Qualitative control for stable and efficient urine nitrification

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Abstract: Low or high nitrite concentrations in urine nitrification reactors prevent an efficient and/or stable operation. By means of in-situ UV-Vis spectrophotometry a precise but inaccurate online nitrite signal can be recorded. However, conventional control algorithms which rely on absolute values fail to optimise and stabilise the process based on such a signal. Therefore we propose a qualitative trend analysis method which can identify the points of interest on this relative signal. In a simulated environment the algorithm enables a rule-based controller to operate a urine nitrification reactor stably and efficiently.

Keywords: nitrite measurement, qualitative trend analysis, signal drift, urine nitrification

INTRODUCTION

Urine nitrification: Urine nitrification is a key process for achieving complete nutrient recovery from source separated urine (Udert and Wächter, 2012). Nitrification halts the volatilisation of nitrogen by oxidising ammonia and it also removes malodourous compounds. Due to a low ratio of ammonia to alkalinity in stored urine, only half of the ammonia can be oxidised. The high concentrations of salt and nitrogen compounds make ammonia oxidising bacteria (AOB) and nitrite oxidising bacteria (NOB) sensitive to disruptions. The current reactor operation controls the pH which is increased by dosing urine and decreased by proton production during nitrification (Fumasoli et al. 2016). Using the pH value as a control measure only addresses the AOB activity, but not the NOB activity. However, a well-balanced activity of AOB and NOB is essential for the overall process stability: even a low accumulation of nitrite can lead to a strong inhibition of the NOB and consequently to a breakdown of the urine nitrification process.

Nitrite measurement and control: In previous studies, in-situ UV and UV-Vis spectral models were calibrated to measure nitrite during urine nitrification (Mašić et al. 2015, Thürlimann et al. 2016). Figure 1 illustrates an example of the nitrite predictions with the latest model and reference measurements as shown in Thürlimann et al. (2016). Despite carefully designed experiments, the nitrite model was not able to give exact values although the signal follows nitrite trends qualitatively. In this study, we provide evidence that conventional control concepts can fail by such inaccurate but precise measurements. More accurate online measurements, however, can only be obtained with prohibitively expensive hardware, which requires intensive maintenance. To still enable the use of faulty signals such as ours, fault tolerant control methods have been proposed (Blanke et al. 2016). They are, however, hampered by *(i)* a lack of redundancy due to limited instrumentation and *(ii)* the slow-changing, gradual characteristics of the faults that occur. For this reason, we propose an alternative control approach based on qualitative trend analysis.

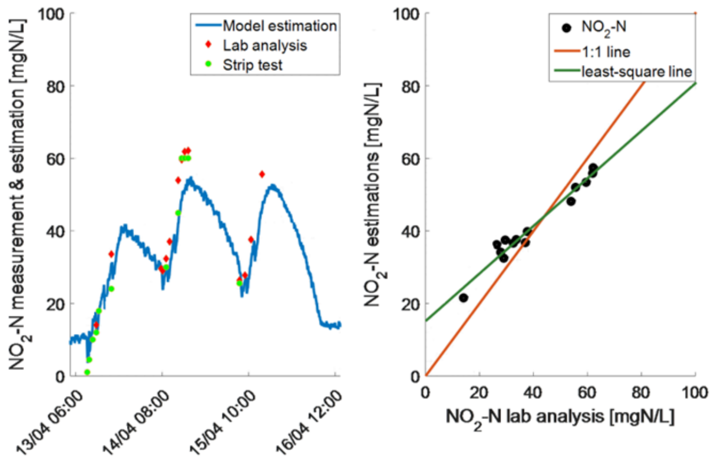

Figure 1: Left: Time series of nitrite measurements and nitrite estimations by in-situ UV-Vis spectra analysis. Red: Lange cuvette test, Green: MQuant™ Nitrite test strip. Right: Comparison of measured and estimated nitrite concentrations from time series (Thürlimann et al. 2016).

METHODS

Model. A simplified two step nitrification model without heterotrophic activity was used to simulate urine nitrification in a 120 L reactor with suspended biomass. This model describes the AOB and NOB by two corresponding biomass concentrations. Both populations have an ammonia and nitrite inhibition term. Moreover, a term for thermodynamic inhibition of AOB at pH 5.4 and below was introduced (Fumasoli et al. 2015). The fed urine has similar concentrations as the male urine described by Fumasoli et al. (2016).

Simulations. The system was brought to pseudo steady-state by simulating 80 days of operation. For the results a ten day operation period was simulated.

Cascade control. In the simulation the implemented controller consisted of two bang-bang controllers in a cascade. The master controller checks the nitrite signal and sets a low pH setpoint range (5.65-5.7) for the slave pH controller in case of high nitrite (>25 mgN/L) or a high pH setpoint range (6.45-6.5) in case of low nitrite (<5 mgN/L). The slave controller in turn, controls the pH within the set range, acting on the inflow pump rate (0 L/d or 70 L/d) to compensate the proton release of the AOB. In the alternative control approach the master controller is replaced by a rule based controller monitoring the results of the signal's qualitative trend analysis. The bang-bang and cascade nature of the control remains unchanged.

Nitrite signal. From day 0 to day 5 the nitrite controller input signal corresponds exactly to the actual concentration. From day 5 on a drift on this nitrite signal is simulated by an offset increasing linearly with time (+2.5 mgNO_2-N/L/d).

RESULTS AND DISCUSSION

Conventional control. Fig. 2 shows the simulated variables relevant to the nitrite inhibition and process control as a function of time. The simulations reveal that the system produces a stable output as long as the measurement does not drift (day 0 to 5 in Fig. 2). However from day 5 on the measurement signal starts to drift resulting in an increasing measurement offset (Fig 2 d). On day 5 the measurement offset is small enough to keep the process working as intended. From day 6 onwards, the offset becomes too large for the controller to successfully act on the process. Despite actual nitrite concentrations below the setpoint the controller does not adjust the pH setpoint range to boost the reactor performance. Even though a stable output in terms of concentrations is produced the hydraulic retention time doubles compared to a perfectly determined system. Thus, operation with such a signal will result in an inefficient use of given reactor volumes. Maintaining a high efficiency is however crucial to preserve a sustainable fertilizer-producing business.

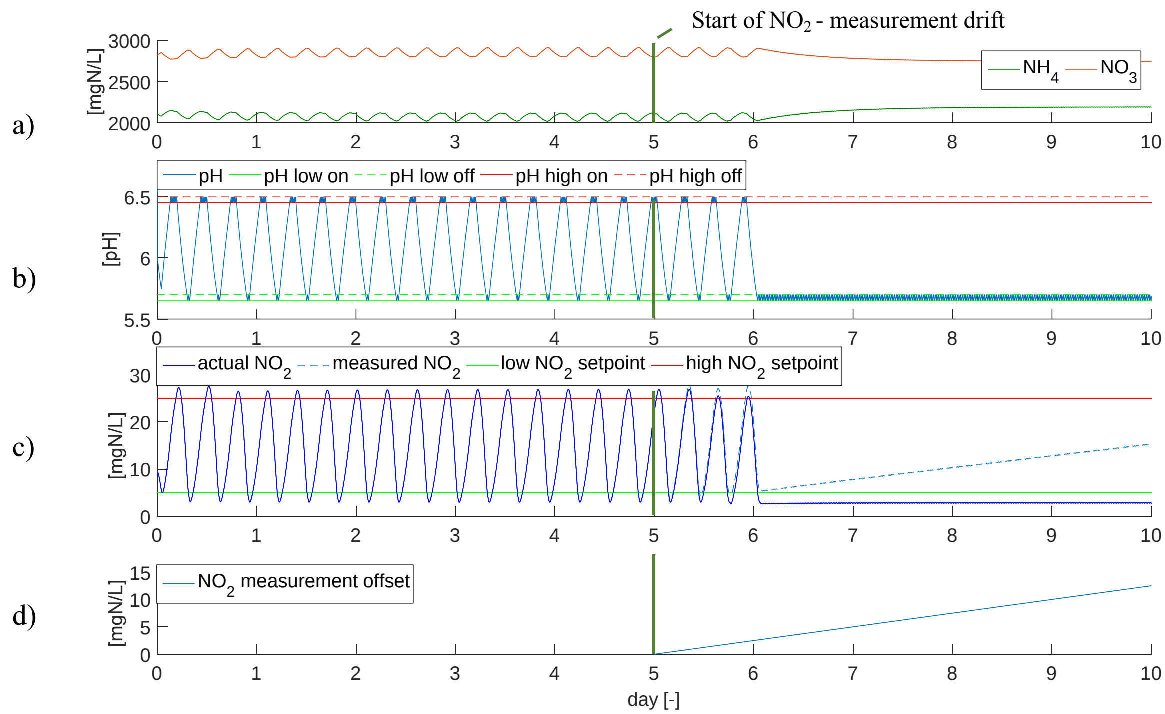

Figure 2: a) NH4 and NO3 concentration. b) pH setpoint ranges and actual pH. c) NO2: Actual concentration, controller input signal (drifts from day 5 on), concentration set-points. d) NO2 measurement offset.

Qualitative based control. We hypothesize that the required intelligence for a successful automation has to come from an alternative signal interpretation. Therefore we implement a controller that will use expert knowledge in combination with the estimated nitrite concentration without any redundant information source to keep the process at a reasonable and stable performance. The algorithm is based on the qualitative state estimation (QSE) algorithm (Thuerlimann et al., 2015). The method detects so called qualitative features such as minimum, maximum, and inflection points. In this particular case we will use inflection points on the drifting nitrite signal.

In Figure 3 visually approximated inflection points on both actual (black arrows) and measured (red arrows) nitrite concentration time series are indicated. These inflection points result from the substrate limitation that the NOB experience at lower nitrite concentrations. As they also occur in the drifting signal, one can use them to identify the end of each nitrite accumulation event.

However, it has to be noted that to obtain these inflection points the sensor and controller have to be designed so that these inflection points appear reliably and at a frequency which has a shorter timescale than the timescale of the signal drift.

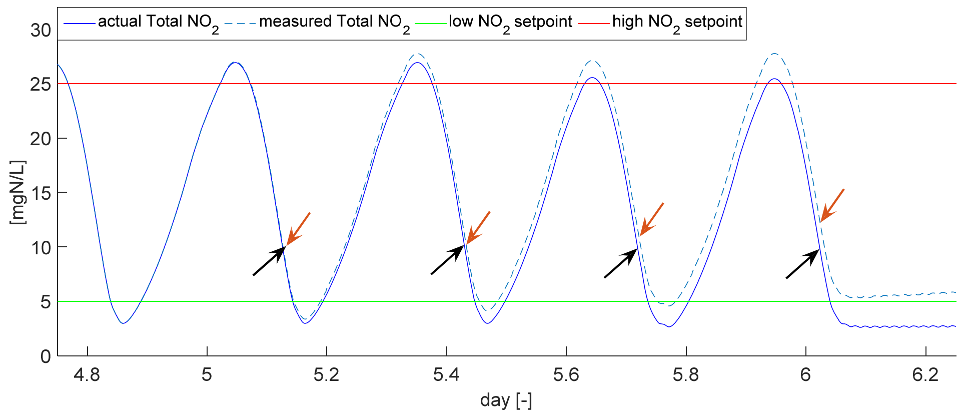

Figure 3: Zoom from Figure 2 c). Actual (blue full line) and measured (blue dashed line) nitrite concentration with visually approximated inflection points. Red arrows for measured signal's inflection points and black for actual concentration's inflection points.

In the currently simulated noise-free drift the identification of the inflection point is relatively easy. However, as shown in Figure 1, the signal is noisy making the identification of a unique inflection point challenging. Therefore additional characteristics of the signal should increase the control effectiveness. One such indication is linked to the identification of a relative stable signal shortly after the inflection point, indicating the stabilisation of the nitrite concentration at a new pseudo steady-state level. This combined indication for low nitrite concentrations replaces the fixed low nitrite setpoint (green line Figure 3) and triggers the controller to increase the pH setpoint range in the slave controller. The high nitrite setpoint (red line Figure 3) is replaced by a maximal difference which the nitrite signal is allowed to increase from the previous registered inflection point.

CONCLUSIONS

This works presents first results for a new method to use inaccurate signals for process control. The relevant information for control is however accurately reflected by qualitative features in the analysed signals. A combination of qualitative information and expert knowledge is proposed to exploit this type of information. Future work will be targeted towards a successful application of the method in a real-world example.

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