Online Phase Length Optimization for a Sequencing Batch Reactor by Means of the Hotelling's T^2 Statistic

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Wastewater treatment systems have, over the past decades, been subjects for optimization and control research. One of the most intricate problems faced is that direct measurements of the variables of interest are seldom available. A large part of research has therefore been aimed at the extraction of suitable information from indirect measurements such as dissolved oxygen, pH, and oxidation reduction potential (ORP). Even if relatively complex tools, such as neural networks and fuzzy logic, have been used to conceive control laws, advantage is seldom taken of such tools with respect to development of the actual control algorithm. In this paper, a simple yet effective tool is presented that allows the detection of a desired process state by means of the Hotelling's T^2 statistic. The detection tool is generic in nature and is thereby applicable to any process where a certain desired state is to be detected by means of measured variables reflecting the targeted state. Its advantages over formerly proposed control strategies are discussed, and the precautions that were taken to render its application robust are presented. It is shown by means of a laboratory-scale sequencing batch reactor (SBR) setup for nutrient removal from wastewater that the proposed controller allows one to detect the targeted endogenous state and that its application leads to effective optimization of the overall system performance. More specifically, the length of the optimized phase is reduced by 41% of its original default length and a reduction of 5% is estimated for the expected energy consumption by the aeration system. In addition, effluent concentrations of total nitrogen and nitrate nitrogen are estimated to be lower by 30 and 25%, respectively. This is attributed to the gained length of the anoxic phase subsequent to the aerobic phase.

Introduction

Online optimization of wastewater treatment plant operation is a subject that has received considerable attention since the beginning of the 1990s.[1,2] An important concept for control of aerobic reactors or aerobic phases of alternating or cyclic systems is the endogenous respiration state. This state is typical for aerated wastewater treatment systems where all (desired) oxidation reactions are finished. This means that (1) organic pollutants (carbonaceous compounds) are oxidized; (2) bulk nitrogen compounds are oxidized (i.e., all ammonia and nitrite is oxidized to nitrate); and (3) the phosphorus uptake rate (PUR) becomes minimal (i.e. the rate at which phosphate accumulating organisms (PAOs) internalize phosphorus becomes small). Ideally, the phosphate concentration in the bulk liquid is then close or equal to zero. In general the three described reactions do not necessarily occur in the same location, at the same time, or with equal intensity, nor are they completed at the same time. Continued aeration beyond the point in time where the endogenous state is reached is economically uninteresting as no improvement of effluent quality can be expected from further investment of aeration energy. On the contrary, secondary phosphorus release has been observed in endogenous conditions[3,4] and extended aeration may deteriorate sludge settling properties.[5] Consequently, the detection of the endogenous state has been an appealing research subject to many.

In the broad spectrum of bioprocessing, a few contributions relate to the detection of reaction end points. These works cover the development of cheap indirect measurements[6,7] or actual algorithms.[8−10] The fact that the latter works in fields other than wastewater treatment have remained largely unconnected so far suggests that phase end detection is a problem typically solved in an ad hoc fashion and that little consensus is available on the optimal way to detect process phase end points.

Indirect Measurements for Inference. Sensors for oxygen, pH, oxidation reduction potential (ORP), and conductivity are abundant and cheap on the market, use no chemicals, require low maintenance, and are generally accepted in industrial practice following decades of experience. Therefore, a fair amount of historical research aimed at the online assessment of the endogenous respiration state in the aerobic phase by means of these sensors. The earliest results have been obtained on the basis of tracking of the oxygen uptake rate (OUR) or the dissolved oxygen (DO) concentration.[3,11−14]

Alternatively, the entry into the endogenous respiration state can be based on the ORP and/or pH profiles of nitrification systems.[15−26] Applications focused on nitrogen removal that combine information in OUR, ORP, and/or pH can be found as well.[27−30] DO, ORP, and pH have also been combined for optimization of a nitrogen and phosphorus removing laboratory-scale plant.[31]

Conductivity is a fourth common measurement and is related to the bulk phosphorus concentration.[27,32] The rate of change of the conductivity approaches zero as phosphorus uptake becomes minimal and thus provides a cheap way for identification of the end of phosphorus uptake.[33] However, convincing

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results regarding conductivity profiles in the context of simultaneous nitrogen and phosphorus removal are not established as yet.

Historical Control Strategies. For systems where rather accurate models can be established, methods have been established to optimally switch between controllers optimal for different situations. For example, multimodel strategies link a set of models to different, locally optimal control laws. By means of online observers, one can select the best-fitting model to recent measurements and one can switch to the corresponding control law.[34] Given an accurate model then, the detection of reaction end points becomes fairly trivial.

Unfortunately, accurate models may be hard to come by in many cases. For such conditions, most academic works suggest the evaluation of a set of preset rules, which are established on the basis of system knowledge or operators' experience. To this end, artificial neural networks (ANNs) can be used to predict or filter nutrient concentration measurements[35−37] or to identify and locate the targeted breakpoints.[38] Fuzzy control is another alternative.[39] Strikingly, in all of the latter applications, the artificial intelligence or data mining part of the method is never used to construct the decision boundary. In addition, redundancy in the used signals is never accounted for when building the reported models or controllers. A single study only delivers the application of a data mining tool, i.e., fuzzy C-means clustering, for control of wastewater treatment plants in which (1) data redundancy is inherently accounted for and (2) the predicted cluster directly leads to the pursued control action.[31] Data samples from the monitored system are grouped by the clustering algorithm into two major groups, representing the exogenous and endogenous respiration state. During active control, a new data sample is assigned to one of the clusters, hereby indicating whether the system is in exogenous or endogenous state. In the cited work, ammonia depletion occurred after completion of phosphorus uptake. As a result, the obtained cluster model may not function well when phosphorus uptake stops before ammonia depletion. As such, the resulting controller may lead to an inappropriate control action.

In this paper, a multivariate control strategy is proposed which does not suffer from the latter problem while it remains simple to implement. Indeed, an approach is presented to shut down the aerobic phase which makes no explicit assumption on the behavior of the data when the process is off-target (exogenous respiration in our case), except for being dissimilar to the on-target behavior (endogenous respiration).

In what follows, the generic conception and design of the proposed controller is given after which the case study is described and the use of the controller is motivated. In Results, the performance of the provided method is evaluated in terms of reaction end-point detection and overall process improvement.

Materials and Methods

In what follows, the applied method, its underlying assumptions, and the proposed integration for control are given. First, the method is described, and implemented adjustments are motivated. Then, the proposed controller including the applied statistical test for similarity is presented. Finally, the real-life case study in which this controller was tested is described.

Model for State Detection. We consider that a specific (temporary) state of the system is often characterized by its values for the process rates. Consequently, assessing whether the state of a process is similar to a desired state may be achieved by assessing the values or trends of process data and comparing them to typical values corresponding to the desired state. The following multivariate strategy is proposed to do so.

Variable and Sample Selection. First, variables of which the values can describe the targeted state are chosen, and historical data samples that reflect the targeted state are selected by operators or process experts. Hence, both these steps require essential knowledge of the system under study. Second, a model that describes these data is established, and one or more tests that allow the evaluation of similarity of new data samples to the selected data are devised. The data-driven modeling approach used in this work avoids the need for an exact mechanistic description of the data behavior in the targeted state. Third, the constructed tests are used to classify new samples as being similar to the data described by the established model or not.

Modeling. While other measures may be valid for the given purpose, the Mahalanobis distance[40] to the mean of the selected historical data samples is used in this study as a measure for similarity. Practically speaking, one computes the mean vector, **m**, and the covariance matrix, **S**, by means of the obtained data matrix, **X** (dimensions $N \times M$):

$$\mathbf{m}(j) = \frac{\sum_{i=1}^{N} \mathbf{X}(i,j)}{N}$$

$$\mathbf{S} = \frac{\sum_{i=1}^{N} (\mathbf{X}(i,...) - \mathbf{m})^{\mathrm{T}} \cdot (\mathbf{X}(i,...) - \mathbf{m})}{N}$$

The Mahalanobis distance, D, is then computed as follows for a (new) multivariate observation, $\mathbf{X}(i,...)$, provided that **S** is invertible:

$$D = (\mathbf{X}(j,...) - \mathbf{m})^{\mathrm{T}} \cdot \mathbf{S}^{-1} \cdot (\mathbf{X}(j,...) - \mathbf{m})$$

To define a critical value for this similarity measure, it is common to assume a multivariate normal distribution. When done so, the Mahalanobis distance is equivalent to the Hotelling's T^2 statistic and follows an F-distribution in the case of new observations and for which a theoretical statistical limit is available.[41] Such limit defines an ellipsoidal region within which—theoretically—a given percentage of the data are expected to lie given the modeled conditions (i.e., under the null hypothesis). As such, the Hotelling's T^2 is used as a metric to define a region in which the belief that the data are similar to the historical data of this targeted state is acceptable. Practically, if the calculated statistic for a new data sample is below its corresponding limit, then the test is positive; i.e., the analyzed data sample is judged to be similar to the data described by the model, and, consequently, the state of the system is judged to be similar to the desired state. If the statistic is above this limit, the test is negative; i.e., the analyzed data sample is considered not to be similar to the described data.

The following assumptions underlying the statistical test are emphasized:

(1) The samples are assumed independent. This means that no autocorrelation exists between consequent measurements. This requires that the mean values of the tracked variables are constant over time for the targeted condition and the same for all batches (constant mean process).

(2) The samples are drawn from a multivariate normal distribution.

Since neither of these two assumptions is normally true, care should be taken when interpreting or implementing the test. In

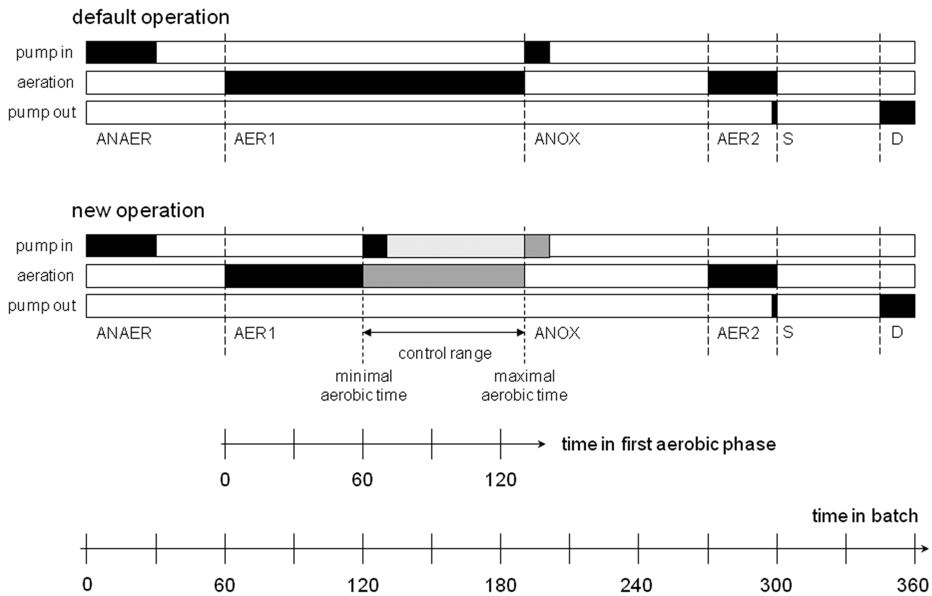

Figure 1. SBR phase scheduling in default and new operation.

view of the latter, pragmatic adjustments to the test are made in the following section.

Adjustments to the Test. Any deviation from the assumptions above may result in an inappropriate calculation of the statistical limit. An overestimation of this limit may result in too many positive tests for samples that are not truly similar to the data described by the model (false acceptance or type II error). An underestimation of the statistical limit may result in too many negative tests for samples that are truly similar to the data described by the model (false rejection or type I error). In this study, a type I error would mean that the phase to be optimized is continued beyond the true starting point of the endogenous respiration (as the desired conversions are completed), therefore possibly leading to an unintended increase of economical cost. A type II error would mean that the phase is ended while the desired (bio)chemical conversions are not completed yet; i.e., the phase is ended too early, hereby leading to unmet targets for the given phase and possibly for the running and upcoming cycles as a whole.

Completing the biochemical conversions was considered of paramount interest in this study. A type II error was thus considered worse than a type I error. Given this and given that the assumption on normally distributed data is not generally valid, the test is adjusted as follows:

(1) A theoretical 90% limit is used. This is lower than the 95 or 99% levels which are more commonly applied. Geometrically speaking, the volume of the ellipsoidal region is made smaller. As a result, the chance for a type I error (too late) is increased and the chance for a type II error (too early) is lowered compared to what common practice would have delivered.

(2) A set number of consecutive positive tests, N_{crit}, have to be established before the process is considered to have reached the desired state. This means that the Hotelling's T^2 test needs to remain below its limit for at least N_{crit} times the sampling interval before the phase is ended by the controller. This actual test is thereby more restrictive and therefore leads to an increase in type I error and decrease of the type II error, as desired.

Integrated Controller. A control strategy, based on the statistical test devised above, is proposed. The strategy is generally applicable to any optimization problem for which the detection of a temporary state is necessary. Until a minimal length of the optimized phase, t_{min}, is reached, a counter, C, is kept to zero. As soon as this minimal time length is reached, the counter is allowed to increase. While the phase is running, preprocessed data are obtained from the raw online data. In this study, data preprocessing consists of a second-order low-pass Butterworth filter. The devised (statistical) test is then used to determine whether the process is in the desired state. If the process is detected to be in this state (T, true) the counter is increased by one; if not (F, false), the counter is reset to zero. If the counter reaches the set N_{crit} or if the running time of the phase has reached its maximal length, the phase is ended and the next phase is started. The latter control action is referred to as the shut-down control action. As a new batch or cycle is started, the control algorithm is reinitialized.

Case Study. The studied process is a sequencing batch reactor (SBR) process for nutrient removal (nitrogen and phosphorus) in which each cycle consists of five major phases. The system is operated with a total fixed cycle length of 6 h, a hydraulic retention time (HRT) of 12 h, and a sludge retention time (SRT) of approximately 15 days. Minimal and maximal operational volumes are 34 and 64 L, respectively. For further details, the reader is referred to the work of Insel et al.[42] A scheme of the standard operation (without phase length optimization) can be found in Figure 1 (top). This standard operation with fixed phase lengths for the constituting phases exhibits an anaerobic phase (60 min, ANAER), including the addition of influent during the first 30 min; a first aerobic phase (130 min, AER1); an anoxic phase (80 min, ANOX), including the addition of some more influent during its first 10 min; a second aerobic phase (30 min, AER2), including sludge wastage in its last minute; a settling phase (45 min, S); and a draw phase (15 min, D). This reference operation was designed on the basis of basic texts such as the IWA Report on SBRs[5] and experience available within the research group.[43,44] In this design, the length of the aerobic phase is longer than needed on average, because the completion of oxidation processes is considered primordial. In both aerobic phases, a PID controller (with antiwindup and bumpless transfer) is used to get and maintain the oxygen level at the desired set point of 2.0 mg/L. The phase that is optimized in terms of length by the proposed control algorithm is the first aerobic phase (AER1). The total length of the batches is however kept constant, by extension of the length of the anoxic phase. Note that this extends the time allowed for the denitrification

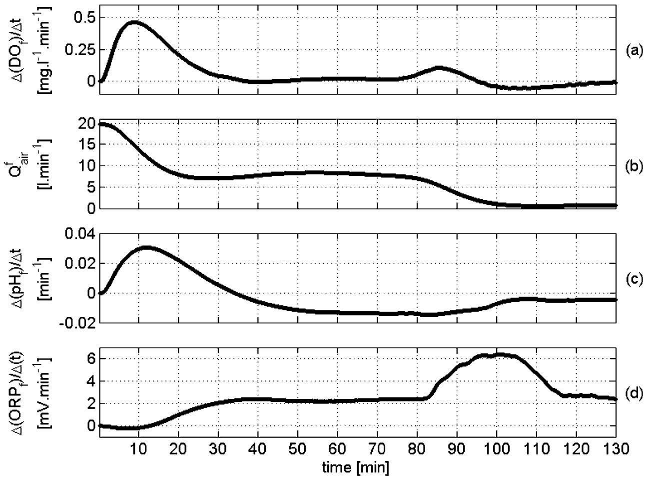

Figure 2. Filtered values of air flow rate ($Q_{f,air}$) (b), and filtered derivatives of DO (a), pH (c), and ORP (d) during the aerobic phase.

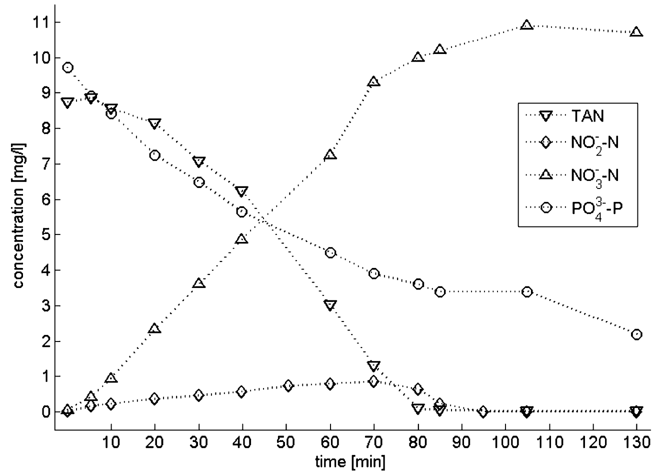

Figure 3. Measured profiles of total ammonia nitrogen (TAN), nitrite nitrogen (NO_2^-−N), nitrate nitrogen (NO_3^-−N), and inorganic phosphorus (PO_4^{3-}−P) during the aerobic phase of an intensively sampled batch.

process increasing the nitrate removal capacity, while reducing the aeration time. This is desirable for the system under study as the nitrate reduction is typically incomplete. The schedule that results is given in Figure 1 (bottom). The minimal length of the aerobic phase was set to 60 min. The maximal length of the aerobic phase was defined to be 130 min, as in the standard operation. The length of the anoxic phase is hereby minimally 80 min and maximally 150 min.

Selection of Modeled Variables and Qualitative Interpretation. The trajectories of the filtered air flow rate and the filtered derivatives of oxygen concentration, pH, and ORP during the studied aerobic phase are shown in Figure 2. The applied Butterworth filters were tuned so as to obtain a cutoff period of 5 min (150 times the sampling interval). The derivative of the DO (dissolved oxygen) is positive until minute 40 in the aerobic phase. This is the point where the (controlled) dissolved oxygen level stabilizes around its set point for the first time (not shown). This correlates with a stabilization of the air flow rate (Figure 2b), which is manipulated to control the oxygen level. The PID controller is sluggish in the exogenous time span of the aerobic phase as the applied tuning aimed at avoiding heavy oscillations in endogenous conditions. The DO level and air flow rate remain around the same level from minute 40 until minute 80 (derivative around zero). At this point, the DO level increases due to a decreased oxygen consumption of the biomass, the DO controller is not able to reject this disturbance immediately, but, at time 100 min, the DO level is again controlled to the desired set point but now at a lower air flow rate. As a result of the described changes in air flow rate, the derivative of the DO level becomes negative and levels off toward zero as the oxygen level stabilizes again around its set point. The latter series of events, starting with the increase of the oxygen level, indicates the start of the endogenous respiration state, which continues until the end of the aerobic phase. Continuation of the aerobic phase beyond minute 105 is therefore considered undesired.

From the start of the phase until minute 34, the pH derivative is positive (Figure 2c). This shows the net positive effect of CO_2-stripping (increases pH) and the first nitrification step (acidifying), also identified as biological ammonia oxidation or nitritation.[45] As the CO_2 concentration decreases, the acidifying effect of nitrification begins to dominate, resulting in a negative sign of the first derivative at minute 34. The sign of the derivative remains below zero for the remainder of the phase. At the onset of the endogenous respiration, the derivative increases from minute 85 to 105 due to a reduced nitrification rate, while CO_2 stripping continues and remains approximately at the same level from minute 105 onward.

The derivative of the ORP level (Figure 2d) increases from minute 10 to 40. From minute 40 to 85 onward, the ORP level exhibits a steady increase, simultaneous with the steady behavior of the air flow rate and oxygen level. This indicates a steady increase in the oxidized nitrogen concentrations (NO_2^-−N, NO_3^-−N). At minute 85, a fast increase in the derivative (acceleration of the ORP level) is observed, as the nitrite−nitrate redox buffer is breached.[46] By minute 85, the second nitrification step (biological nitrite oxidation, nitratation) is thus completed. By minute 115 the ORP derivative stabilizes again, indicative of the next redox buffer (i.e., [O_2/H_2O]). In summary, the described variables reach a certain level in the endogenous respiration state and remain close to that level afterward.

It is noted that the conductivity measurements were available but have not been included as a variable to be described by the constructed model. This is supported by (1) the fact that unambiguous interpretation of conductivity profiles in wastewater treatment systems is not reported as yet and (2) the quality of this sensor's data was insufficient for inclusion in the model.[47]

An intensive measurement campaign was set up to measure the effluent quality variables total nitrogen (TN), total ammonia nitrogen (TAN), nitrite nitrogen (NO_2^-−N), nitrate nitrogen (NO_3^-−N), and inorganic phosphorus (PO_4^{3-}−P) during the batch corresponding to the online measurement profiles described above. Figure 3 shows the trajectories of these variables during the aerobic phase of this batch. As can be seen, the ammonia level lowers from about 9 mg of N/L at the beginning of the phase to approximately zero at minute 80, due to biological ammonia oxidation. As a result, nitrite is produced and further oxidized into nitrate. The nitrite level increases during the aerobic phase until minute 70, due to an apparently lower rate of the nitrite oxidation. As the production of nitrite decreases afterward, nitrite levels decrease again to approximately zero by minute 85. The nitrate level increases during the aerobic phase, from approximately zero at the beginning up to 11 mg of N/L at minute 115. Not surprisingly, the entry into the endogenous respiration state as described in the previous paragraph occurs simultaneously with the depletion of ammonia and nitrite.

It is observed that the total nitrogen concentration at the end of the aerobic phase (as NO_3^-−N) is larger than the original nitrogen concentration at the beginning (as TAN). Two sources

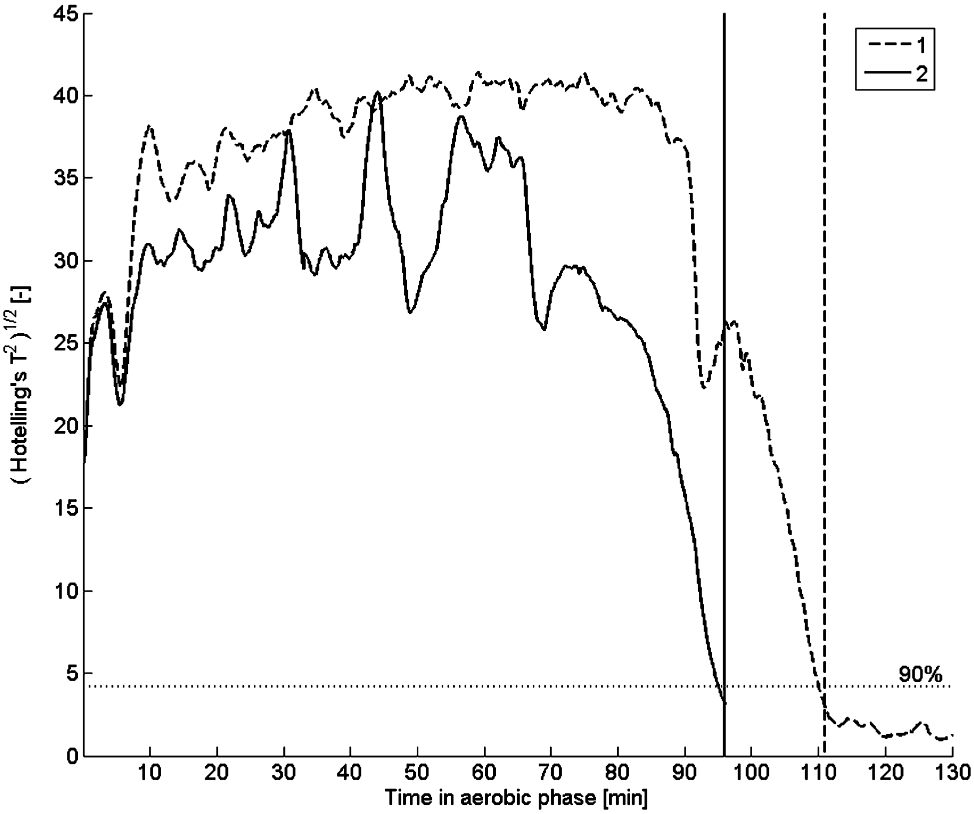

Figure 4. Square root of Hotelling's T^2 statistic during the first aerobic phase of a test batch (1) and the first batch with online phase optimization (2). Vertical lines indicate when the shut-down of the aerobic phase is commanded. The horizontal line indicates the applied 90% limit.

for this discrepancy are identified. First, due to filtering of the samples, the TAN measurement only represents bulk ammonia nitrogen and thus excludes cell−internal ammonia and nitrogen bound to organic materials such as in proteins. Second, disintegration of biomass and hydrolysis processes continues during the aerobic phase and results in the release of new ammonia nitrogen during the aerobic phase. As a result of both effects, the TAN value at the beginning of the aerobic phase does not represent all the nitrogen that is eventually converted to nitrate and released to the bulk liquid.

Biological phosphorus uptake takes place simultaneously with the described nitrogen oxidation processes indicating no electron acceptor competition, as is expected at abundant oxygen levels of 2 mg/L. The inorganic phosphorus is internalized by the PAOs, hereby leading to a reduction of the bulk inorganic phosphorus concentration, which is measured. This process halts at minute 85, right at the start of the endogenous respiration. The measurements suggest that the inorganic phosphorus concentration lowers further from minute 105 to the end of the aerobic phase. Still, the larger part of the phosphorus uptake (approximately 80%) takes place at a relatively fast rate before the endogenous respiration state is observed in the online measurements.

It can therefore be concluded that the intensive measurement campaign confirms that when the endogenous respiration is reached, the nitrogen oxidation processes are finished and a larger part of the phosphorus is taken up by the PAO biomass. As such, it is considered desirable to end the aerobic phase when the endogenous respiration state is reached. This state is detectable on the basis of the described online measurements as was shown above. Therefore, these four described online measurable variables have been included into the statistical model. In addition, the derivative of the air flow rate is added as a fifth variable. The latter is a valid measure for similarity to data stemming from endogenous respiration as well, given that the steady behavior of the air flow rate during endogenous respiration results in a derivative close to zero.

Sample Selection and Applied Model Parameters. The data samples used to construct the model were selected as follows. First, a set of 10 batches exhibiting endogenous respiration behavior at the end of the first aerobic phase were selected by the operators among the batches run in the week before the phase shut-down controller implementation. The point at which the operators believed that the variables showed endogenous respiration behavior was determined for all of them. When opinions differed, the latest point in time indicated among the operators was chosen. All data samples after this point in time and before the end of the aerobic phase were used for modeling. As mentioned before, a 90% limit was used for a single statistical test and a cutoff period of 5 min was applied for data filtering. To shut down the aerobic phase, the statistical test was required to be below its limit for 30 consecutive tests (= 1 min).

Results

Detection Performance. In Figure 4 the Hotelling's T^2 statistic is shown as evaluated during the aerobic phases of two batches. Batch 1 is a batch in which the implementation of the control algorithm in LabView was verified without execution of the shut-down control action if commanded. The Hotelling's T^2 statistic remains above its 90% limit until 110 min in the batch. In the following minute, the statistic did not rise above the set limit and the shut-down of the aerobic phase is therefore commanded by the algorithm at 111 min in the aerobic phase (i.e., after 30 consecutive positive tests). Since the command was not passed on to the actuators (aeration, pumps), the Hotelling's T^2 statistic could be evaluated beyond this point in time. As can be seen, the statistic did not rise above the set

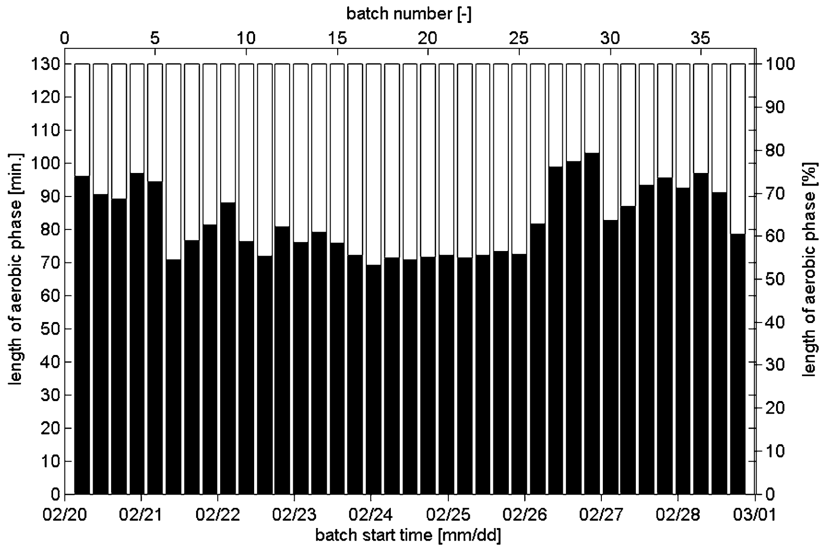

Figure 5. Length of the aerobic phase during active phase length optimization.

limit again. This was equally concluded for three other consecutive batches (not shown).

With respect to the supplied air, the proportional volume of air (and thus energy) that would be saved by the controller amounts to 1.6% (for the test batches). This is a relatively low reduction and is largely due to the fact that a PID controller for the oxygen level was already active in the reference operation. Indeed, it was shown already that the air flow rate is reduced significantly by the PID controller in response to the reduced oxygen consumption by the biomass.

The plant operators also confirm that endogenous respiration was achieved when the end of the aerobic phase is commanded by the controller for these test batches. On the basis of these preliminary tests, it was decided to activate the control algorithm, i.e., to actually execute the shut-down control action when commanded. The Hotelling's T^2 statistic trajectory for the first batch in which the control algorithm was completely activated is also shown in Figure 4. In this batch, the Hotelling's T^2 statistic remains above the 90% limit until 95 min into the aerobic phase. In the minute following this point in time, the Hotelling's T^2 statistic remains below the set limit. As a result, the transition from the aerobic phase to the anoxic phase at 96 min in the aerobic phase is commanded. Consequently, the aeration is switched off and the anoxic filling is started at minute 96, hereby gaining a precious 34 min for denitrification.

For a testing period of 10 days, Figure 5 indicates the time instant at which the aerobic phase was ended and the anoxic phase was started. As can be seen, in each of the 37 batches, the aerobic phase is ended by the controller before its default end, hereby leading to an effective shortening of the aerobic phase in each batch. The mean time at which the aerobic phase was ended was 76 min, i.e., 54 min before the default end of the aeration time. Put otherwise, a mean reduction of 41% of the length of the aerobic phase was obtained. The mean added length for the anoxic phase compared to its default length is 78%.

The saved air volume was estimated by assuming that the air flow rate would remain equal to the air flow rate at shut-down time until the end of the aerobic phase. As such, the fraction of air that is saved is estimated to be 5.3% over the testing period. This is an optimistic value as it can be expected that the respiration rate drops further after reaching the endogenous respiration state. With the same way of estimation, i.e., assuming a constant air flow rate beyond phase shut-down, the estimated reduction would be 2.1% for the batches used during algorithm testing, as opposed to the actual 1.6% observed above.

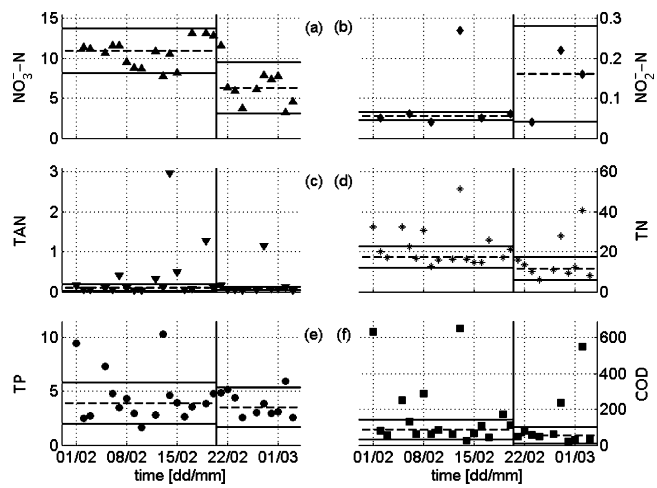

Figure 6. Effluent concentrations before and after controller implementation: (a) NO_3^-−N, (b) NO_2^-−N, (c) TAN, (d) TN, (e) TP, and (f) COD. In each graph, the vertical full line separates the periods before and after the activation of the controller. The horizontal dashed lines indicate the median values in each period. The horizontal full lines indicate the median ± 2(MAD) (mean absolute deviation) values in each period.

System Performance. In Figure 6, the daily measurements of the effluent quality variables nitrate nitrogen (NO_3^-−N), nitrite nitrogen (NO_2^-−N), total ammonia nitrogen (TAN), total nitrogen (TN), total phosphorus (TP), and chemical oxygen demand (COD) are shown from 20 days before implementation of the controller until 11 days after implementation. For descriptive purposes, the medians (MED) of the measurements in the periods before and after implementation are shown together with the medians plus and minus twice the median absolute deviation (MAD) from these medians. The former indicate the central tendencies of the measurements during the respective periods, while the latter are indicators for the spread of the measurements. These descriptors are more robust toward outliers than the classic mean and standard deviations. To evaluate the effect of the controller implementation on the process performance, the two-tailed Mann−Whitney-U statistical test[48] (MWU) is applied to the measured effluent qualities. The two groups are defined as the considered effluent quality

Table 1. *p*-Values and *Z*-Scores for the Two-Way Mann−Whitney-U Test Statistic for Effluent Concentrations of NO_3^-−N, NO_2^-−N, TAN, TN, TP, and COD

pollutant	*p*-value	*Z*-score	pollutant	*p*-value	*Z*-score
NO_3^-−N	0.00018	0.000089	TN	0.0089	0.0045
NO_2^-−N	0.71	0.64	TP	0.94	0.47
TAN	0.28	0.14	COD	0.057	0.028

measurements *before* and *after*, respectively, controller implementation. The null hypothesis for the test is then that there is no difference between the two groups; i.e., that the controller implementation had no effect. This nonparametric test does not assume normality and is less prone to the influence of outliers (in contrast to its parametric equivalent, the Student's *t* test) at the cost of statistical power. The *p*-values as well as the so-called *Z*-scores (for the sample before implementation) are computed. Practically, the latter scores are positive (negative) in the case of a raising (lowering) effect. The null hypotheses are to be rejected at 0.05 (5%) significance level. Results are found in Table 1.

For the effluent nitrate concentrations, the two-tailed MWU test delivers a *p*-value of 0.00018. In other words, the probability that the controller implementation delivers no effect is estimated to be less than 1 in 5000. The negative value for the corresponding *Z*-score indicates that the effect is negative; i.e., the phase shut-down controller has decreased nitrate effluent concentrations. This is visually confirmed in Figure 6a. A 25% reduction is estimated on the basis of the median nitrate values for both periods. Even though visual inspection may suggest higher nitrite values in the period after implementation (Figure 6b), no effect is statistically acceptable on the basis of the MWU test. It is noted that less samples were taken for nitrite concentration measurement, hereby reducing the statistical power of the test. The TAN measurements (Figure 6c) are generally low, which suggests that nitrification is completed during the larger part of the batches both before and after the controller implementation. This hypothesis is accepted on the basis of the two-tailed MWU test (p-value = 0.28). The phase shut-down controller has a lowering effect on the TN values (p-value = 0.0089, negative *Z*-score) as is suggested by visual inspection of Figure 6d. On the basis of the median values, a reduction of more than 30% in effluent nitrogen is computed, which is largely due to the confirmed reduction in nitrate effluent. Indeed, ammonia and nitrite concentrations did not change significantly. Total phosphorus concentrations were not influenced by the phase shut-down controller as can be concluded from both the two-tailed MWU test as from visual inspection (Figure 6e). Though visual inspection of the COD values suggests a lowering and stabilizing effect of the controller on COD (Figure 6f), the MWU test does not reject the null hypothesis and an effect of the controller implementation on the COD concentrations is therefore not considered proven.

Given the former evaluations of effluent quality criteria, the evaluated effects of the controller implementation on the overall performance of the system can be summarized as follows. The implementation of the controller has led to an effective reduction of the effluent nitrate nitrogen and total nitrogen while the levels of ammonia nitrogen, nitrite nitrogen, total phosphorus, and COD before and after controller implementation are not significantly different. It can therefore be concluded that the implementation of the controller has unambiguously led to an overall improvement of the effluent quality.

Discussion

An online phase length optimization strategy is proposed on the basis of the evaluation of a simple multivariate distance measure, the Hotelling's T^2 statistic. By doing so, correlation between variables included in the inference mechanism is directly accounted for, as opposed to the major part of methods for SBR phase length optimization found in literature. In addition, the method avoids the description or modeling of other conditions than the targeted one. As a consequence, the performance is not affected by the path by which the target state is attained. Also, the implementation of the underlying statistical model is straightforward and leads directly to the control decision as opposed to a larger part of applications based on data-driven tools found in literature. Large type II error rates (switching too early to the anoxic phase) were avoided by requiring multiple consecutive positive tests before the actual shut-down decision and by adopting a relatively low confidence limit.

A successful application of our method depends on the following. First of all, the ellipsoidal region defined by the critical Mahalanobis distance must reflect the desired final state for the optimized given phase only. In other words, no other prior status of the process should be characterized by similar data. Signals that allow defining such a region should therefore be available and appropriately selected, in turn requiring sound understanding of the system to be optimized. Second, the algorithm requires the inversion of the covariance matrix, **S**. Thus, this matrix needs to be properly conditioned. If this is not the case, we suggest the use of robust covariance estimators or factorization methods such as principal component analysis[41] to tackle this problem.

The proposed algorithm was successfully tested and led to a mean phase length reduction of 41%. One should note that this number highly depends on the default operation. In our case, the aerobic phase in the original operation was characterized by a 130 min length so to obtain full nitrification by default, on the basis of a heuristic design accounting for large variations in biomass activity. On the basis of Figure 5, one may consider that one should compare our strategy with a fixed, default length of 80 min for the aerobic phase, by which one may achieve similar results as for online phase shut-down controller. Still, such a strategy would not account for changes in load and biomass activity and may lead to incomplete nitrification in some cycles, which favors the use of an online controller such as ours. As indicated before, complete nitrification was of utmost importance.

The estimated proportional reduction in air supply is estimated to be at most 5.3%. As such, improved effluent quality is the predominant factor supporting an implementation of the given phase shut-down controller.

The effluent quality improvement is mainly attributed to the increased lengths of the anoxic phases, which result in reduced effluent nitrate concentrations. Similar observations were made in literature.[13] In another study,[24] a better effluent quality is obtained by extension of the aerobic time resulting from ORP-based control, largely reducing the effluent ammonia concentrations, thus requiring a different bargain between effluent quality and aeration cost. Contrasting to our study, sufficient denitrification is observed in the reference operation in several cases.[30,31,37] The total cycle lengths of the optimized systems are not kept constant in these studies so that an increased loading capacity results. We would expect similar results if for the studied system only a reduction of the aerobic phase length was pursued and not an extension of the anoxic phase to keep the total cycle length constant.

The fact that no effect on the effluent phosphorus concentration is observed requires some further reflection. It is important to note that the studied SBR[42−44] suffers from nitrogen overload which, given complete nitrification and incomplete denitrification, leads to a high nitrate concentration at the end of the cycle. This leads to NO_3^-−N being present at the start of the subsequent cycle scavenging the volatile fatty acids (VFAs) that are essential for phosphorus release. If better denitrification would however occur (e.g., for less challenging influent conditions), more influent VFAs would be available at a start of a new cycle, leading to a true anaerobic state in which phosphorus release can occur.[44] The released phosphorus can then be expected to be taken up again in consequent aerobic phases. Given that the intensified process of phosphorus release and uptake leads to increased growth of PAOs, it can be expected that a longer testing period would have led to improved P-removal. Indeed, very good P-removal was observed for the same SBR system when N-removal was run over NO_2^-−N and much better denitrification performance was achieved.[43]

To be fair, it must be stated that the success of the applied strategy shown here is partly thanks to the fact that the modeling step was performed on data obtained shortly before the actual implementation of the proposed controller. Indeed, the behavior of online measurements during the SBR process cycles is not expected to be quantitatively the same over long periods of time (e.g., due to changes in the microbial population and/or behavior, possibly affecting substrate affinities and growth rates); a larger delay between the modeling and implementation might have led to less convincing results. The automated updating of the applied model is therefore considered for future research. To this end, one may opt for selected batches in which the shut-down decision (to end the aerobic phase) is delayed or suppressed as a whole so as to obtain new data reflecting endogenous respiration at regular intervals. Deactivation of the shut-down controller may ideally be scheduled when optimization is of lesser importance, e.g., when the system is underloaded or when energy costs are minimal. The model updating itself may be based on a moving window approach[49] or based on recursive updating of the covariance matrix.[50]

Conclusions

A controller for online phase length optimization for alternating systems is proposed and evaluated in an online real-life experiment. The newly proposed algorithm integrates the Hotelling's T^2 statistic, commonly used in the field of multivariate statistical process monitoring (MVSPC) with a straightforward control scheme. The resulting controller is simpler than the historically proposed multivariate methods and is not affected by the way the desired state is attained. It was successfully tested on a pilot-scale sequencing batch reactor (SBR) for nutrient removal, in particular for optimization of one of its constituting aerobic phases. A clear proof of concept is given by the effective shortening of the aerobic phase with 41%. Only marginal effects were observed for the air supply, by virtue of a PID controller which already optimizes this aspect of the process. A much larger impact is observed on the effluent quality of the system, which is shown to be improved, especially regarding nitrate nitrogen levels.

It was noted that the underlying assumptions of the applied statistical test are not generally valid. The use of a rather low confidence level and the requirement for a series of consecutive positive tests are two adjustments that minimize the risk of erroneous switching to the anoxic phase. Future research may however aim at the construction and use of (statistical) models that do not violate their underlying assumptions. Also, adaptation of the model to changing system properties may be necessary.

Importantly, the proposed controller is general in nature and is not limited to the reported application nor to the phase that was chosen for optimization. Future applications may therefore be aimed at the optimization of other phases that are typical for the studied SBR and other alternating processes. We underline that effective optimization was possible on the basis of indirect but reliable measurements, indicating that the method is applicable while avoiding the installation of complex and expensive direct sensors for compounds of interest, in casu the nutrients to be removed. The optimization of anoxic (detection of the end of denitrification) or anaerobic (detection of the end of phosphorus release) phases are relevant additional goals when optimizing cyclic nutrient removing systems. More generally, the proposed controller allows optimizing any process with respect to its phase lengths given that the targeted state is uniquely described by data obtained online.

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