Parameter				
<i>Initial value</i>	$\eta_{eff}[\text{bar.h}]$	R_k	β	Q_{cr}	C_{BF}
	$1.16e^{-11}$	1.16	0.4	$2.1e^{-7}$	0.5

The dynamic optimization is carried out following the direct one-shot sequential method (Biegler and Grossmann, 2004) where the decision variables, Q_C and Q_P , are parameterized and the equations are integrated over some time horizon in order to evaluate the cost index as part of the optimization algorithm inner loop. Notice that the MPC controller proposes the values of Q_C and Q_P to the corresponding two PID controllers in the regulatory layer which are in charge of driving the pumps accordingly.

There are some challenges to be addressed. The first one is related to the high computational demand since the problem is of a batch type, and so the model has to be simulated to its completion when all the assigned beer is processed. This can be alleviated by realizing that all CIP cycles can be considered identical since the state of the model is always reset at the beginning to the known non-fouled state. So, there is only the need of simulating until the first chemical cleaning. The number of CIPs (N_{CIP}) is then calculated as part of the simulation. Strictly speaking, N_{CIP} is an integer, but here we treat it as a real variable, accepting the resulting sub-optimality, in order not to further complicate the problem with mixed integer non-linear optimization issues. On the hand, a non-integer result for N_{CIP} simply means that the last chemical cycle may not run to completion.

Another simplification is the use of a reduced model which, in this case, is going to be taken as the one previously described but retaining the minimum meaningful number of finite volume discretizations that, for this case, is of only two.

For this simulation study, the process to operate would be the full order distributed parameter model seen previously. Notice that the model used for optimization and the one representing the plant are quite different; however it is hoped that the reduced one is able to capture the main trade-offs of the process. This plant-model mismatch is, in any case, unavoidable due to the inherent uncertainties and constitutes a second important challenge, which is here faced by adopting the receding horizon scheme characteristic of the MPC approach, combined with the frequent updating of the reduced model used for optimization.

So, there is a second ancillary optimization problem E (24) to be solved with this scheme, related to the model parameter

estimation. Only a subset of five of the most significant parameters of the model, which were chosen by a previous off-line sensitivity study, will be adjusted on-line (see table 1). The problem E minimizes the square of the difference of the TMP variable measured with the one offered by the model and should evidently comply with the restrictions imposed by the model and with the already implemented Q_P and Q_C profiles that were proposed by the primary economic optimization problem since the beginning of the process.

$$E = \min_{Q_{cr}, \eta_{eff}, \beta, R_k, C_{BF}} \sum_{i=1}^{N_f} \left(\sum_{t=0}^{t=t_f} (TMP - TMP_{estim.})^2 \right) \quad (24)$$

A last important challenge to be sorted out derives from the intrinsic discontinuous character of the problem. This implies that the sensitivities of the optimization problem, defined as the derivatives of the state with respect to the parameters, may have discontinuities whose number may change for even the slightest modification of those parameters. For example, a small change in some parameter may change by one the number of backflushes.

This kind of numerical difficulty renders the use of gradient based local optimization algorithm, such as SQP, as highly problematic. So a gradient-free genetic algorithm was chosen for the implementation of the economic primary optimization. For the estimation problem however, the least computationally expensive SQP is appropriate, since the optimization is, in this case, carried out taking into account the already executed actions with complete knowledge of the time of occurrence of all the past discontinuities.

4. RESULTS

The solution has been tested in simulation. The fixed parameters of both models, the full one representing the plant and the reduced model used for control, have been taken to represent a really existing pilot plant having a filter with only one fibre, so the numbers are consequently quite low.

The task is to filter a total volume 0.051 m^3 in less than 5 days. The proposed Q_C and Q_P should not exceed the limits $0.021 \text{ m}^3/\text{h}$ and $0.0007 \text{ m}^3/\text{h}$ respectively. The data has been sampled every 0.02 h but the updating of the model by means of the estimation optimization step has been carried out with 0.14 h period. The economic optimization has been launched with a slower frequency every 0.42 h.

Figure 6 shows the resulting optimal measured TMP variable evolution over an entire chemical cycle. The output of the reduced model is superimposed showing the acceptable agreement reached by applying the model updating optimization.

The parameterization imposed on the profile for both flowrates is the simplest possible: a constant value for each one until the end of CIP cycle. This does not imply constant actual resulting profiles, as evidenced in figure 7, due to the on-line cyclic nature of the MPC adopted scheme which implies a periodic recalculation as the means of handling perturbations and model uncertainties.

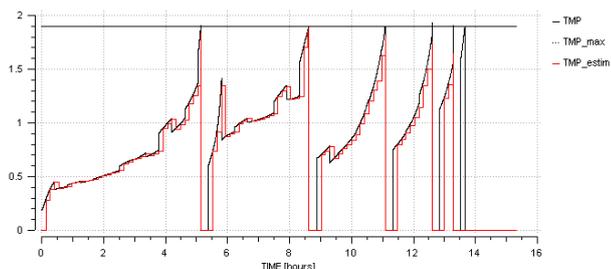


Figure 6. Process and model TMP variable.

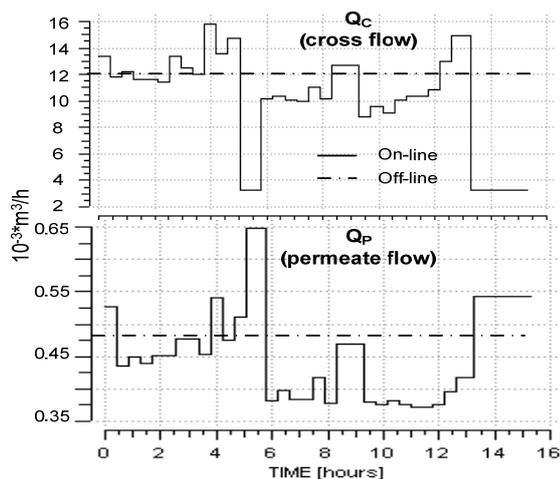


Figure 7. Optimal cross flow and permeate profiles. Solid on-line MPC solution; dotted off-line best fixed values.

The model updating procedure implies recurrent adjustment of the model free parameters whose evolution is shown in figure 8. It should be observed that the variation exhibited by most parameters is not too large and this fact provides a good measure of confidence in the expressiveness of the reduced model. The R_K parameter, related to the membrane original resistance, grows consistently along the adjustment procedure. This type of behaviour is not too surprising due to the considerable difference introduced between model and the simulated process; particularly by considering the full extent of the distributed nature of membrane fouling that affects precisely its resistance.

Table 2. Optimization results

	<i>Cost (€)</i>	N_{CIP}	$N_{BF/cycle}$
On-line	27.08	9.16	6
Off-line	27.85	9.43	6

In table 2 the final results of the on-line model-based scheme is shown. The final cost of processing the assigned beer in this scale-down plant, consisting of a single fibre, is of 7.08 euros, needing 9 full CIP cycles with 6 BF per cycle. The table 2 also shows the results of an off-line optimization exercise that uses the full distributed model to obtain the best constant values for cross and permeate flow. These fixed values are also depicted in fig. 7.

The comparison is encouraging: the proposed economic MPC scheme, with a much reduced model, is able to outperform the traditional manner of conducting the plant with constant cross and permeate flow, even if these fixed values are the optimal ones obtained with a “perfect” model. Even more, since the computer processing time of the on-line controller is not too high, (148 seconds maximum for each estimation/controller cycle in a 1.83GHz PC computer) there is still room for increasing the complexity of either the model or control parameterization or both.

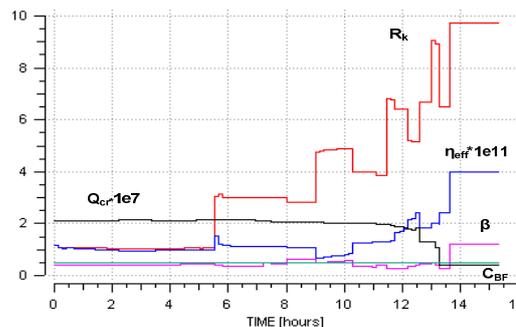


Figure 8. Evolution of adjustment parameters.

ACKNOWLEDGEMENTS

This research has been supported by the Computer-aided food processes for control engineering (CAFE) VII Framework programme European project.

REFERENCES

Biegler, L.T. and Grossmann, I.E. (2004). Retrospective on optimization. *Computers & Chemical Engineering*, 28(8), 1169 - 1192.

Blankert, B. (2007). Short to medium term optimization of dead-end ultrafiltration. Ph.D. thesis, University of Groningen, The Netherlands.

Engell, S. (2007). International scientific & technical encyclopedia (iste). *Journal of Process Control*, 17, 203-219.

Rodríguez, M., Sarabia, D., and Prada, C. (2007). Taming Heterogeneity and Complexity of Embedded Control, chapter Hybrid predictive control of a simulated chemical plant, 617-634.

Romero, C.A. and Davis, R.H. (1990). Transient model of crossflow microfiltration. *Chemical Engineering Science*, 45(1), 13 - 25.

van der Sman, R. and Vollebregt, H. (2013). Transient critical flux due to coupling of fouling mechanisms during crossflow micro-filltration of beer. *Journal of Membrane Science*, 435(0), 21 - 37.

van der Sman, R., Vollebregt, H., Mepschen, A., and Noordman, T. (2012). Review of hypotheses for fouling during beer clarification using membranes. *Journal of Membrane Science*, 396(0), 22 - 31.

Vollebregt, H.M., van der Sman, R.G.M., and Boom, R.M. (2010). Suspension flow modelling in particle migration and micro-filtration. *Soft Matter*, 6, 6052-6064.