RUN-TO-RUN CONTROL OF MEMBRANE FILTRATION IN WASTEWATER TREATMENT - AN EXPERIMENTAL STUDY [1]

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Abstract: Membrane filtration processes are often operated cyclically with alternating filtration and backwashing phases. Typically, fixed values of the controls are employed, leaving much of the economical potential unexplored. In previous publications, a model-based run-to-run process control approach has been introduced, in which the controls are optimized after each filtration cycle. This contribution focuses on the experimental validation of the approach at a pilot-scale membrane bioreactor for wastewater treatment. Modifications to the approach and details on its implementation are discussed. The controller yields very satisfying results with respect to prediction quality, optimization results, and stability.

Keywords: run-to-run control, online control, online optimization, membrane filtration, wastewater treatment

1. INTRODUCTION

Filtration and membrane filtration are established technologies for the separation of particles, macromolecules or even dissolved molecules from fluids. The driving force in the applications considered in the following is a transmembrane pressure difference (TMP), pushing the feed fluid and those particles through the membrane pores, which are small enough to pass, and rejecting the remainder. Typical particle sizes in these so-called micro- and ultrafiltration applications range between nanometers and several hundred microns.

Due to *membrane fouling*, the filter efficiency decreases over time. Membrane fouling can have multiple causes, e.g. filter cake and biofilm formation, anorganic scaling, concentration polarization, and pore blocking. During process operation, there are two main approaches to limit membrane fouling. Firstly, cross-flow along the membrane surface reduces several fouling effects. The cross-flow typically contributes most of the operational cost. Secondly, the flow direction through the membrane is periodically reversed, such that the membrane pores are flushed with permeate. This backwashing causes loss of product and production time and leads to a a cyclic process behavior with alternating filtration and backwashing phases.

State-of-the-art process control for filtration processes usually employs fixed values for the controls, which are based on experience and heuristics, and which are only adjusted to meet the required net flux

$$J_{\text{net}} = \frac{J_f \cdot \Delta t_f - J_b \cdot \Delta t_b}{\Delta t_f + \Delta t_b} \ . \tag{1}$$

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The manipulated variables (controls) are the permeate and the backwashing fluxes J_f and J_b and the filtration and backwashing durations Δt_f and Δt_b, respectively. A further manipulated variable is the cross-flow intensity u_c.

The reason for the rather simple control strategies lies in the high process complexity. It is characterized by the periodic change between filtration and backwashing, the drift of the membrane permeability due to irreversible membrane fouling, and the typically non-steady-state operation. Furthermore, only very limited measurement information is available in industrial installations.

In previous publications (Busch and Marquardt, 2006; Busch *et al.*, 2007), a model-based control approach is proposed to operate the filtration process at its economical optimum at every point in time while regarding safety constraints despite these challenges. As will be seen, the approach comprises elements of different concepts such as dynamic real-time optimization (D-RTO), nonlinear model predictive control (NMPC), and run-to-run control. An economic objective function is considered as in D-RTO, and the estimation and control problems are solved in a moving horizon fashion as in NMPC. Since the most characteristic feature is the exploitation of the cyclic process behavior, it is however most related to the concept of run-to-run control.

So far, the controller has been validated in simulation studies, revealing a large savings potential as compared to conventional plant operation. This contribution addresses the implementation and evaluation of the approach at a pilot-scale membrane bioreactor for municipal wastewater treatment. Section 2 briefly reviews the process model and controller design and discusses necessary modifications related to the plant characteristics. The controller's implementation at the plant and its performance are presented and discussed in Section 3.

2. RUN-TO-RUN CONTROL OF MEMBRANE FILTRATION IN WASTEWATER TREATMENT

In *run-to-run process control*, optimal setpoints for the controls are computed by the run-to-run controller between two runs (or cycles), and these setpoints are realized by PID-type controllers during the run (del Castillo and Hurwitz, 1997). For the filtration systems treated in this paper, a very general problem formulation is required, which accounts for nonlinear, dynamic process models and constraints and also for the fact that each cycle is divided into a filtration and a backwashing phase. The generic problem formulation as well as the derivation of a controller for membrane bioreactors has been presented by Busch and Marquardt (2006). The equations describing the process model and the resulting run-to-run controller are briefly revisited in the following. A focus is on those modifications, which reflect the requirements of a real plant installation as compared to simulation scenarios.

2.1 Process model

The model proposed in the following is based on simple descriptions of the main phenomena of membrane filtration processes. The transmembrane pressure difference Δp is described using Darcy's law,

$$\Delta p = J \cdot \eta \cdot R \ , \tag{2}$$

where J is the flux, η is the fluid viscosity, and R is the membrane resistance. While J is a manipulated variable, η depends on the feed suspension properties. As the TMP is assumed to be measurable, Eq. (2) represents the system's output equation. The resistance needs to be described by state equations for the filtration and the backwashing phase.

2.1.1. Filtration phase During a filtration phase, the membrane resistance R_f is described by

$$\frac{dR_f}{dt} = m \cdot J_f^{\alpha} \cdot u_c^{\beta} \ , \ t \in [t_0, t_f] \ , \tag{3}$$

$$R_f\left(t_0\right) = R_f^0 \ , \ t_f = t_0 + \Delta t_f \ . \tag{4}$$

R_f^0 is the initial membrane resistance, and t is the time. Assuming that the filtration flux J_f and the cross-flow intensity u_c are approximately constant, a linear increase of membrane resistance results. It describes the cake layer formation, which is the dominating effect on this timescale and which shows a strong dependence on the flux and on the cross-flow. m, α, and β are model parameters. Since in the following case study the cross-flow is realized by an intermittently operated air stream injected at the bottom of the membrane modules, the cross-flow intensity u_c is defined as

$$u_c = Q \cdot \frac{t_{\text{on}}}{t_{\text{on}} + t_{\text{off}}} \ , \tag{5}$$

where Q is the air flow, and t_{on} and t_{off} are the periods with the aeration turned on and off, respectively. In the following, Q and t_{on} are assumed to be constant, and t_{off} replaces u_c as the manipulated variable.

2.1.2. Backwashing phase In the controllers presented in previous publications, a model for the backwashing phase is included. However, during implementation at the plant it had to be realized that the quality of the plant measurement data is not sufficient to identify the proposed model. The reason lies in the high measurement noise, the unmodeled ramp-up of the pumps, and the comparatively short backwashing duration Δt_b. It was decided to exclude the backwashing model and consequently to remove the backwashing flux J_b and the backwashing duration Δt_b from the vector of optimized variables. Instead, they are determined based on heuristics according to

$$J_b = J_f \ , \ \Delta t_b = \Delta t_b^* \ , \tag{6}$$

where Δt_b^* is a fixed duration of the backwashing phase. The loss of controller performance is limited, as the filtration phase lasts considerably longer than the backwashing phase, and the degrees of freedom during backwashing are limited: The aeration is constantly turned on to remove the detached filter cake from the membrane module, and the time Δt_b^* is the estimated time required to fulfill this task. Still, the loss of product and production time reduces the process efficiency by up to 15% in the case study application. The reduction of this loss is therefore subject of current research.

2.1.3. Cost function and constraints The operating cost, that can be influenced by the process control system, are the cost for electrical energy to provide the TMP (E_p) and the cross-flow (E_c) and the cost for membrane replacement (E_r). The cost model for the TMP is given in Busch and Marquardt (2006), and the cost for the cross-flow are described based on standard models for the polytropic compression of air.

The cost for membrane replacement E_r cannot be described as straightforwardly, since no rigorous model describing the membrane lifetime depending on the manipulated variables is available. However, qualitative process insight allows for an empirical correlation for membrane replacement cost. It is known that a strong increase of the TMP in one filtration phase indicates an overstraining of the membrane, and that the longer a filtration phase lasts, the more the reversible resistance turns irreversible. Therefore, the TMP increase in each phase is penalized, and the penalty increases exponentially with time according to

$$E_r = \xi_1 \cdot \big(\Delta p\,(t_f) - \Delta p\,(t_0)\big) \cdot e^{\frac{\Delta t_f}{\xi_2}} \ . \tag{7}$$

ξ_1 and ξ_2 are tuning parameters. The overall process cost ϕ for one cycle is given by

$$\phi = E_p + E_c + E_r \ . \tag{8}$$

Constraints are formulated for the minimum and maximum values of the TMP and for the manipulated variables $\mathbf{u}$, where $\mathbf{u} = [J_f, \Delta t_f, t_{\text{off}}]^T$:

$$\Delta p_{\min} \leq \Delta p \leq \Delta p_{\max} \ , \ \mathbf{u}_{\min} \leq \mathbf{u} \leq \mathbf{u}_{\max} \ . \tag{9}$$

2.2 Run-to-run controller

In industrial practice, only the TMP across the membrane modules is measured. In order to make the proposed approach widely applicable, it is therefore assumed that only this TMP is available as measurement. The unknown model parameter m and the initial state R_f^0 are estimated at the end of cycle k from the measurement data of cycle k by solving a classical least-squares optimization problem according to

$$\min_{R_f^0, m} \sum_{l=1}^{n} \frac{1}{2} \left(\Delta \tilde{p}_l - \Delta p_l\right)^2 \tag{P1}$$

$$\text{s.t. } \Delta p_l = \overline{J_f} \cdot \eta \cdot R_{f,l} \ , \tag{10}$$

$$R_{f,l} = R_f^0 + m \cdot \overline{J_f}^{\alpha} \cdot \overline{u_c}^{\beta} \cdot t_l \ , \tag{11}$$

$$t_l \in [t_0, t_f] \ , \ l \in \{1, \ldots, n\} \ . \tag{12}$$

n is the number of discrete TMP measurements $\Delta \tilde{p}_l$ and simulated TMP samples Δp_l. The index cycle k is omitted for simplicity here and in the following. Note that Eq. (11) is the analytical, discretized solution of Eq. (3) for constant filtration flux J_f and cross-flow intensity u_c. Since in reality these properties are not perfectly constant, their mean values after the ramp-up time of the pumps are introduced as $\overline{J_f}$ and $\overline{u_c}$, respectively. This inaccuracy is small against the measurement noise and simplifies the estimation problem.

Problem (P1) gives estimates of R_f^0 and m on the data from the previous cycle k as in classical run-to-run control. However, α and β are not simultaneously identifiable on the data of one cycle alone. This is due to the so-called *dual control problem* and can be perceived from Eq. (3). For a constant filtration flux J_f and cross-flow intensity u_c, only one of the parameters m, α, and β is identifiable. Therefore, α and β are estimated from data on larger estimation horizons, e.g. on the three last cycles. The Hessian matrix of the estimation problem is used to estimate the certainty with which α and β can be estimated from the given set of data. Only if the certainty is sufficiently high, the parameter values are adopted. The reader is referred to Busch *et al.* (2007) for details.

The obtained parameter values are used in the optimization problem for cycle $k+1$, as it can be assumed that the process behavior does not change drastically between two cycles. The optimization problem is stated as

$$\min_{J_f, \Delta t_f, t_{\text{off}}} \phi \tag{P2}$$

$$\text{s.t. } \Delta p = J_f \cdot \eta \cdot R_f \ , \tag{13}$$

$$R_f = R_f^0 + m \cdot J_f^{\alpha} \cdot u_c^{\beta} \cdot t \ , \tag{14}$$

$$u_c = Q \cdot \frac{t_{\text{on}}}{t_{\text{on}} + t_{\text{off}}} \ , \tag{15}$$

$$J_{\text{net}} = \frac{J_f \cdot \Delta t_f - J_b \cdot \Delta t_b}{\Delta t_f + \Delta t_b} \ , \tag{16}$$

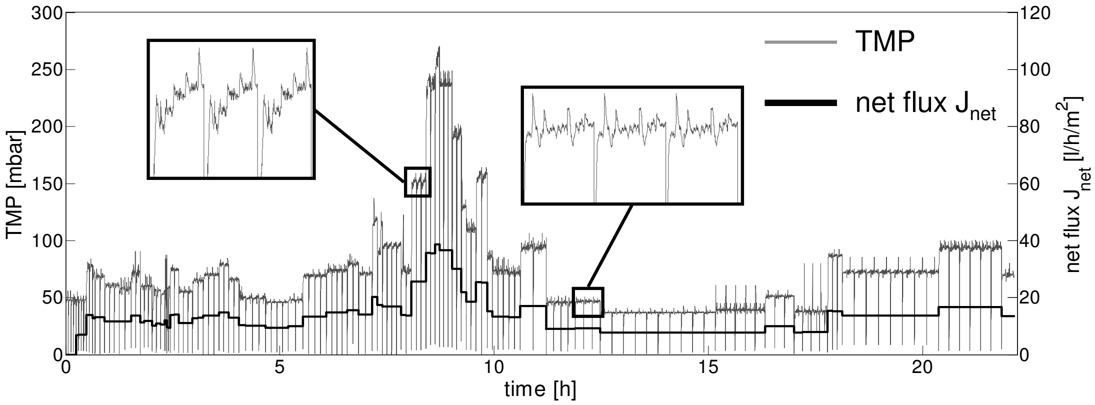

Fig. 1. Inflow-proportional operation of the controlled system for one day

$$J_b = J_f \ , \ \Delta t_b = \Delta t_b^* \ , \quad (17)$$
$$\Delta p_{\min} \leq \Delta p \leq \Delta p_{\max} \ , \quad (18)$$
$$\mathbf{u}_{\min} \leq \mathbf{u} \leq \mathbf{u}_{\max} \ , \quad (19)$$
$$t \in [t_0, t_f] \ , \ t_f = t_0 + \Delta t_f \ . \quad (20)$$

ϕ is defined according to Eq. (8). Problem (P2) results in optimal setpoints for J_f, Δt_f, and t_{off} for the next cycle $k+1$.

The algorithm is implemented as follows. Since it is not necessary to wait for the backwashing data, the backwashing phase in cycle k is used to import the filtration data and to solve the parameter estimation and setpoint optimization problems (P1) and (P2). Working with real plant data requires a preprocessing step to account for missing data, outliers etc. Robustness against all possible types of errors is vital for the successful implementation of the controller. When useful data is available, the parameter estimation is performed, and with the updated model, the optimal setpoints for the manipulated variables J_f, Δt_f, and t_{off} are computed. They are communicated to the process and realized in cycle $k+1$. In the rare case that the computation takes longer than the backwashing phase in cycle k, there is some delay in the implementation of the new setpoints, and cycle $k+1$ is initiated with the old setpoints, until the new setpoints are available.

3. EXPERIMENTAL STUDY

The proposed run-to-run controller is implemented at a membrane bioreactor located at Simmerath, Germany, which is operated by KOCH Membrane Systems GmbH. The pilot plant treats a bypass from the conventional municipal wastewater treatment plant Simmerath. The pilot plant includes a mechanical pretreatment to remove larger particles, denitrification and nitrification basins for biological degradation, and a basin with three membrane modules. The membranes separate the biomass from the purified water. The biomass concentration is around 13 g/l, and typical particle sizes are in the range of 1 to 100 microns. For the case study presented here, a PURON hollow fibre module with 29 m^2 filtration area is employed.

The process is operated via a WinCC (Siemens) platform. The run-to-run controller is implemented in MATLAB (The MathWorks), which has been installed on the same PC as WinCC. No additional sensors were installed, such that the cost for implementing the controller were low.

The rather simple communication architecture requires a further delay of one cycle in the communication of the measurement data, such that the model parameters are adapted with one cycle delay. These delays have not caused stability problems or a noticeable loss of performance. Still, at some cycles no useful measurement information was available, such that the setpoints from the previous cycle were used again for the next cycle. The implementation of an OPC-based communication infrastructure in the near future will eliminate these problems.

Different choices for the tuning parameters ξ_1 and ξ_2 in Eq. (7) are evaluated in offline simulation studies. Heuristically, they are set to $\xi_1 = 1\frac{\text{m}^3}{\text{s}}$ and $\xi_2 = 1200\,\text{s}$ for the following online studies. Δt_b^* is fixed to 20 s, and the maximum aeration pause is 80 s. The remaining constraints on the manipulated variables and the TMP are not active and their values are omitted for brevity.

3.1 Results

First, the controlled system's stability is evaluated in an uninterrupted one day run. The net flux across the membrane J_{net} is chosen proportional to the actual plant inflow. Between two filtration cycles, the controller updates the model and determines the optimal setpoints for the filtration flux J_f, the phase duration Δt_f, and the aeration pause t_{off}. Fig. 1 depicts the net flux J_{net} and the

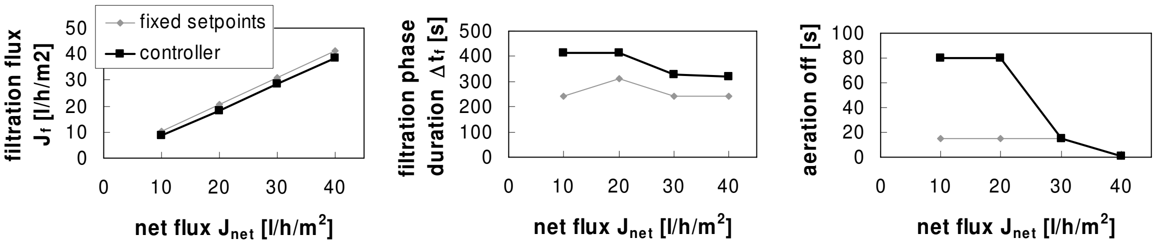

Fig. 2. Values of the manipulated variables during the operation with fixed setpoints (grey) as compared to the operation with the run-to-run controller (black)

resulting TMP during the filtration phases. It is observed that the TMP follows the trend of the net flux, which is expected since the TMP rises with the filtration flux (Eq. (2)). After about 8 h, a rain fall leads to a strong increase in the plant inflow, which in turn leads to a high net flux and a high TMP. Stable plant operation is achieved in spite of these strong inflow variations.

Fig. 1 also shows two detailed TMP plots at different net fluxes. It can be observed that at high fluxes, the increase of TMP during each cycle is severe (left). Following the heuristics introduced above, this points to a high membrane strain. It will be shown, that the reduction of membrane strain dominates the control objective in such a situation. At lower fluxes, the TMP increase is smaller (right). It can also be observed, that especially in the second half of the 1-day-horizon, when the model parameters are properly adapted, there is a tendency to choose higher filtration phase durations at lower net fluxes.

Having ensured the controller's reliability, its efficiency is compared to conventional plant operation. For this purpose, the membrane system is operated at four different net fluxes J_{net}, namely 10, 20, 30 and 40 l/h/m^2. At each net flux, the plant is first operated manually with fixed typical setpoints of the manipulated variables, and afterwards employing the run-to-run controller. The setpoints and the performance measures are recorded for each operating point and operating strategy as discussed in the following. The prediction quality of the model is also examined, but the results are not depicted here due to limited space. The prediction quality is good, with a standard deviation of the relative prediction error of 4%.

Fig. 2 depicts the mean values of the manipulated variables at the different operating points and for manual and controlled operation. The filtration flux J_f increases with increasing net flux J_{net}. The backwashing flux J_b (not depicted) equals the filtration flux according to Eq. (6). The run-to-run controller always realizes a little lower filtration and backwashing fluxes J_f and J_b and longer filtration phase durations Δt_f as compared to the fixed setpoints. This leads to less strain on the membranes due to lower flux, yet also to a lower backwashing frequency. This in turn lowers the energy demand, since the aeration is constantly turned on during backwashing, but is only intermittently turned on during filtration. The controller shortens the filtration phases at high net fluxes, which implies a more frequent backwashing and lower maximum TMP at the end of each filtration cycle. The length of the aeration pauses t_{off} are comparable at high net fluxes, but at lower net fluxes the controller strongly increases the aeration pauses.

Fig. 3 shows the cost function values during operation with fixed setpoints and with the run-to-run controller. The cost function is separated into energy cost ($E_p + E_c$) and membrane strain (E_r). During filtration with low net fluxes (10 and 20 l/h/m^2), the controller operates the process at comparable membrane strain, but with only about 50% of the energy consumption. This is mostly due to the longer aeration pauses (Fig. 2).

At 20 l/h/m^2, the overall objective function value ϕ is lower with the fixed setpoints due to lower computed membrane replacement cost E_r. Considering that here membrane fouling is already very low and that the interesting aspect is indeed the minimization of the energy consumption, this plant-model mismatch is found to be acceptable.

At higher fluxes (30 and 40 l/h/m^2), the energy consumption is only slightly lowered by the controller as compared to the operation with fixed setpoints. The aeration, contributing the largest part of the energy cost, is at maximum in both settings, and the remaining energy savings can be attributed to the different values of the filtration flux and phase duration (Fig. 2). However, in these demanding operating conditions, the high membrane strain is reduced by 40–50% by the run-to-run controller (Fig. 3).

Note that these results are subject to the tuning of the controller, i.e. the choice of the parameters ξ_1 and ξ_2 in Eq. (7). Altering these parameters allows to operate the membrane more conservatively or aggressively with respect to membrane strain, which in turn increases or decreases the

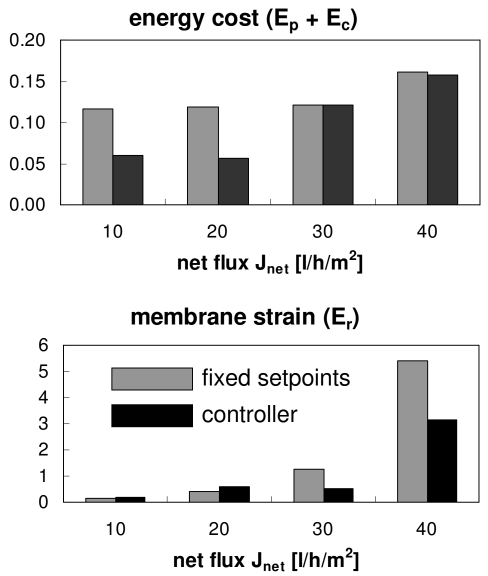

Fig. 3. Energy cost and membrane strain at different net fluxes during manual operation (grey) and during operation with the run-to-run controller (black)

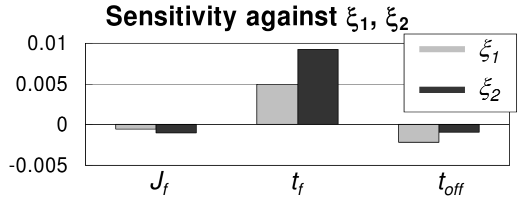

Fig. 4. Sensitivity of manipulated variables against an increase of the tuning parameters ξ_1 (grey) and ξ_2 (black) by 1 %

energy demand, respectively. Although the dependency of the optimization results on the tuning parameters is nonlinear and different for each operating point, the mean values obtained from an offline parameter study give an idea of the influence of ξ_1 and ξ_2. Fig. 4 shows the mean change of the optimal setpoints of the manipulated variables J_f, t_f, and t_{off}, when ξ_1 or ξ_2 are increased by 1 %. For both of them, the increase leads to lower filtration fluxes, longer filtration phases, and shorter filtration pauses, implying a more gentle filtration. It is obeserved that ξ_1 has a greater relative influence on the aeration, while ξ_2 has a relatively larger impact on the filtration flux and duration. This allows for an independent tuning of both parameters to obtain the desired filtration characteristics.

3.2 Discussion

Due to a lack of appropriate models and long-term experiments and the considerable process uncertainty, it is not possible to state the overall optimal operation policy over the lifetime of a membrane module for each and every cycle. However, when compared to the industrial standard policy of manual, heuristic operation, the run-to-run controller presented here decreases the energy consumption or the membrane strain by up to 50%. Low flux situations are exploited to save energy especially by reducing the aeration intensity. In high flux situations, adapting the filtration flux and phase duration leads to a substantial decrease of the estimated membrane strain.

The results presented here can also be related to the prominent *concept of critical flux* for membrane bioreactors (Pollice *et al.*, 2005). The concept states that below a certain critical flux, no or very limited fouling takes place. With respect to the results shown here it can be argued that during filtration above a critical flux, fouling is strong, and the main control objective is to limit the harmful fouling effects. During filtration below the critical flux, fouling is small, and the controller focuses on the minimization of energy consumption. In the transition between the two regimes, both objectives are similarly important.

4. CONCLUSIONS

A model-based run-to-run controller for membrane filtration processes is developed. The key idea is to optimize the available manipulated variables at each filtration cycle instead of employing fixed setpoints. The controller requires only TMP measurements. A specialized controller for submerged membrane filtration in wastewater treatment is derived from the general framework. It is evaluated at a pilot plant. The controller is able to predict the process behavior within small margins of error. Depending on the required net flux, the energy consumption or the estimated membrane strain can be reduced by 40-50%. Additionally, the operational safety is greatly increased by the automatic adaptation of the filtration strategy to changing operating conditions.

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