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Flux Optimization Using Genetic Algorithms in Membrane Bioreactor

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Abstract The behavior of submerged membrane bioreactor (SMBR) filtration systems utilizing rapid air backpulsing as a cleaning technique to remove reversible foulants was investigated using a genetic algorithm (GA). A customized genetic algorithm with suitable genetic operators was used to generate optimal time profiles. From experiments utilizing short and long periods of forward and reverse filtration, various experimental process parameters were determined. The GA indicated that the optimal values for the net flux fell between 263–270 LMH when the forward filtration time (t_f) was 30–37 s and the backward filtration time (t_b) was 0.19–0.27 s. The experimental data confirmed the optimal backpulse duration and frequency that maximized the net flux, which represented a four-fold improvement in 24-h backpulsing experiments compared with the absence of backpulsing. Consequently, the identification of a region of feasible parameters and nonlinear flux optimization were both successfully performed by the genetic algorithm, meaning the genetic algorithm-based optimization proved to be useful for solving SMBR flux optimization problems.

Key words: Membrane bioreactor, flux optimization, genetic algorithm, backpulse frequency

A submerged membrane bioreactor (SMBR) is a useful unit for treating various types of wastewater under different operating conditions. However, porous media filtration presents a critical problem, as the filtrate flux declines with time. This phenomenon, commonly termed "membrane fouling" reduces production rates and increases the complexity of the membrane filtration operations. Thus, most research about MBRs is related to identifying, analyzing, and controlling membrane fouling. However, the prediction and control of membrane fouling is difficult in an MBR owing to various factors in the bioreactor, such as the biomass characteristics, membrane characteristics, and operating conditions [1, 2, 4, 12, 14, 17]. As such, numerous empirical and theoretical models have been proposed to describe membrane fouling, such as the resistance-in-series model [10, 19], dead-end filtration theory [6], and hydrodynamic approach [21]. One physical method of reducing membrane fouling is to use backwashing technology, where the permeate flow through the membrane is reversed using a high frequency of short air pulses, thereby providing *in situ* cleaning by removing some of the foulants from the membrane surface pores. Several other groups have also obtained flux enhancements by backpulsing. Kennedy *et al.* [8] investigated the effect of backwashing conditions, such as the pressure and duration, and found that the efficiency of backwashing was more dependent on the backwashing time than on the pressure. Serra *et al.* [18] showed that air sparging during backwashing improved its efficiency, whereas Sondhi and Bhave [20] demonstrated that backpulsing in cross-flow filtration minimized membrane fouling in ceramic membranes. However, to make this cleaning technique as economical as possible, the net flux should be maximized by optimizing the backpulsing conditions. Redkar and Davis [15] formulated a model in which the flux declines during forward filtration according to the dead-end filtration theory, plus the instant and complete removal of the cake is assumed during each backpulse. Experimental data for washed yeast suspensions showed an optimal backpulse frequency, as predicted by the model, yet the observed net permeated fluxes were generally higher than the model predictions. Thus, Redkar *et al.* [16] modified the model to account for a delay in the cake formation once the forward filtration is restored after each backpulse. The new model matched well with experiments using washed yeast cells. Kuberkar *et al.* [9] also formulated a model based on the idea that cleaning only occurs in a fraction of the membrane surface, with the backpulses instantaneously removing all

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the foulants in certain areas and none from the remainder of the membrane. Thus, the efficiency of backpulsing is dependent on optimizing certain parameters, such as the pressure, frequency, single or multiple pulses, and duration.

However, the optimization of such systems is complicated, owing to a lack of linearity. If the objective or fitness functions (membrane net flux) were linear, a powerful method known as linear programming could be used to solve the optimization problem. However most natural problems are nonlinear. Therefore, to solve the problems associated with such nonlinearities, the present study used genetic algorithms (GAs). The application of GAs to bioprocess optimization was first reported in early 1996 [5]. Genetic algorithms are stochastic search algorithms based on the tenets of Darwin's principle of natural selection and are thus able to evolve solutions to fit real world problems [5]. The power of GAs lies in their ability to avoid focusing on local optima, and rather range over the entire domain of the function to be optimized. Moreover, GAs are not restricted to the conditions of continuity, sensitivity, and nonlinearity of objective functions and constraints. The common feature shared by almost all optimization techniques is the control process flow, such as the flow input, output, and recycling rates. Furthermore, the flexibility offered by GAs, also allows optimum values to be determined from many reaction parameters (e.g. the fraction of cake removal, cake growth time constant, etc). Another powerful use of GAs is their ability to search for a region of interest. If there is no information about the optimum region, many researchers will initially use trial-and-error methods. However, this is invariably time-consuming and uneconomical. In contrast, GAs can be used to find the optimum region very easily because of their stochastic characteristics, which is why they are used for the parameter estimation in this study. Although several researchers have already applied genetic algorithms to the optimization of various processes [3, 7, 11], few reports have been published on the flux optimization of MBRs using a genetic algorithm approach.

Accordingly, this work further expands the application of GAs to the optimization of controllable process variables to improve the performance of membrane filtration and search for a feasible region. Finally, the predicted and experimental values are compared and the implications discussed.

MATERIALS AND METHODS

SMBR System

The filtration unit used consisted of a module containing one submerged membrane module (Korea Membrane Separation Co., Korea) with an internal diameter of 350 μm, length of 60 cm, and surface area of 2 m^2. The

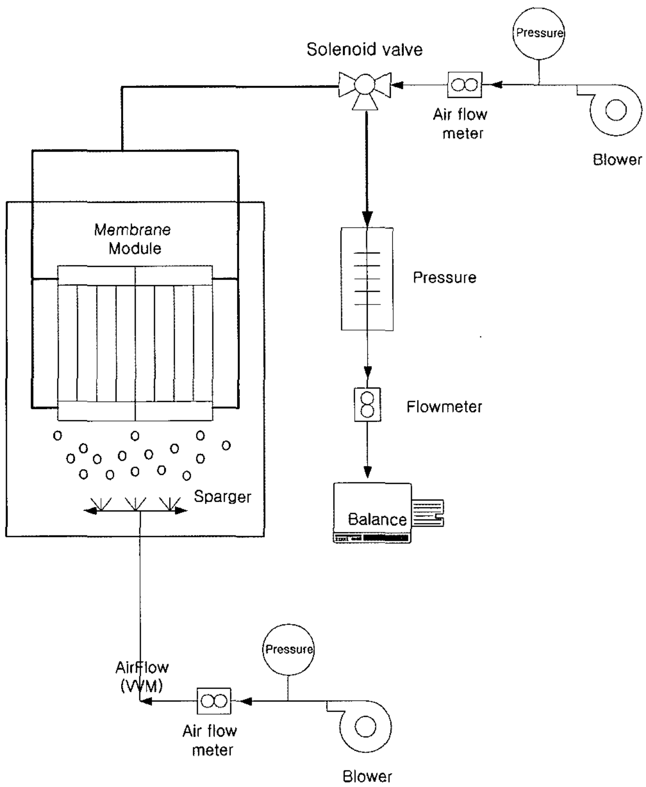

Fig. 1. Schematic diagram of submerged MBR system.

membrane, comprised of hydrophilized polypropylene with a mean pore size of 0.4 μm, was bound to ABS resin. Figure 1 shows a diagram of the experimental setup used in this study. Two cylindrical tanks (2×20 l) made of transparent PVC were used as the precipitation tanks, and a 60 l PVC reactor used as the SMBR, in which the membrane module was submerged.

In addition, an air diffuser was located just below the membrane module. The permeate from the membrane modules was continuously maintained using a peristaltic pump (Millipore Co., U.S.A.), and the membrane flux calculated by automatic weighting using an autoreader (Setra Model 1200, Denver, CO, U.S.A.). All the filtrations were run at room temperature (22±3°C). The feed suspension was pumped using a peristaltic pump from a reservoir (2×30 l) to the membrane module. The feed pressure was provided by the peristaltic pump, and the backpulsing delivered using a solenoid valve. The wastewater (Ibjang Lake, Cheonan, Korea; suspended solids: 20±10 mg/l; COD: 50–2,000 mg/l) was fed directly into the SMBR.

Theory of Flux Model

The SMBR flux maximization model was represented using a set of coupled nonlinear equations. The set of nonlinear equations used were as described by Mores *et al.* [13] and were as follows:

$$\langle J\rangle=\frac{\int_0^{t_f} J_f dt+\int_{t_f}^{t_f+t_b} J_b dt}{t_f+t_b} \tag{1}$$

$$J_f(t)=\frac{\beta_b J_0}{(1+t/\tau_f)^{1/2}}+(1-\beta_b)J_s \tag{2}$$

$$J_b(t)=-\alpha\{\beta(t)J_0+[\beta_b-\beta(t)]J_0/(1+t_f/\tau_f)^{1/2}\} \\ -\alpha(1-\beta_b)Js \tag{3}$$

where J_f is the positive flux during forward filtration, J_b is the negative flux during rapid backpulsing, t_f is the duration of the forward filtration period between backpulses, t_b is the backpulse duration, J_0 is the clean-membrane flux, J_s is the fouled-membrane flux, α is the ratio of the reverse to forward transmembrane pressure (TMP), τ_f is the time constant for the flux decline due to cake growth, and β is the fraction of the membrane cleaned by time t during a backpulse, as described by a simple exponential equation:

$$\beta(t)=\beta_{max}[1-e^{-(t-t_f)/\tau_b}] \tag{4}$$

where β_{max} is the maximum possible fraction of the membrane that can be cleaned and τ_b is the time constant for cake removal. At the end of a backpulse of duration t_b, the fraction of the membrane cleaned is then $\beta_b=\beta_{max}(1-e^{-t_b/\tau_b})$.

This expression can be used to determine the flux-maximizing values for the backpulse duration (t_b) and forward filtration time (t_f) or, alternatively, the backpulse frequency ($1/(t_b+t_f)$). There are two opposing factors that create the maximum. If the backpulses are too frequent or too long, the permeate loss is excessive during the reverse flow periods. Conversely, if the backpulses are too short or infrequent, the cleaning is ineffective and the flux declines during forward filtration. In an SMBR, membrane fouling is controlled using coarse bubble aeration of the membrane fibers to provide the cross-flow needed to prevent the accumulation of solids [22]. However, the use of coarse bubble aeration for fouling control and a membrane for solid-liquid separation can influence the SMBR sludge properties. In contrast to the use of the model in Mores *et al.* [13], this study addressed the air flow effect on a SMBR system. Ueda [22] previously reported on submerged membranes, and found the air flow rates required to achieve certain cake thicknesses. He also found an optimum value above which there was no further diminution in the cake layer. Thus, to apply the model to the effects of a pulsed air flow, the following simple power law function involving state variables was considered:

$$\beta_{air}=\frac{kB}{1+K_A B} \tag{5}$$

where k and K_A are constants, β_{air} is the fraction of the membrane that can be cleaned by the air flow, β_{air} is the units of vvm (volumetric flow per reactor volume), k is a function of the bubble size, air uplifting velocity, and air pressure, and K_A is a function of the viscosity of the treated water. When combining β and Equation (5),

$$\beta_t=\beta_{air}+\beta_b=\frac{kB}{1+K_A B}+\beta_{max}(1-e^{-t_b/\tau_b}) \\ =f(air)+f(time) \tag{6}$$

Genetic Algorithm

The programs were written using Mathematica (Wolfram Co., Ver 4.0) and followed the generation model based on a population size of 32 (bits), crossover rate of 2 per generation, mutation rate of 2 per generation, string length of 100, and maximum number of generations of 500. These parameters were maintained for all the optimization runs in this study.

The working strategy of a genetic algorithm is as follows: First, the algorithm begins by creating a random initial population. Second, the algorithm creates a sequence of new populations or generations. In each step, the algorithm uses the individuals (any point to which the fitness function applies) in the current generation to create the next generation. Finally, to prevent unlimited loops or unnecessary computer calculations, the algorithm stops when one of the stopping criteria is met. In this study, the stopping criteria were a generation limit (500 generations), fitness limit (no further change in the fitness function), and stall generation limit. A stall generation occurs when the algorithm computes a specified number of generations with no improvement in the fitness function.

RESULTS AND DISCUSSION

Determination of Initial Flux and Cake Growth Time Constant

The first flux experiments were run to observe the initial flux (J_0) and steady flux (J_s). Wastewater from the precipitation tank was allowed to run into the SMBR for 24 h at a constant TMP of 78.44 kPa. As shown in Fig. 2A, the initial flux was 540 LMH (l/m^2/h), while the final fouled flux was 22.4 LMH. Membrane fouling occurred rapidly after 5 min, and then continued slowly. The steady flux (J_s) was determined by nonlinear regression, and then the cake growth time constant (τ_f) was determined from the initial flux data. From Equation (2), assuming the cake removal ratio (β_b) is equal to 1:

$$\frac{J_f(t)}{J_0}=\frac{1}{(1+t/\tau_f)^{1/2}}$$

$$\left(\frac{J_0}{J_f(t)}\right)^2=t/\tau_f+1$$

$$y=ax+b \tag{7}$$

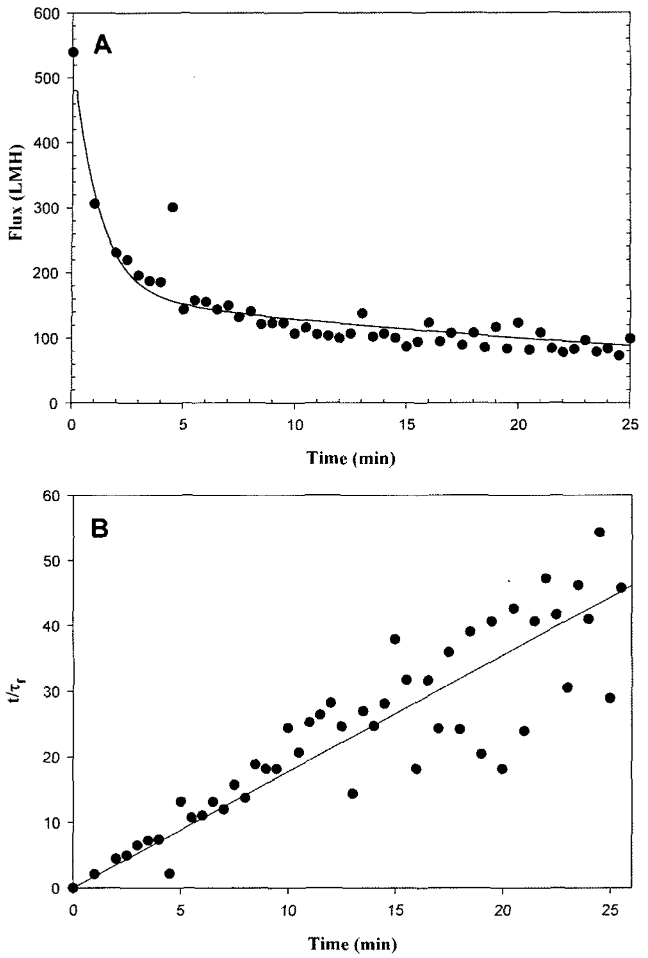

Fig. 2. Determination of initial flux (**A**) and cake growth time constant (**B**).

where Equation (7) is a first-order linear equation of slope $1/\tau_f$. Figure 2B indicates that the slope was 1.77 with a 93% confidence level, which means the value of the cake growth time constant (τ_f) was 33.84 s.

Cake Removing Efficiency According to Air Flow Rate

To examine the effect of the air flow rate on the TMP, the air flow rate was reduced from 0.06 to 0.01 vvm, and the optimum point set at 0.03 vvm (data not shown). Although the TMP decreased when increasing the air flow rate up to a certain critical value, any further increase thereafter in the air flow rate had virtually no effect on the TMP. Consequently, this optimum value was determined as the operational air flow rate to avoid any over-supply of air and to reduce power consumption.

Single Backpulsing Experiments

Single backpulse experiments were run to observe how the magnitude of the recovered flux depended on the duration and strength of the backpulse. The results were then used

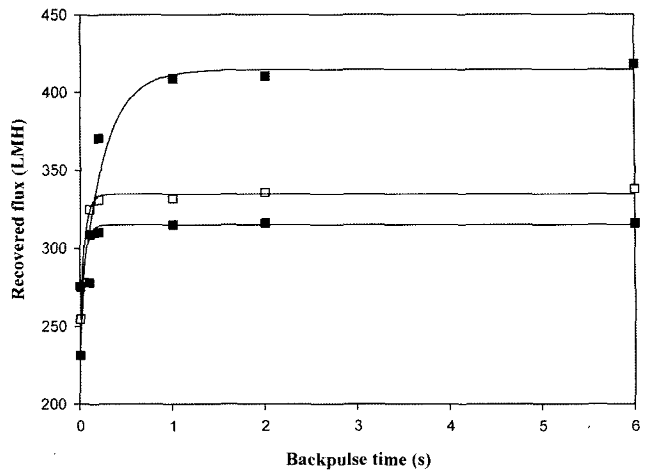

Fig. 3. Experimental (symbols) and model (curves) values of recovered flux vs. cumulative duration of single backpulse when ΔP_b=78.44 kPa.
The model curves were obtained by fitting Eq. (8) to the data.

in further experiments to determine values for τ_b, the time constant for the cake removal and β_{max}, and the maximum fraction of the cake that could be removed. To fit the single backpulse experiments, the following equation was used:

$$J_r=\beta_b J_0+(1-\beta_b)J_s=\beta_{max}(1-e^{-t_b/\tau_b})J_0 + [1-\beta_{max}(1-e1-e^{-t_b/\tau_b})]J_s \quad (8)$$

where J_r is the recovered flux and t_b is the cumulative backpulse duration. The first term on the right-hand side of Eq. (8) represents the fraction β_b of the membrane surface cleaned by the backpulse(s), and the second term represents the remaining fraction $(1-\beta_b)$ that was not cleaned. As shown in Fig. 3, the experimental results for the recovered flux increased with the cumulative backpulse duration until t_b=1 s, and then little or no further foulant was removed after the cumulative backpulse time exceeded about 1 s. However, a variation in the net recovered flux was observed among repeated experiments, possibly due to the stochastic nature of the cleaning. That is, the factors of the cake removed by the backpulses may have differed between experiments even under the same set of conditions. The best fit values for τ_b and β_{max} were found to be 0.12±0.02 and 0.42±0.1, respectively, with a 90% confidence level when using a multiple regression method.

GA Optimization

Figure 4 shows the best and mean fitness values in each generation. Note that the vertical axis had negative values. Since the optimization functions in the present programmed genetic algorithm minimized the fitness function, maximizing the objective function meant minimizing -f(x), as the point at which the minimum -f(x) occurred was the same as the point at which the maximum f(x) occurred. As shown in

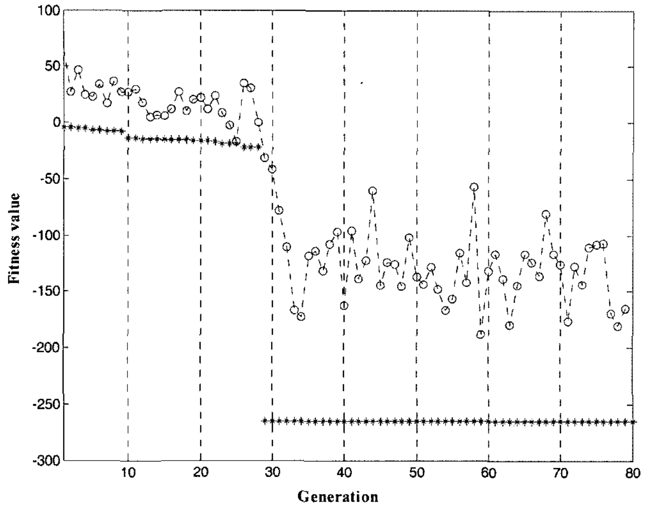

Fig. 4. Best (*) and mean fitness (○) trends of GA.
The best fitness value improved rapidly at around 27 generations, and no further changes were observed after 30 generations.

Fig. 4, the best fitness value improved rapidly at around 27 generations, when further individuals were removed from the optimum. Yet, after 30 generations, no more changes were observed in the best fitness value, as the populations were closer to the optimal point. Therefore, from these results, the maximum point for the net flux was 265.37 LMH, which was predicted to occur with a forward filtration time (t_f) of 31 s and backward filtration time (t_b) of 0.22 s when using the following model parameters; α=1, τ_f=33.84 s, τ_b=0.12 s, air flow rate=0.03 vvm, β_{max}=0.42, J_0=540 LMH, and J_s=22.4 LMH.

Rapid Backpulsing Experiments

Rapid backpulsing experiments were then conducted with different backward and forward filtration durations and air flow rates during 24-h experiments. Figures 5A and 5B show the average net fluxes according to backpulse and forward filtration times of t_b=0.1–1.0 s and t_f=0–60 s, respectively, plus the genetic algorithm results. Figure 5A shows the net flux versus the forward filtration time for a fixed backpulse duration of t_b=0.22 s, and Fig. 5B shows the net flux versus the backpulse duration for a fixed forward filtration time of t_f=31 s, where both fixed values resulted from the GA parameter estimation. The symbols used are the global average net fluxes for two or three repeat experiments, and the error bars represent plus and minus one standard deviation. Note that the genetic algorithm shows the optimum as an area instead of a point (shadow area in Fig. 5), due to the stochastic characteristic of GAs. That is, a GA makes random choices, thereby producing slightly different results each time the genetic algorithm is run. Consequently, optima ranges are shown. The net flux values were computed by taking the fluid gained in the filtrate reservoir and dividing this by the

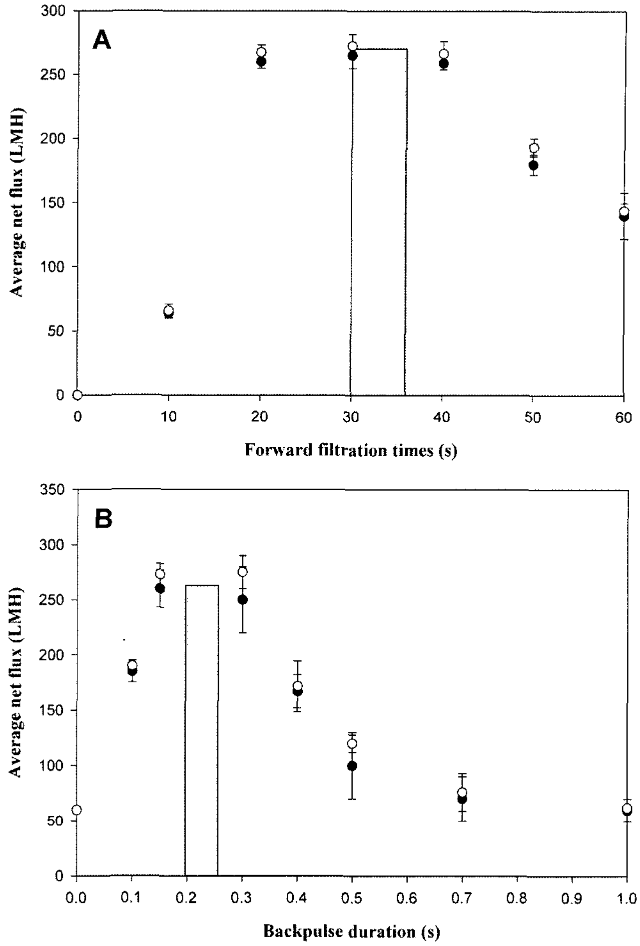

Fig. 5. Average net flux versus forward filtration time (**A**) and backpulse duration (**B**).
A. The net flux versus the forward filtration time for a fixed backpulse duration of t_b=0.22 s. **B.** The net flux versus the backpulse duration for a fixed forward filtration time of t_f=31 s. The error bars represent plus and minus one standard deviation for two or three repeats. The air flow (○) enhanced the average net flux up to about 2.7% compared with that without an air supply (●). The shadowed area indicates the optimum area as determined by the GA. The maximum net flux calculated by the GA indicated (**A**) 270.378 LMH at t_f within the range of 30–36.37 s and (**B**) 263.149 LMH at t_b within the range 0.185–0.268 s.

membrane area and experiment duration. As a result, the forward filtration duration at 30 s showed that the average net flux was maximized with a backpulse duration of approximately 0.19–0.27 s, meaning that longer and shorter backpulses were both inefficient as regards removing the foulants effectively. As shown in Fig. 5, the maximum average net flux with backpulsing was about 4–5-fold greater than that obtained without backpulsing. Moreover, the air flow enhanced the average net flux up to about 2.7% compared to that without an air supply. The optimal backpulse duration range was 0.19–0.27 s, whereas the optimal forward filtration time range was 30–40 s. The overall optimum values were found to be $\langle J\rangle^{opt}$=265 LMH, which was predicted to occur at t_f^{opt}=31 s and t_b^{opt}=0.22 s when using the model parameters of τ_b=0.12 s, β_{max}=0.42, air flow rate=0.03 vvm, α=1, J_0=540 LMH, J_s= 22.4 LMH, and τ_f=28 s.

In conclusion, a genetic algorithm was applied to a submerged MBR system that shows high levels of nonlinearity. The customized genetic model was able to adequately fit the experimental data and provided further information allowing improved process optimization. Parameters like the cake growth time constant and fraction of the membrane cleaned at time t during backpulsing were also used in the optimization, owing to the flexibility provided by genetic optimization. Thus, the genetic algorithm-based optimization proved to be a useful for solving SMBR flux optimization problems.

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NOMENCLATURE

Roman Symbols

B : volumetric flow rate per reactor volume (vvm)
J : permeate or volumetric flux
$\langle J \rangle$: net flux (LMH=L/m^2/h)
$\langle J \rangle^{opt}$: optimal net flux for all backpulse durations and frequencies (LMH)
J_b : flux during reverse filtration (LMH)
J_f : flux during forward filtration (LMH)
J_0 : clean membrane flux (LMH)
J_s : fouled membrane flux (LMH)
J_r : recovered flux (LMH)
k : constant for air effect equation
K_A : constant for air effect equation
ΔP_b : magnitude of reverse transmembrane pressure (kPa)
ΔP_f : magnitude of forward transmembrane pressure (kPa)
t : time (s)
t_b : backpulse duration (s)
t_b^{opt} : optimal backpulse duration maximizing net flux (s)
t_f : forward filtration time (s)
t_f^{opt} : optimal forward filtration time maximizing net flux (s)

Greek Symbols

α : transmembrane pressure ratio, $|\Delta Pb/\Delta Pf|$
β : fraction of membrane cleaned by time t during backpulse
β_{air} : cake removal ratio by air flow
β_b : total fraction of membrane cleaned by end of each backpulse
β_{max} : maximum possible fraction of membrane that can be cleaned
τ_f : time constant for cake buildup (s)
τ_b : time constant for cake removal (s)

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