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Identifying the performance of on-site wastewater treatment plants

M.Y. Schneider[1,2*], J.P. Carbajal[2], V. Furrer[1,2], K. Villez[2], M. Maurer[1,2]
[1] Institute of Civil, Environmental and Geomatic Engineering, ETH Zürich, Rämistrasse 101, 8092 Zurich, Switzerland
[2] Eawag, Swiss Federal Institute of Aquatic Science and Technology, Überlandstrasse 133, 8600 Dübendorf, Switzerland

* Presenting author: mariane.schneider@eawag.ch
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INTRODUCTION

Decisions made on the degree of centralisation of wastewater treatment systems are often not cost optimal. Eggimann et al. (submitted) found that in particular Austria, Luxemburg, and Switzerland have connected more houses to centralised systems than what economics would suggest. This is partly because the alternative to centralised systems, on-site wastewater treatment plants (WWTP), have a poor reputation due to a lack of continuous performance monitoring.

Un-staffed on-site WWTPs face specific challenges in terms of monitoring and performance evaluation. High frequency sampling is not realistic and online sensors – if used – must be relatively cheap and low-maintenance. However, for operation and maintenance purposes, an online signal indicating the correct functioning of the on-site WWTP is sufficient. In this context, unmaintained model-based proxy sensors can supply valuable information. Similar research has been conducted with a model-based sensing approach for small WWTPs, not considering the aging of the sensors (Aguado et al. 2006). We used completion of ammonium oxidation as information about the absence of ammonium in the effluent and an unterminated oxidation as a possible unit failure. In this paper, we present preliminary results of a sensor model that predicts ammonium effluent concentrations for batch cycles of a pilot scale on-site sequencing batch reactor (SBR) based on signals from low-maintenance online pH sensors. The predictions are compared with the ones from a sensor maintained on a weekly basis. The sensor model can be used for remote monitoring and continuous evaluation of system performance under minimal sensor maintenance conditions.

MATERIALS AND METHODS

Experimental setup: Experiments were conducted in a two population-equivalent SBR (430 L) equipped with multiple sensors and fed with municipal wastewater. Urine was dosed to the feed wastewater to vary the ammonium concentration in a representative range for on-site WWTPs. The *sensor signals* comprise values for pH, oxidation/reduction potential (ORP), optical dissolved oxygen and turbidity (all Endress & Hauser) in a 10 second resolution over a period of 303 days to date. All sensors were deployed minimally in duplicates, with one sensor undergoing maintenance and calibration on a weekly basis and the other with no maintenance whatsoever. In parallel, more than 100 samples of influent and effluent have been analysed for ammonium (FIA).

Unit performance model: Translates the *sensor signals* into *performance variables* (Eq. 1).

$$\textit{performance variables} = \textit{unit performance model}(\textit{sensor signals}) + \textit{Error term} \qquad (1)$$

To date, we have tested the following algorithms for the *unit performance model*: principal component regression (PCR), automatic relevance determination regression, and linear regression with engineered features. We used the Scikit-learn python package (Pedregosa et al. 2011). Here, we report on the so far most promising modelling approach: cycle phase categorisation followed by a PCR analysis of the pH signals. The performance criteria are first complete ammonium oxidation and second ammonium effluent concentration.

RESULTS AND DISCUSSION

Data pre-processing: SBR cycles are automatically categorized into ammonium valley detected and not detected. The ammonium valley is a local pH minimum that occurs during the aeration phase once all ammonium is oxidised to nitrate (Al-Ghusain et al. 1994). The hypothesis was that the presence of the ammonium valley indicates an ammonium concentration below 0.5 mg_N/L.

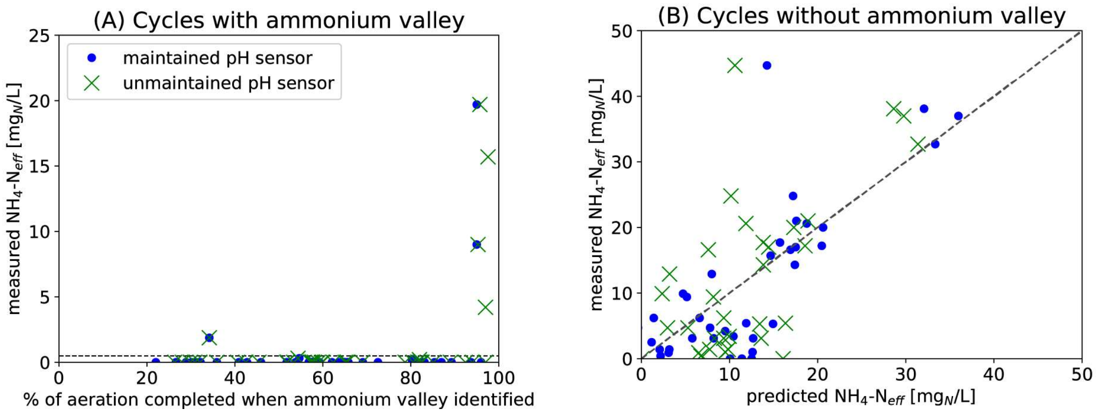

Figure 1: (A - left) Ammonium concentration measured in the effluent against the % of the aeration phase completed when the ammonium valley was identified. (B - right) Measured ammonium concentration in the effluent against the predicted concentration for all cycles where no ammonium valley was detected.

Of the 80 SBR cycles where an ammonium valley was identified automatically, only three of the maintained and five of the unmaintained pH sensor predicted effluent concentrations above 0.5 mg_N/L (Fig. 1A). The misclassifications mostly occurred when the valley was identified at the very end of the aeration phase (close to 100% completion in Fig 1A). This suggests that the time of the occurrence of the ammonium valley could also be used as a feature, which will further improve our prediction.

For the cycles in which no ammonium valley was identified, a PCR with 7 principal components was used to predict the ammonium effluent concentration (Fig. 1B). For the PCR, a Scikit-learn (Pedregosa et al. 2011) variance score of 0.57 was reached for the maintained sensors' data and 0.44 for the unmaintained sensors' data. We find that for predicting the absence of ammonium in the effluent, the performance of the unmaintained sensors is nearly as good as of the maintained ones. However, to predict the ammonium effluent concentration, the variance score shows a better prediction for the maintained pH sensor.

CONCLUSIONS

We have shown that a signal from an unmaintained pH sensor can be used to predict the completion of ammonium oxidation. The PCR shows that the unmaintained pH signal is a strong indicator for the degree of ammonium oxidation. In a next step, we will assimilate signals from other sensor types (ORP, dissolved oxygen and turbidity) to gain insight into the potential for robust monitoring of the biological performance of on-site SBRs and explore the indication for the performance of an entire system of on-site wastewater treatment units.

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