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Optimal adaptive scheduling and control of beer membrane filtration

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ABSTRACT

An adaptive optimal scheduling and controller design is presented that attempts to improve the performance of beer membrane filtration over the ones currently obtained by operators. The research was performed as part of a large European research project called EU Cafe with the aim to investigate the potential of advanced modelling and control to improve the production and quality of food. Significant improvements are demonstrated in this paper through simulation experiments. Optimal scheduling and control comprises a mixed integer non-linear programming problem (MINLP). By making some suitable assumptions that are approximately satisfied in practice, we manage to significantly simplify the problem by turning it into an ordinary non-linear programming problem (NLP) for which solution methods are readily available. The adaptive part of our scheduler and controller performs model parameter adaptations. These are also obtained by solving associated NLP problems. During cleaning stages in between membrane filtrations enough time is available to solve the NLP problems. This allows for real-time implementation.

1. Introduction

Large industrial process designs are generally separated into parts to simplify and manage the designs. The separation is generally obtained from a hierarchical decomposition (Antelo, Banga, & Alonso, 2008). When scheduling and control are both involved these are usually separated by the hierarchy. But in general, separation leads to loss of performance especially if the scheduling and control heavily interact. Beer membrane filtration is an example of an industrial process with significant interaction between scheduling and control. This is because different long and short term phenomena and goals exist. Fouling concentrations of beer change very slowly whereas beer flow inside the membrane changes very rapidly. In between are the fouling phenomena of the membrane. The long term goal is to filter enough beer in time while the short term goal is to prolong the filtration stages as much as possible because membrane cleaning is costly. The filtration stage is prolonged through removal of parts of the fouling cake layer on the membrane. They are flushed back into the beer.

Currently beer membrane filtration is performed by supplying default set-points for flows in the filtration system. Sometimes these set-points are adjusted from their default values by operators, based on experience and measured values of the pressure over the membrane (transmembrane pressure). This happens mainly when the amount of filtered beer is too low or when membrane fouling occurs too fast. By adjusting these set-point also the scheduling of different phases occurring during beer membrane filtration, is affected. Fig. 1 shows the block diagram of beer membrane filtration (BMF). The set points concern the flow of beer into the membrane filter F^i and the flow out of filtered beer F^o. These together determine the cross flow F^c because $F^i - F^o = F^c$. F^i, F^o and F^c should always be nonnegative. To ensure this our adaptive optimal scheduling and control system design considers F^o and F^c to be the control variables which are taken to be non-negative. Then $F^i = F^o + F^c$ is also non-negative.

Fig. 2 shows the phases which make up the schedule associated with beer membrane filtration. In it backflushes (BF) occur. These are stages where beer filtration is suspended and water is flushed backwards through the membrane to clean it. This type of cleaning fully removes cake fouling on top of the membrane but only partially removes membrane pore fouling by aggregates. Another thorough way of cleaning the membrane is by chemicals. This is more costly but fully removes membrane cake and pore fouling at the expense of deterioration of the quality and strength of the membrane. Chemical cleaning stages are denoted by (C) in Fig. 2. The cheapest way of removing fouling is by manipulating the beer flow during filtration. In this way part of the cake layer fouling on top of the membrane can be removed. The associated costs relate to pumping costs during filtration stages (F). These are very small compared to the costs of backflushes (BF) and chemical cleaning stages (C).

The scheduling and control problem can be briefly stated as follows. Besides the set-point values for flow during each filtration

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stage (F), in the schedule represented by Fig. 2 the number of filtration cycles (FC) within a single chemical cleaning cycle (CC) needs to be optimised. In Fig. 2 this number is two, but in general it must be higher. Also the duration of each single filtration stage (F) needs optimisation. Backflushes (BF) have a fixed duration. Finally the filtration of beer consists of several chemical cleaning cycles (CC). Their number also needs optimisation. So a complicated scheduling and control problem results. Scheduling and control problems of a similar nature have been reviewed, classified and unified in (Wang, Gao, & Doyle, 2009). But, as opposed to (Wang et al., 2009), in this paper the process model used for adaptive scheduling and control is a non-linear first principles model, instead of a series of linear models. Also, instead of tracking *a-priori* fixed trajectories, the trajectories and associated controls are adjusted by minimising a cost function reflecting the overall control goal while at the same time satisfying state and control constraints. The latter aspects are similar to what is called non-linear model predictive control that also uses a non-linear systems model and a cost function (Camacho & Bordons, 2007). But non-linear model predictive control excludes scheduling. Estimation of model parameters is generally excluded as well. To the best our knowledge this is the first time an adaptive optimal scheduling and control system for this type of process is proposed that is implementable in real-time.

The control objective associated with beer membrane filtration is to minimise the filtration costs per unit filtered beer while satisfying the constraint that a given amount of beer must be filtered in a given amount of time. The costs are determined by costs of chemical cleaning stages (C), costs associated with backflushes (BF) and costs associated with energy needed to realise flows during filtration stages (F) (Zondervan, Betlem, Blankert, & Roffel, 2008a). Besides costs, optimal controller design relies on a dynamic state-space model representing the process behaviour. A first principles model is used in this research because it allows for explicit computation of costs associated with beer membrane filtration. Furthermore first principles models provide insight which is very helpful when searching for errors and improvements. From a scientific perspective the insight provided by first principles models reveal structure and provide understanding and explanation of the process and underlying mechanisms. These enable easy modification and extension of the model and the associated process design. Also operators may benefit from further insight into the process.

A first principles models of membrane filtration has been presented (van der Sman & Vollebregt, 2013). Control system design for membrane filtration has been performed (Zondervan et al., 2008a). When truly optimising all features of the control and schedule just mentioned, a mixed-integer non-linear programming problem (MINLP) is obtained (Zondervan, Blankert, Betlem, & Roffel, 2008b). These types of problems are most complicated and possibly intractable. When tractable their computation is expensive and therefore generally unsuitable for real-time control purposes (Belottia, Leeb, Libertic, Margotd, & Wächterb, 2009).

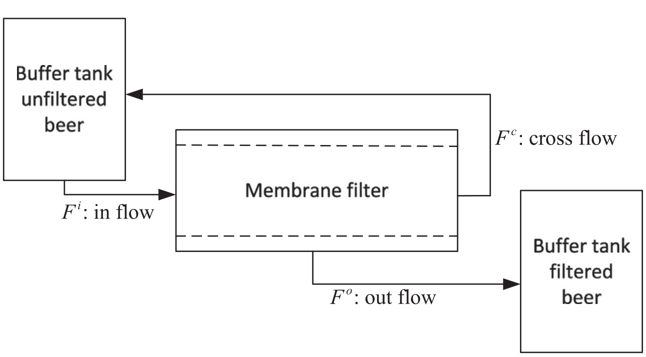

Fig. 1. Block diagram of beer membrane filtration (BMF).

By making some dedicated suitable process assumptions that are approximately satisfied, in this paper we manage to reduce the scheduling and control problem to an ordinary non-linear programming problem (NLP). It turns out that our NLP problem suffers from local minima. Therefore a global search algorithm is used to solve it at the expense of loss of computational efficiency. The adaptation of the schedule and control is performed as follows. During each chemical cleaning stage (C) a new schedule and control is computed based on transmembrane pressure measurements of the previous part of this chemical cleaning cycle (CC). These measurements are used to estimate both the initial state of the next chemical cleaning cycle (CC) and some critical model parameters. Next the initial state estimate and the adapted model are used to compute a new optimal schedule and control. Only the control computed for the next chemical cleaning cycle (CC) is applied to the process. The global search algorithm to estimate the initial state and critical model parameters as well as the one to compute the optimal schedule and control is constrained to stop within a fixed amount of time. This ensures their execution not to exceed the time required by a chemical cleaning stage (C) in which they have to be performed.

The first principles model used for the adaptive optimal scheduling and control is presented in Section 2 while the scheduling and control problem is defined in Section 3. To arrive at the adaptive optimal scheduling and control scheme Section 4 first describes open loop optimal control computations. Next Section 5 presents the adaptive optimal scheduler and controller. Results obtained with it in simulation experiments incorporating both parameter and measurement errors are reported. Section 6 presents conclusions an important one being that measurements related to membrane and beer fouling are crucial to the success of adaptive optimal scheduling and control of beer membrane filtration. Although technically feasible they are very much lacking in current industrial practice.

2. Modelling beer membrane flow and fouling

For reasons mentioned in the introduction a first principles model is used to design the adaptive optimal scheduling and control system. The model is developed to describe industrial beer membrane filtration currently in use at different locations. Critical parameters are estimated and experiments are performed on a scaled down pilot plant. The full model is published in (van der Sman & Vollebregt, 2013). Here we only present the most important parts needed to understand the adaptive scheduling and control system design. Also the presentation of the model is quite different from (van der Sman & Vollebregt, 2013) which was inspired by physics. Here a state-space representation is adopted that provides the model structure required for control. The model describes the flow of beer through the membrane and computes the associated

Chemical Cleaning Cycle (CC)				
Filtration Cycle (FC)		Filtration Cycle (FC)		Chemical Cleaning (C)
Filtration (F)	Back Flush (BF)	Filtration (F)	Back Flush (BF)	Chemical Cleaning (C)

Fig. 2. Scheduling and control stages and cycles.

membrane fouling and pressure as a function of time t [s]and axial location x [m] alongside the membrane $0 \le x \le l_m$ where l_m is the length of the membrane fibre. The model assumes radial symmetry of the membrane. As mentioned in the introduction the axial cross flow F^c $[\mathrm{m^3 s^{-1}}]$and the radial flow out F^o $[\mathrm{m^3 s^{-1}}]$are control variables. Together they determine,

$$F^i(t) = F^c(t) + F^o(t). \tag{2.1}$$

Radial symmetry of the system with respect to the axis at the centre of the membrane fibre is assumed. Moving outwards from this centre axis, see Fig. 3, we first have space through which beer is flowing. Then close to the edge of the membrane a cake fouling layer is found. Next there is the membrane itself consisting of two layers. The first layer is called the support layer characterised by larger pores. Finally there is the selective layer having small pores. Because of the radial symmetry the model is made up of one dimensional partial differential equations with spatial coordinate $0 \le x \le l_m$ where l_m is membrane length. The spatial coordinate x represents position along the centre axis of the membrane.

$$-\frac{\partial r(x,t)}{\partial t} = -\frac{\partial q(x,t)}{\partial x} + \phi^b(t) u^w(x,t), \tag{2.2}$$

$$\phi^c(x)\frac{\partial V_x^p(x,t)}{\partial t} = (1-k(x,t))(1-\beta(x,t))\phi^a(t)u_x^w(x,t)2\pi r(x,t). \tag{2.3}$$

In Eqs. (2.2) and (2.3) $V_x^p(x,t)$ $[\mathrm{m^3 m^{-1}}]$ is the volume of membrane pore fouling that occurs in the selective cake layer per unit of x. The latter is indicated by the subscript x and also by the unit $[\mathrm{m^3 m^{-1}}]$. This notational convention will be used throughout this paper. In Eqs. (2.2) and (2.3) $r(x,t)$ [m] is the constricted inner radius of the membrane fibre. The constriction is due to the fouling cake layer. Furthermore $q(x,t)$ $[\mathrm{m^{-1}}]$is the particle flux entering the fouling cake layer, $\phi^b(t)$ $[-]$ volume fraction of yeast cells and large aggregates in $F^i(t)$ forming the fouling cake layer and $u_x^w(x,t)$ $[\mathrm{ms^{-1}m^{-1}}]$ radial beer velocity through the membrane per unit x. Also $\phi^a(t)$ $[-]$ is the volume fraction of beer aggregates responsible for this fouling and $0 < \phi^c(x,t) \le 1$ $[-]$ a compression factor of the fouling cake layer. When uncompressed it is equal to 1. Eq. (2.2) describes cake layer mass balances and sheer induced diffusion (van der Sman & Vollebregt, 2013). Finally $0 \le \beta(x,t) < 1$ is the capturing coefficient of the membrane selective layer and $0 \le k(x,t) < 1$ the screening coefficient of the cake layer. Eq. (2.3) describes mass balances associated with membrane selective layer fouling.

The hydraulic equations describing the flow of beer through the system are considered to operate on time scales very much shorter than those involved in Eqs.(2.2) and (2.3). Therefore they are considered to be in quasi-steady state which is represented by algebraic equations.

$$u_x^w(x,t) = \frac{Q_x^r(x,t)}{A_x(x,t)}, \tag{2.4}$$

where $Q_x^r(x,t)$ $[\mathrm{m^3\ s^{-1} m^{-1}}]$ is the radial beer flow through the membrane per unit x and $A_x(x,t)$ $[\mathrm{m^2 m^{-1}}]$ the surface area available for out flow through the membrane per unit x.

$$Q_x^r(x,t) = \frac{p^m(x,t) - p^o}{R_x^r(x,t)}, \tag{2.5}$$

$$A_x(x,t) = 2\pi r(x,t), \tag{2.6}$$

where $p^m(x,t) - p^o$ [Pa] is the transmembrane pressure, p^o [Pa] the pressure at the outlet of the membrane which is assumed constant and $R_x^r(x,t)$ $[\mathrm{Pa\ m^{-3} sm^{-1}}]$ the resistance of the membrane to radial flow of beer per unit x. The axial flow $Q^a(x,t)[\mathrm{m^3 s^{-1}}]$ of beer in the x direction through the membrane is described by,

$$Q^a(x,t)R^a(x,t) = \frac{dp^m(x,t)}{dx}, \tag{2.7}$$

where $R^a(x,t)$ $[\mathrm{Pa\ m^{-3} s}]$ is the resistance to beer flow in the axial x direction. Finally at each time t we have the following boundary conditions,

$$Q^a(0,t) = F^i(t), Q^a(l_m,t) = F^c(t), \int_0^{l_m} Q_x^r(x,t)dx = F^o(t). \tag{2.8}$$

In addition to these equations there are some additional assumptions and equations relating to the build-up and break down of the cake and selective layer. We have omitted these rather complicated algebraic relations here because the focus of this paper is on the controller design and performance. They can however be found (van der Sman & Vollebregt, 2013; Cristea, Mazaeda, & de Prada, 2013).

Observe from Eqs. (2.2)–(2.7) that r and V^p may be considered the states of the model. The computation of state behaviour is performed as follows. Let t_c denote the current time. Then given the current values of the state $r(x,t_c)$ and $V^p(x,t_c)$ the flow resistances $R^r(x,t_c)$, $R^a(x,t_c)$, which are fully and algebraically determined by them, are computed. For reasons mentioned earlier also these algebraic relations have been omitted here but can be found in (van der Sman & Vollebregt, 2013; Cristea et al., 2013). After spatial discretisation of x the resistances $R^r(x,t_c)$, $R^a(x,t_c)$ make up a linear resistance network between $F^i(t_c)$, $F^o(t_c)$ and $F^c(t_c)$. Knowing the controls $F^o(t_c)$ and $F^c(t_c)$ we know $F^i(t_c)$ from (2.1). Knowing also p^o we calculate the

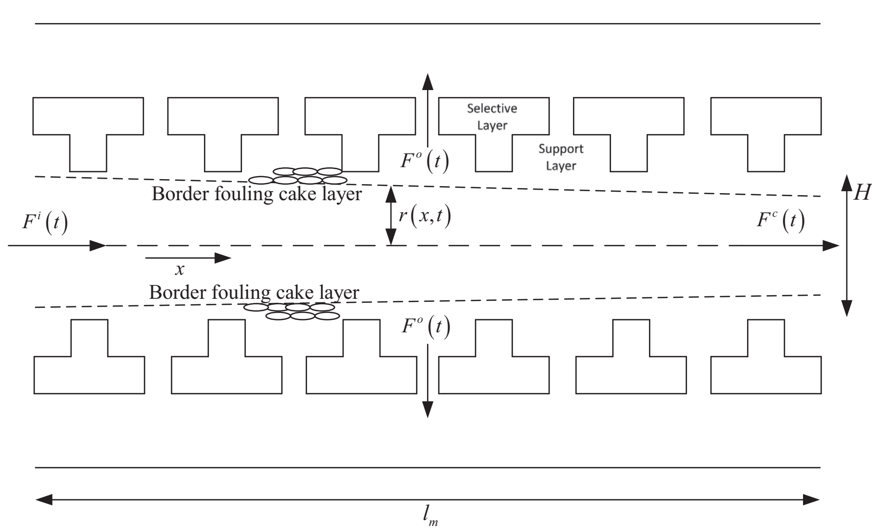

Fig. 3. Radial symmetry of membrane.

beer flow distribution through the membrane $Q^r(x,t_c)$, $Q^a(x,t_c)$ by applying a closed form solution of the associated linear flow network (Nilsson & Riedel, 2007) at the current time t_c. Also the associated pressure distribution $p^m(x,t_c)$ is obtained. This comes down to solving Eqs. (2.4)–(2.8). Next we compute the right hand sides of Eqs. (2.2) and (2.3) to find the time derivatives of the states $r(x,t)$ and $V^p(x,t)$ at the current time t_c. From these time derivatives we calculate associated small time increments of the states.

As to the state behaviour during backflushes (BF) and chemical cleaning stages (C) the model assumes the following. Backflushes are assumed to remove all cake and selective layer fouling on top of the membrane and a fixed fraction of the pore fouling aggregates inside the membrane. This fixed fraction is one of the parameters that will be estimated by the optimal adaptive scheduling and control system. Chemical cleanings are assumed to remove totally all fouling on top and within the pores of the membrane. These assumptions determine the states $V^p(x,t)$ and $r(x,t)$ at the start of each new filtration cycle (FC). For example after a chemical cleaning stage (C), $V^p(x,t)=0$ and $r(x,t)=H/2$ where H is the diameter of the membrane in Fig. 3.

3. Scheduling and control

Given the significant interaction between scheduling and control of beer membrane filtration we design them simultaneously at the expense of obtaining a more difficult design problem. To state this problem reconsider Fig. 2 representing one chemical cleaning cycle. Let N^C denote the total number of chemical cleaning cycles needed to filter a given amount of beer. Furthermore let N_i^F denote the number of filtration cycles (FC) or filtration stages (F) within chemical cleaning cycle i, $i=1,2,\ldots,N^C$.

Let the subscript j,i denote filtration stage j during chemical cleaning cycle i with $j=1,2,\ldots,N_i^F$, $i=1,2,\ldots,N^C$. Let $T_{j,i}^F$ denote the times required to execute these filtration stages (F) and T^B, T^C the fixed time required for a back flush (BF) and a chemical cleaning stage (C) respectively. Assuming the controls $F_{j,i}^o$, $F_{j,i}^c$ to be constant during a single filtration stage (F) the scheduling and control problem is to find these values as well as $T_{j,i}^F$, $i=1,2,\ldots,N^C$, $j=1,2,\ldots,N_i^F$ together with N_i^F, $i=1,2,\ldots,N^C$ and N^C so as to fulfil requirements which will be stated next. The controls $F_{j,i}^o$, $F_{j,i}^c$ are upper and lower bounded to prevent membrane damage and membrane blocking due to fouling. This is described by,

$$F^{o,l} \le F_{j,i}^o \le F^{o,u}, \tag{3.1}$$

$$F^{c,l} \le F_{j,i}^c \le F^{c,u}, \tag{3.2}$$

$$0 < F^{o,l} < F^{o,u} < F^{c,l} < F^{c,u}, \tag{3.3}$$

where the superscripts l,u denote lower and upper bound respectively.

Observe from Fig. 2 and the previous assignments that the total time of beer membrane filtration T^M is,

$$T^M = N^C T^C + N^C \sum_{j=1}^{N_i^F} T^B + \sum_{i=1}^{N^C} \sum_{j=1}^{N_i^F} T_{j,i}^F. \tag{3.4}$$

Requirements that have to be fulfilled are threefold. (1) A given volume V^B of beer must be filtered within a given amount of time T^E. This is represented by,

$$V^B = \sum_{i=1}^{N^C} \sum_{j=1}^{N_i^F} \int_o^{T_{j,i}^F} \int_0^{l_m} Q^r(x,t)dx\,dt, \tag{3.5}$$

$$T^M = N^C T^C + N^C \sum_{j=1}^{N_i^F} T^B + \sum_{i=1}^{N^C} \sum_{j=1}^{N_i^F} T_{j,i}^F \le T^E, \tag{3.6}$$

where the double integral in (3.5) represents the total out flow of filtered beer during filtration stage with indices j,i. (2) An upper bound for the transmembrane pressure must be respected to prevent damage of the membranes. This is represented by,

$$p^m(x,t) \le p^{m,u},\ 0 \le t \le T_{j,i}^F, \tag{3.7}$$

where $p^{m,u}$ represents the upper bound. Eq. (3.7) must hold for each filtration stage with indices $j=1,2,\ldots,N_i^F$, $i=1,2,\ldots,N^C$. (3) Costs associated with membrane filtration must be minimised. Given the need to filter a fixed amount of beer it is common practice to represent these costs per unit area of the membrane [€/m^2] (Zondervan et al., 2008a). It is also interesting to represent the costs per unit of filtered beer [€/l] as we shall also do when representing the results. Fixed costs C^B and C^C [€/m^2] are associated with a single backflush (BF) and a chemical cleaning stage (C) respectively. Costs are also associated with energy required to realise the beer flow. These are calculated from the pressure $p^m(x,t)$ and the radial and axial flows $Q^r(x,t)$, $Q^a(x,t)$. For filtration stage with index j,i the energy $E_{j,i}^F$ to realise the flows is computed as follows:

$$\begin{aligned} E_{j,i}^F &= E_{j,i}^c + E_{j,i}^o, \\ E_{j,i}^c &= \frac{1}{p^e}\int_0^{T_{j,i}^F} (p^m(0,t)-p^m(l_m,t))Q^a(l_m,t)dt, \\ E_{j,i}^o &= \frac{1}{p^e}\int_0^{T_{j,i}^F}\int_0^{l_m} (p^m(x,t)-p^o)Q_x^r(x,t)dx\,dt. \end{aligned} \tag{3.8}$$

In Eq. (3.8) $0 < p^e \le 1$ is the pump or energy efficiency and E^c is the energy required for cross flow which is the associated power integrated over time with power equal to pressure drop times flow. Similar arguments apply to E^o the energy associated with total radial out flow which needs an additional integration over x. Using Eq. (2.8) we can express the second Eq. (3.8) in terms of the cross flow $F^c(t)$,

$$E_{j,i}^c = \frac{1}{p^e}\int_0^{T_{j,i}^F} (p^m(0,t)-p^m(l_m,t))F^c(t)dt, \tag{3.9}$$

If p^E is the price of one unit energy then,

$$C_{j,i}^F = p^E E_{j,i}^F / A^M \tag{3.10}$$

is the associated energy costs [€/m^2] per unit membrane area to realise beer flow where A^M denotes membrane area [m^2]. The total costs C^M[€/m^2] of beer membrane filtration can now be computed as,

$$C^M = N^C C^C + N^C \sum_{j=1}^{N_i^F} C^B + \sum_{i=1}^{N^C} \sum_{j=1}^{N_i^F} C_{j,i}^F \tag{3.11}$$

To convert the costs (3.11) from [€/m^2] to [€/l] we should multiply by A^M/V^B.

3.1. Optimal scheduling and control problem formulation

Given the system (2.1)–(2.8) together with its initial state and parameter values and given the costs C^B, C^C and parameters p^e, p^E in (3.8) and (3.10) find the integers N^C,N_i^F, and the associated real values $F_{j,i}^o$,$F_{j,i}^c$,$T_{j,i}^F$, $j=1,2,\ldots,N_i^F$, $i=1,2,\ldots,N^C$ such that C^M in (3.11) is minimised while satisfying the constraints (3.1)–(3.3), (3.6), (3.7).

As mentioned in this section $F_{j,i}^o$, $F_{j,i}^c$, $j=1,2,..,N_i^F$ $i=1,2,\ldots,N^C$ are optimised but considered constant. In that case our problem is a mixed integer non-linear programming problem (MINLP). Operators sometimes adjust $F_{j,i}^o$, $F_{j,i}^c$ during a single filtration stage. So an interesting more difficult optimal scheduling and control problem is obtained by dropping the assumption that $F_{j,i}^o$, $F_{j,i}^c$ are constant during each single filtration stage. Then the problem is to find $F_{j,i}^o(t)$, $F_{j,i}^c(t)$, $0 \le t \le T_{j,i}^F$. This is no longer an MINLP problem but it becomes one if we apply control parameterisation over each filtration stage (Ross & Fahroob, 2006). This type of problem is also briefly addressed in this paper.

4. Optimal open loop scheduling and control

Being a MINLP problem our optimal scheduling and control problem belongs to one of the most difficult classes of optimisation problems (Antelo et al., 2008). Although MINLP solvers have been developed and are commercially available, they are computationally expensive and may not find solutions. Since our goal is industrial implementation, it would be advantageous to simplify the problem into one that can be more reliably and efficiently solved. By making some suitable assumptions that can be very well motivated our scheduling and control problem is turned into an ordinary nonlinear programming problem (NLP) for which solvers are readily available. Compared with MINLP solvers these are efficient and reliable.

In Section 4.1 we present the assumptions and conversion into an NLP problem. Current practice is to select the controls as follows,

$$F^o_{j,i}(t) = F^o, F^c_{j,i}(t) = F^c, 0 \le t \le T^F_{j,i}, j = 1,2,\ldots,N^F_i, i = 1,2,\ldots,N^C. \tag{4.1}$$

According to (4.1) over each filtration stage (F) each control is not only constant, but also identical and equal to F^o, F^c respectively. This type of control scheme we will denote by CF. A much more sophisticated control scheme is represented by,

$$F^o_{j,i}(t) = F^o_{j,i}, F^c_{j,i}(t) = F^c_{j,i}, 0 \le t \le T^F_{j,i}, j = 1,2,\ldots N^F_i, i = 1,2,\ldots,N^C. \quad .(4.2)$$

According to (4.2) different filtration stages (F), indexed by j,i, have different but constant controls $F^o_{j,i}$ and $F^c_{j,i}$ respectively. This type of control scheme we will denote by CV. Finally the most advanced control scheme, but also the one that is computationally most demanding, has $F^o_{j,i}(t)$, $F^c_{j,i}(t)$, $0 \le t \le T^F_{j,i}$ variable within each filtration stage (F). Through *control parameterisation* (Ross & Fahroob, 2006) $F^o_{j,i}(t)$, $F^c_{j,i}(t)$, $0 \le t \le T^F_{j,i}$ are determined by *finitely* many parameters enabling conversion to a MINLP problem. Polynomials are generally used for control parameterisation there coefficients being the parameters (Ross & Fahroob, 2006). This type of control scheme we will denote by CVP. Control schemes CF, CV are actually simple special cases of control parameterisation where the number of parameters determining $F^o_{j,i}(t)$ for some j,i is just one and similarly for $F^c_{j,i}(t)$. The associated polynomials have order zero in this simple special case.

4.1. Model assumptions and conversion into an NLP problem

To transform our original optimal scheduling and control problem from a MINLP to a NLP a dedicated problem reformulation is developed in this section. To explain this problem formulation reconsider the costs (3.11) of filtering the desired amount of beer. The mixed integer character of the problem relates to the variable number N^C of chemical cleaning cycles (CC) as well as the variable number N^F_i, $i = 1,2,\ldots,N^C$ of filtration cycles (FC) within each chemical cleaning cycle (CC). Our dedicated assumptions to turn the problem into an NLP problem are twofold. First we assume all chemical cleaning cycles $i = 1,2,\ldots N^C$ needed to filter the beer to be *identical*. Next instead of an integer we take the number of chemical cleaning cycles N^C to be *continuous*. Then the costs (3.11) simplify to,

$$C^M = N^C C^C + N^C N^F C^B + N^C N^F \sum_{j=1}^{N^F} C^F_j. \tag{4.3}$$

In Eq. (4.3) the index $i = 1,2,\ldots,N^C$ counting the number of chemical cleaning cycles has disappeared because all chemical cleaning cycles are considered identical. Only the index $j = 1,2,\ldots,N^F$ remains leaving still one integer N^F to optimise.

If, for the moment, we consider N^F fixed and known the optimisation of control scheme (4.2) comes down to finding the constants F^o_j, F^c_j, $T^F_j\, j = 1,2,\ldots,N^F$, which determine the control that minimises C^M in (4.3) while satisfying the constraints (3.1)–(3.3), (3.6), (3.7). Given a choice of F^o_j, F^c_j, $j = 1,2,\ldots,N^F$ satisfying constraints (3.1)–(3.3), both $T^F_j\, j = 1,2,\ldots,N^F$ and C^M may be computed as follows. For each filtration stage, using the controls and initial condition, the system is numerically integrated forward in time until constraint (3.7) is violated. In this way terminal times $T^F_j\, j = 1,2,..,N^F$ of each filtration stage are obtained because the control bounds (3.1)–(3.3) guarantee that constraint (3.7) will ultimately be violated. This type of numerical integration also enables computation of the amount of filtered beer $V^{B,1}$ during this single chemical cleaning cycle,

$$V^{B,1} = \sum_{i=1}^{N^F_i} \int_o^{T^F_{j,i}} \int_0^{l_m} Q^r_x(x,t)dx\, dt. \tag{4.4}$$

Given the assumptions of identical chemical cleaning cycles and a continuous value for the number of chemical cleaning cycles N^C we compute this continuous value to be,

$$N^C = V^B / V^{B,1}, \tag{4.5}$$

where V^B is the given desired amount of filtered beer. Also from the numerical integration we compute (3.8) needed to compute C^M through (3.10), (3.11), (4.5). The only constraint that is not *a-priori* satisfied by this computational procedure is the terminal time constraint (3.6).

Summarising, in case of control scheme (4.2) the problem has now been reduced to finding the upper and lower bounded control values F^o_j, F^c_j, $j = 1,2,\ldots,N^F$ that minimise C^M while satisfying constraint (3.6). In case of control scheme (4.1) this reduces to finding the two upper and lower bounded control values F^0, F^c. Applying our computational scheme both C^M and constraint (3.6) become functions of the control values. So the problem is turned into an NLP problem. To arrive at it we assumed the number of backflushes N^F during each chemical cleaning cycle to be fixed and known. However, N^F needs optimisation. One way to achieve this is to solve the NLP problem for different fixed values of N^F and pick the best solution. It turns out that for our problem four values of N^F are generally sufficient to find what appears to be the best solution. This is the approach adopted in this paper. As to the model assumptions made to arrive at this approach, justifications for them will be provided in Section 5.

Focus of this paper is on control schemes (4.1) and (4.2) because these are more close to current industrial practice and are less demanding computationally than the control scheme which has $F^o_{j,i}(t)$, $F^c_{j,i}(t)$, $0 \le t \le T^F_{j,i}$ variable. Therefore they seem more suitable for implementation and convincing industry. We will however also consider the most advanced control scheme which has $F^o_{j,i}(t)$, $F^c_{j,i}(t)$, $0 \le t \le T^F_{j,i}$ variable to see what might be gained. In this case the control parameters are no longer directly linked with the control bounds (3.1)–(3.3). Therefore (3.1)–(3.3) must now be implemented as constraints which must be evaluated each time during numerical integration.

4.2. Optimal open loop scheduling and control results

Having described the conversion and associated computations into NLP problems in the previous section open loop optimal schedules and controls and associated computation times are presented in this section. Our NLP problem suffers from local minima and also is non-smooth due to non-smoothness of the equations describing cake formation and membrane pore fouling. Therefore the NLP solver we used is one from the MATLAB global optimisation toolbox called patternsearch where we selected the Nelder–Mead search procedure. Table 1 compares standard operation (S) of the

Table 1
Costs [€/m²], [€/l] described by Eq. (4.3) of standard (*S*) and optimal controls of type CF, CV and CVP using Chebyshev polynomials of order 1.

	S [€/m²]	S [€/l]	CF [€/m²]	CF [€/l]	CV [€/m²]	CV [€/l]	CVP [€/m²]	CVP [€/l]
$\sum_{j=1}^{N^F} C_j^F$	2.201E−03	1.709E−06	2.752E−03	1.832E−06	3.789E−03	2.252E−06	3.434E−03	2.031E−06
$N^F C^B$	1.200E−02	9.317E−06	1.200E−02	7.989E−06	1.200E−02	7.134E−06	1.200E−02	7.097E−06
C^C	1.500E−02	1.165E−05	1.500E−02	9.986E−06	1.500E−02	8.917E−06	1.500E−02	8.872E−06
C^M	3.341E−01	2.267E−05	2.919E−01	1.981E−05	2.697E−01	1.830E−05	2.653E−01	1.800E−05
N^F	6	6	6	6	6	6	6	6
N^C	11.442	11.442	9.810	9.810	8.761	8.761	8.716	8.716

Table 2
Costs C^M [€/m²],[€/l] described by eq. (4.3) of optimal controls of type CF, CV and CVP using Chebyshev polynomials of order 1 for different numbers of back flushes N^F.

N^F	CF [€/m²]	CF [€/l]	CV [€/m²]	CV [€/l]	CVP [€/m²]	CVP [€/l]
3	2.728E−01	1.851E−05	2.611E−01	1.772E−05	2.461E−01	1.670E−05
4	2.736E−01	1.857E−05	2.557E−01	1.735E−05	2.439E−01	1.655E−05
5	2.814E−01	1.909E−05	2.593E−01	1.760E−05	2.590E−01	1.757E−05
6	2.919E−01	1.981E−05	2.697E−01	1.830E−05	2.653E−01	1.800E−05

down scaled beer membrane filtration unit (BMF) with optimal ones using control schemes CF, CV and CVP. For CVP, Chebyshev polynomials are selected because of their accuracy and convergence properties as it comes to control parameterisation (Vlassenbroeck & Van Dooren, 1988). It turns out that the computational load becomes too high for real-time implementation if polynomial orders larger than one are implemented. Another justification for choosing this very low polynomial order may be found in the next section.

The standard settings in Table 1 were scaled down settings suitable to filter the required amount of filtered beer V^B. They have six filtration cycles (FC) per chemical cleaning cycle (CC) and ten chemical cleaning cycles. The costs in Table 1 are decomposed according to Eq. (3.11).

Whereas in Table 1 the number of back flushes N^F during each chemical cleaning cycle was fixed as in standard operation, Table 2 tabulates optimal control results for fixed values $N^F=3,4,5,6$ and our three control schemes. Table 2 reveals what may be gained by allowing settings to vary over time in different manners. As expected, the more advanced the control scheme the less the costs. Also Table 2 shows that except for control scheme (4.1) $N^F=4$ is optimal.

4.3. Optimal open loop control of a single beer filtration stage

In this section we further investigate what may be gained by allowing for variable controls $F^o_{j,i}(t), F^c_{j,i}(t), 0 \le t \le T^F_{j,i}$ during individual filtration stage (F). Observe that column CVP in Table 2 already represents an example because the controls $F^o_{j,i}(t)$, $F^c_{j,i}(t)$, $0 \le t \le T^F_{j,i}$ are allowed to be linear functions of time since the order n^p of the Chebyshev polynomial parameterising them was one. If the order of this polynomial is further increased the optimisation results in Table 2 are ever harder to obtain due to the increasing number of NLP parameters that have to be solved. Their number n^o equals,

$$n^o = 2N^F\left(n^p+1\right). \tag{4.6}$$

Since our objective is real-time optimal adaptive scheduling and control the computational load must be limited. To limit computational load we might alternatively optimise over a single filtration phase only. This effectively sets $N^F=1$ in (4.6). This requires the development of a cost function that applies over a single filtration phase. This cost function should incorporate both long and short term cleaning objectives. To develop this cost function it is important to realise that all beer fouling removed by filtration is either stored in the cake layer or in the small pores of the membrane. Removal of beer fouling can therefore take place in three different ways.

1. By removal of the fouled cake layer and part of the pore fouling through back flushes.
2. By chemically removing the fouled cake layer and fully cleaning the fouled pores.
3. By removal of fouled beer from the system.

The last option has not been explicitly considered by the optimal scheduling and control procedure developed in this paper so far. Interestingly, simulations of this adaptive optimal scheduling and control scheme to be presented in Section 5.1 reveal that the desired amount of beer is never totally filtered at the end, leaving some beer left that captures fouling. The assumption of identical chemical cleaning cycles underlying the adaptive optimal scheduling and control scheme is violated mainly because of the increase of fouling aggregate concentrations during filtration. This is an important cause of beer to be left over at the end. As such this realises the 3rd point mentioned above.

Current practice is to add beer to the system regularly. Doing so higher fouling concentrations of beer are reduced. These higher fouling concentrations occur due to parts of the cake layer being flushed back into the beer regularly, by increasing the cross flow. The latter is a method used by operators to prolong the duration of a single filtration stage without violating the maximum transmembrane pressure. Although this prolongs the filtration stage it destroys the short term possibility to remove the fouling captured by the cake layer. All this fouling is sent back into the beer and ultimately has to be captured again to remove it.

To develop the cost function it is finally important to note that chemically cleaning the membrane pores is much more expensive then performing back flushes removing the cake layer. These in turn are much more expensive than pumping costs. As a result the cheapest way of removing fouling is through 1 and 3 listed above. Therefore our cost function promotes formation of cake fouling and punishes pore fouling per unit of filtered beer. Furthermore it reduces energy costs associated with pumping per unit of filtered beer. The cost function J is given by,

$$J = \frac{1}{\int_0^{T^F}\int_0^{l^m} Q^r_x(x,t)dx\,dt}\left[-10^{10}V^c(t_f)+10^{11}V^p(t_f)+10^{-3}J^E\right],$$

$$J^E = \frac{1.33p^E}{A}\left[\int_0^{T^F}\frac{F^o(t)\int_0^{l^m}(p^m(x,t)-p^o)dx}{\eta^o}dt + \int_0^{T^F}\frac{\left(F^o(t)+F^c(t)\right)\left(p^m\left(l^m\right)-p^m(0)\right)}{\eta^c}dt\right] \tag{4.7}$$

where V^c is the total volume of the fouling cake layer [m^3], V^p the total pore fouling volume [m^3], A the total area of the membrane [m^2] and J^E the energy costs associated with pumping per unit filtered beer [€/m^3]. Moreover η^0, $\eta^c \in [0, 1]$ are pump efficiencies of pumps realising out flow and cross flow respectively. Finally the numbers -10^{10}, 10^{11} and 10^{-3} in (4.7) are weighing factors promoting (when negative) and discouraging (when positive) quantities they multiply. The following constraint is included that prescribes a minimum amount of filtered beer per time unit associated with a single filtration cycle (FC),

$$\int_0^{T^F}\int_0^{l^m} Q_x^r(x,t)dxdt \geq \frac{0.4}{3.6\times10^6}\left(T^F+T^B\right). \tag{4.8}$$

Constraint (4.8) states that the amount of filtered beer should be at least 0.4 L/h.

Using the cost function (4.7) optimal controls have been computed using control parameterisation up to order six of the Chebyshev polynomials. The results are listed in Table 3. Note that Chebyshev polynomials of order zero represent controls that are constant over each filtration stage as described by Eq. (4.2). So what may be gained by allowing controls to vary over each filtration can be read from Table 3, especially from the first and last column. The results show that, for the cost function (4.7), significant improvements are obtained by allowing for variable controls over each single filtration stage (F). Variable controls increase the ability to control both the cake and pore fouling as can be seen from Table 2.

5. Adaptive optimal closed loop scheduling and control

The open loop optimal control and scheduling results presented in Table 2 and 3 indicate that selecting constant controls that are also identical over each single filtration stage (F), denoted by CF, leads to a loss of optimality of less than 10.0% as compared to the most advanced control, denoted by CVP, that has $F_{j,i}^o(t)$, $F_{j,i}^c(t)$, $0 \leq t \leq T_{j,i}^F$ variable within each filtration stage (F). To limit the number of optimisation parameters, the optimal control and scheduling computation presented in this section uses CF leaving only two parameters to be optimised. This may seem a very small number but it is selected due to the need to for a global search algorithm in combination with function evaluations that are expensive due to the implicit differential algebraic nature of the spatially distributed model that has to be integrated repeatedly. This is illustrated by Fig. 4 showing typical improvements of *unscaled costs* and associated computation times during global optimisation. With only two parameters a simple grid search might be considered an alternative. As it turns out a simple grid search is either less accurate or computationally more expensive when the accuracy is increased by increasing the density of the grid.

As already mentioned in Section 4.3, the assumption of identical chemical cleaning cycles underlying the results of the previous section is violated mainly because of the increase of fouling aggregate concentrations during filtration. In Section 4.3 we also argued that this partly realises removal of beer fouling through beer that is left over. Also note that the computed optimal schedule and control is only applied during the next chemical cleaning cycle after which it is adjusted and recomputed based on estimated new values of fouling parameters and the remaining amount of to be filtered beer. So the *actual* control is different during each chemical cleaning cycle. Therefore the sub optimality caused by the assumption of identical chemical cleaning cycles is limited when performing real-time scheduling and control. The adaptive part of the optimal scheduling and control scheme relates to critical fouling parameters and some other critical model parameters that are estimated. These are explicitly mentioned and explained in the next section.

5.1. Description and simulation results

To investigate the applicability and potential of the adaptive optimal closed loop scheduling and control scheme simulations results are presented in this section. To mimic modelling and measurement errors, errors in four critical model parameters are simulated. At the same time these erroneous parameters are estimated using the model and transmembrane measurements and an ordinary least squares criterion. The selection of these four parameters was guided by the fact that volume fractions of yeast cells and aggregates in beer, represented by ϕ^a, ϕ^b, are uncertain and difficult or very expensive to measure, while they significantly influence filtration. The same arguments apply to parameters p^c and Q^c related

Table 3
Costs J [€/m^2], [€/l] of optimal control policies over a single filtration stage for different orders O_C of Chebyshev polynomial control parameterisations.

O_C	J [€/m^2]	J [€/l]
0	−7.910E−02	−5.367E−06
3	−7.971E−02	−5.409E−06
6	−8.040E−02	−5.456E−06
9	−8.048E−02	−5.461E−06

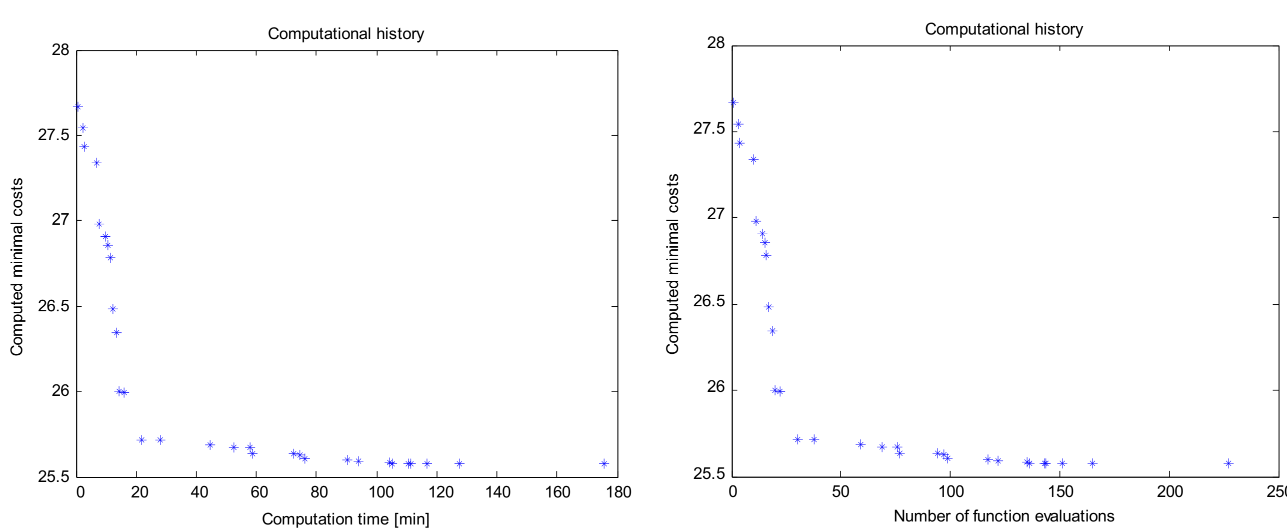

Fig. 4. Typical improvements and computation times during global optimisation.

to cake layer compression and build up on the membrane respectively. The latter two parameters appear in the algebraic part of the model not described in this paper but in (van der Sman & Vollebregt, 2013). The selection was also based on results from (van der Sman, Van Willigenburg, Vollebregt, & Eisner, 2013) that considers the identifiability of parameters from transmembrane pressure measurements. The estimation of these four parameters comprises another NLP problem. Again patternsearch of MATLAB's global optimisation toolbox, selecting Nelder-Mead as the algorithm, is used to solve it.

Following the description just given, in the closed loop control system simulation, the system parameters denoted by the superscript s are equal to the model parameters except for the following

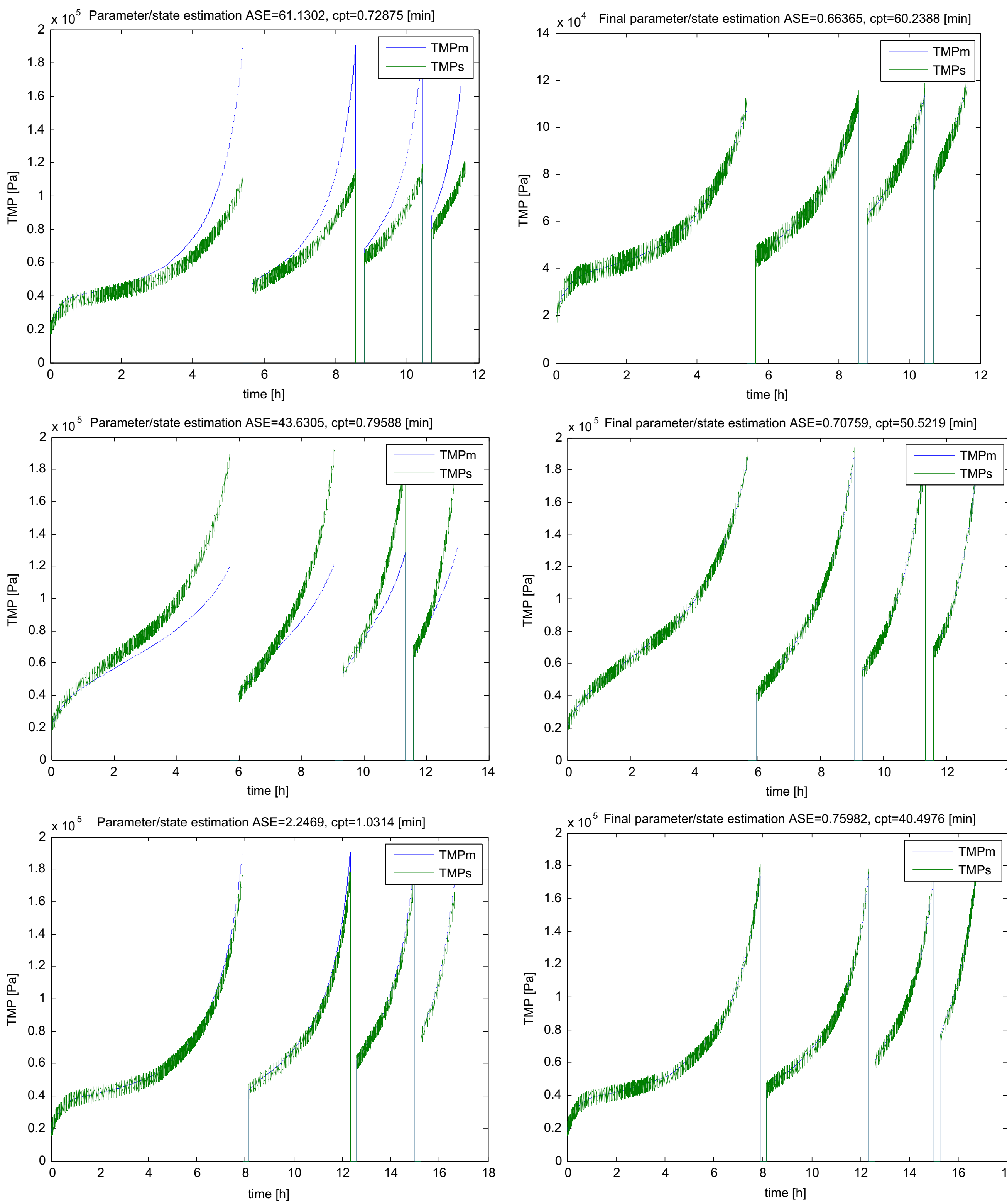

Fig. 5. Plots closed loop adaptive scheduling and control simulation 1. TMPm (blue) represents the transmembrane pressure predicted by the model of the adaptive controller. TMPs (green) represents the true noisy transmembrane pressure measured by the controller.

four critical system parameters that are estimated,

$$Q^{c,s}=1.1Q^c, p^{c,s}=1.05p^c, \phi^{b,s}=0.95\phi^b, \phi^{a,s}=0.9\phi^a \quad (4.9)$$

Observe from Eqs. (2.2) and (2.3) that ϕ^a, ϕ^b are not really parameters because they change over time. But they change slowly and therefore will be considered constant during each single chemical cleaning stage (CC). Because of their slow change over time only transmembrane measurements of the last chemical cleaning cycle (CC) are used to estimate parameters, not ones from previous chemical cleaning cycles (CC). In this respect our approach necessarily differs from what is more common, i.e. using all previous measurements to estimate parameters (Forgione, Mesbah, Bombois, & Van den Hof, 2012). The transmembrane pressure $p^m(x,t)-p^o$ has an upper bound 1.9×10^5. The associated measurements are corrupted by additive white noise having intensity 10^4. The optimal scheduling and control computations use the fixed value $N^F=4$ for the number of backflushes in the identical chemical cleaning cycles. As mentioned in Section 4.1, N^F needs optimisation which can be realised by optimising for different fixed values of N^F. Due to limited computational resources and given the fact that experiments reveal that $N^F=4$ is often optimal this choice was made. The initial state of the system $r\left(x,t_j^0\right), V_x^P\left(x,t_j^0\right)$, needed for the real-time optimal scheduling and control computations where t_j^0 denotes the time where the jth chemical cleaning cycle starts, is given by,

$$r\left(x,t_j^0\right)=r^m, V_x^P\left(x,t_j^0\right)=0, \quad (4.10)$$

where r^m [m] represents the inner radius of the membrane. Eq. (4.10) represents the assumption that after a chemical cleaning the membrane is completely free of cake and membrane fouling.

Fig. 5 and Table 4 show several outcomes obtained from one simulation of the adaptive optimal scheduling and control system. The system initially differs from the model used to perform the optimal scheduling and control computations in the manner described by Eq. (4.9). Therefore, initially, emphasis should be on estimating the parameters. The total computation available for both parameter estimation and optimal control computation is one hour. Also the optimal control for the first chemical cleaning cycle can be computed off-line. Assuming the parameter estimates become more accurate with every chemical cleaning cycle the computation time for parameter estimation T^p and the computation time for optimal control computation T^o are set to,

$$T^p=(7-i)600[\mathrm{s}], T^o=(i-1)600[\mathrm{s}], i=1,2,\ldots,N^C=6 \quad (4.11)$$

where i, like before, counts the number of chemical cleaning cycles. Because the system differs from the model, initially the computed optimal control for the first chemical cleaning cycle, when applied to the system, shows a significant deviation from the optimal behaviour computed from the model as can be seen in Fig. 5. Table 4 shows the computed optimal costs according to the model J^m with the model parameters and the real costs of the system J^s computed using the model with the real system parameter values. Values of the parameters Q^c, p^c, ϕ^b and ϕ^a used in the model that computes the optimal control are denoted by the superscript m in Table 4, the true values used by the simulated system by the superscript s and the ones obtained after parameter estimation by the superscript e.

The parameter values with superscript m used by the model are obtained from parameter estimation and/or a-priori knowledge of the previous CC cycle. Therefore the parameter values with superscript m are also the initial values used for parameter estimation over the associated CC cycle in Table 4. As a result in Table 4 the latest parameter estimates $Q^{c,e}$, $p^{c,e}$ equal those used by the model i.e. $Q^{c,m}$, $p^{c,m}$ during the next chemical cleaning cycle. As noted earlier the true values and estimates of ϕ^b, ϕ^a are different for consequtive chemical cleaning cycles because they slowly change over time according to Eqs. (2.2) and (2.3). Using the estimates $\phi^{b,e}$, $\phi^{a,e}$ obtained from the previous chemical cleaning cycle and having measured or calculated from the model the amount of filtered beer and removed fouling new values $\phi^{b,m}$, $\phi^{a,m}$ are calculated which are therefore different from $\phi^{b,e}$, $\phi^{a,e}$ as seen in Table 4.

As can be seen from Fig. 5 and Table 4 The parameter estimation performed after the first chemical cleaning cycle already achieves a small sum of squared errors. In Fig. 5 ASE indicates the average scaled squared error $(1/N)\Sigma_{k=1}^N(10^{-4}e(k))^2$ where N is the number of measurements over time and e represents the difference between the model (blue) and measured output (green), the latter being corrupted by artificial white noise as can be seen from Fig. 5. Measurements where simulated every 10 s during each filtration stage. The small ASE values and the associated proper fits of the measurements suggest accurate parameter estimates if these are identifiable from the transmembrane pressure measurements. Comparing the parameter estimates with the true system values in Table 4 and also considering the presence of artificial white measurement noise suggests the latter is the case. As a consequence already after the first chemical cleaning cycle the model is accurate and more emphasis and computation time may be spent on optimal control computations. Finally from the number of chemical cleaning cycles in Table 4 observe that the actual control requires more than four chemical cleaning cycles. The fixed four chemical cleaning cycles assumed by each optimal control computation act as a receding horizon.

Finally in this section we present the results of a second closed loop adaptive control system simulation starting from parameter errors opposite to the ones in (4.9) assumed in the first experiment,

$$Q^{c,s}=0.9Q^c,\ p^{c,s}=0.95p^c,\ \phi^{b,s}=1.05\ \phi^b,\ \phi^{a,s}=1.1\ \phi^a. \quad (4.12)$$

Table 4
Results adaptive optimal scheduling and control simulation 1.

CC cycle	J^m	J^s	$Q^{c,m}$	$Q^{c,s}$	$Q^{c,e}$	$p^{c,m}$	$p^{c,s}$	$p^{c,e}$
1	0.274	0.273	2.100E−07	2.310E−07	2.216E−07	4.000	4.200	4.511
2	0.186	0.211	2.216E−07	2.310E−07	2.233E−07	4.511	4.200	4.239
3	0.163	0.163	2.233E−07	2.310E−07	2.274E−07	4.239	4.200	4.288
4	0.123	0.124	2.274E−07	2.310E−07	2.294E−07	4.288	4.200	4.291
5	0.091	0.092	2.294E−07	2.310E−07	2.294E−07	4.291	4.200	4.291
6	0.071	0.075	2.294E−07	2.310E−07	2.294E−07	4.291	4.200	4.291

CC cycle	$\phi^{b,m}$	$\phi^{b,s}$	$\phi^{b,e}$	$\phi^{a,m}$	$\phi^{a,s}$	$\phi^{a,e}$
1	3.000E−04	2.850E−04	2.778E−04	2.000E−06	1.800E−06	1.803E−06
2	2.993E−04	3.072E−04	3.019E−04	1.648E−06	1.645E−06	1.680E−06
3	3.256E−04	3.318E−04	3.322E−04	1.536E−06	1.502E−06	1.528E−06
4	3.734E−04	3.734E−04	3.783E−04	1.327E−06	1.303E−06	1.346E−06
5	4.414E−04	4.366E−04	4.635E−04	1.132E−06	1.092E−06	1.132E−06
6	5.698E−04	5.380E−04	5.698E−04	9.188E−07	8.758E−07	9.647E−07

Similar to Fig. 5 and Table 4, Fig. 6 and Table 5 represent the associated results.

This second simulation experiment reveals a phenomenon not shown by the first simulation experiment that relates to the transmembrane pressure bounds that may not be violated during control to prevent damage of the membrane. As opposed to the parameter errors (4.9), the parameter errors (4.12) result in an initial open loop optimal control computation that causes the system to violate the transmembrane pressure bounds. This violation is detected by the measurements. These in turn trigger a back flush thereby ignoring the

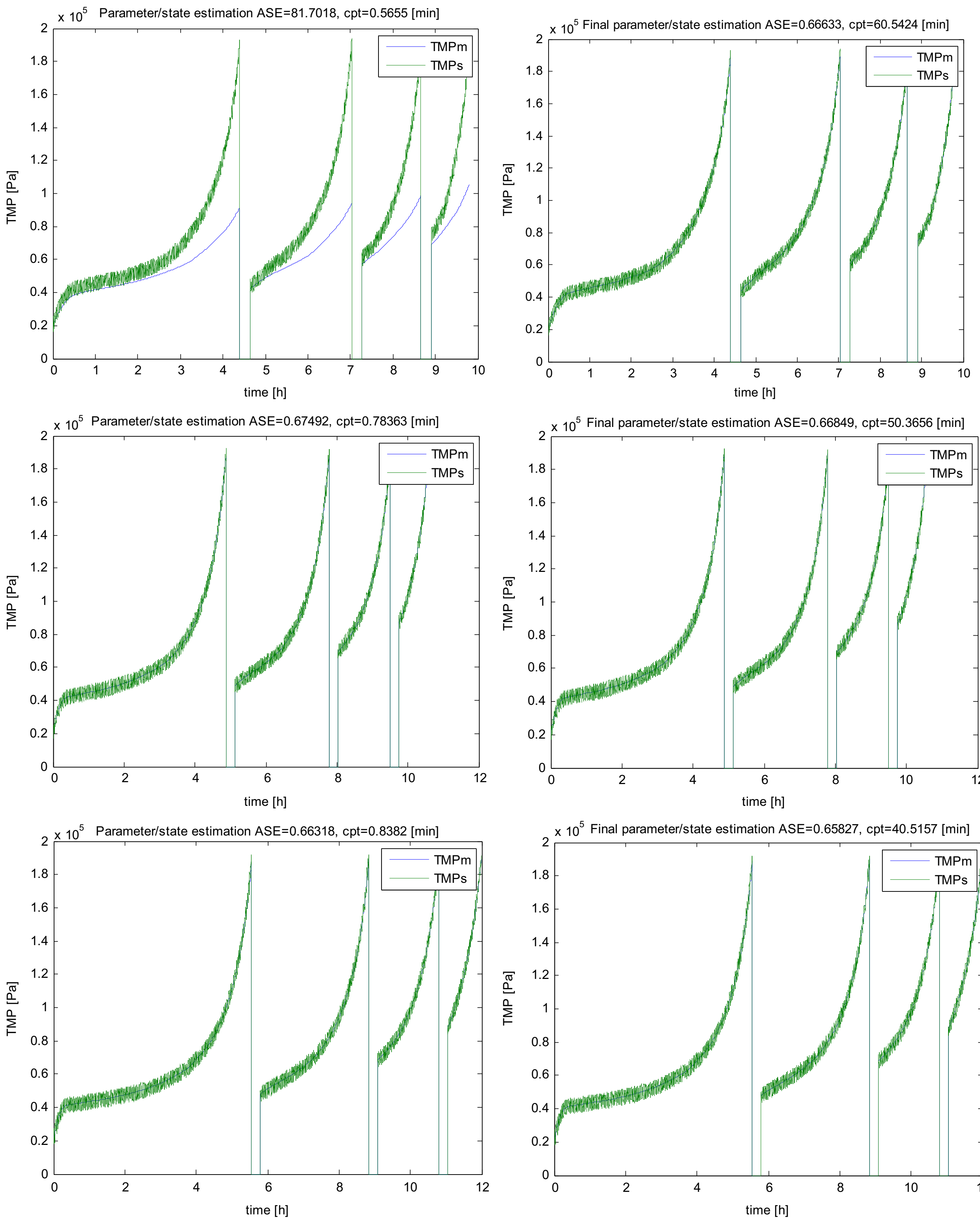

Fig. 6. Plots closed loop adaptive scheduling and control simulation 2.

Table 5
Results adaptive optimal scheduling and control simulation 2.

CC Cycle	J^m	J^s	$Q^{c,m}$	$Q^{c,s}$	$Q^{c,e}$	$p^{c,m}$	$p^{c,s}$	$p^{c,e}$
1	0.274	0.321	2.100E−07	1.890E−07	1.916E−07	4.000	3.800	3.807
2	0.273	0.273	1.916E−07	1.890E−07	1.936E−07	3.807	3.800	3.818
3	0.228	0.228	1.936E−07	1.890E−07	1.939E−07	3.818	3.800	3.809
4	0.184	0.184	1.939E−07	1.890E−07	1.939E−07	3.809	3.800	3.809
5	0.141	0.141	1.939E−07	1.890E−07	1.939E−07	3.809	3.800	3.809
6	0.110	0.110	1.939E−07	1.890E−07	1.939E−07	3.809	3.800	3.809

CC cycle	$\phi^{b,m}$	$\phi^{b,s}$	$\phi^{b,e}$	$\phi^{a,m}$	$\phi^{a,s}$	$\phi^{a,e}$
1	3.150E−04	3.202E−04	3.202E−04	2.000E−06	2.200E−06	2.198E−06
2	3.334E−04	3.446E−04	3.446E−04	2.051E−06	2.053E−06	2.053E−06
3	3.588E−04	3.692E−04	3.692E−04	1.880E−06	1.879E−06	1.879E−06
4	3.929E−04	4.043E−04	4.043E−04	1.686E−06	1.686E−06	1.686E−06
5	4.407E−04	4.535E−04	4.535E−04	1.469E−06	1.469E−06	1.469E−06
6	5.146E−04	5.297E−04	5.297E−04	1.218E−06	1.218E−06	1.218E−06

remaining part of the optimal open-loop control computed for the current filtration stage (F).

Assuming (4.9) and (4.12) to be the only (major) modelling errors is probably optimistic. In principle our strategy allows to incorporate arbitrary parameter errors. But do observe that an important assumption underlying success, i.e. ultimate convergence of the strategy, is that the model structure is sufficiently accurate. Another is that uncertain parameters are identifiable from the measurements. Experimental results and additional measurements are needed to further investigate the potential of our optimal adaptive scheduling and control strategy.

6. Conclusions

To the best of our knowledge real-time adaptive optimal scheduling and control of beer membrane filtration was proposed and realised in this paper for the first time. It comprises a complicated mathematical problem belonging to the class of MINLP problems. By exploiting certain specific system and control characteristics of this MINLP problem, we managed to approximate it by a much simpler NLP problem that was solved numerically. This simplification was enabled by our use of a detailed physical model describing beer membrane filtration. Such a model is also needed to compute and gain insight in the costs and control associated with beer membrane filtration. Also it provides clues for operators to improve manual control that is currently being used.

Despite its complexity the same model can be used for real-time adaptive optimal scheduling and control as demonstrated in this paper. Simulations of the on-line adaptive scheduling and control system show the potential to decrease filtration costs in the order of 25% as compared to current industrial practice. Beer membrane filtration is especially sensitive to fouling parameters of both the beer and membrane. Therefore mismatches in these parameters may lead to significant losses of performance as compared to the optimal one. In the simulations presented in this paper we have very much limited these mismatches. In practice therefore the reduction of filtration costs may well exceed 25% if proper measurements concerning membrane fouling become available during or before the adaptive scheduling and control. We believe that the successful application of advanced adaptive control schemes like the one proposed in this paper depends very much on the availability of measurements providing information on membrane fouling. Part of the EU Cafe research project was therefore concerned with sensor development to provide these types of measurements. Initial results showed the difficulty of providing these.

Beer membrane filtration is a partly continuous process where unfiltered beer is regularly added to the system. Our research revealed three fundamental ways of removing fouling from the beer. The one that removes fouling by removing heavily fouled beer from the system has not been used and considered so far in industry. After the simulations presented in this paper beer is left over in the system. Also our simulations and computations have discarded the remaining beer by reasoning that the process will be continuous in practice. Considering explicitly the opportunity to remove fouling by removing heavily fouled beer might further improve performance of beer membrane filtration.

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